CRANFIELD UNIVERSITY

VARVARA MYTILINOU

A FRAMEWORK FOR PLANNING OF OFFSHORE WIND ENERGY PROJECTS BASED ON MULTI-OBJECTIVE OPTIMISATION AND MULTI-CRITERIA DECISION ANALYSIS

SCHOOL OF ENERGY, ENVIRONMENT AND WATER
RENEWABLE ENERGY MARINE STRUCTURES (REMS)

EngD
Academic Year: 2014- 2018

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This thesis is submitted in partial fulfilment of the requirements for the degree of EngD

ABSTRACT

The wind industry is determined to lower the costs of producing energy in all phases of the offshore wind project. During 2015–2016, projects achieved a levelized cost of energy (LCOE) of £97 and more recently it was announced that Ørsted guaranteed £57.5/MWh. Significant price increases on structural materials directly impact on larger scale wind projects, the overall cost of turbines, establishing effective supply chains, improving the consent procedures for new developments, governmental mechanisms and support, improving grid connections and finally reducing overall uncertainty and costs etc. The most important decisions at the planning stage of new investment are the selection of a profitable, cost-effective suitable offshore location and a support structure type, which greatly impact on the overall Life Cycle Costs (LCC).

This research aims to introduce and apply a scalable framework to reveal and select the optimal offshore location deployment and support structure in Round 3 zones in the UK by considering the interplay of LCC aspects at the planning stage of development.

This research produced a portfolio of five studies while developing the framework above. First, a comparative Political Economic Social Technological Legal Environmental (PESTLE) analysis on wind energy was performed. The analysis focused on Europe, Germany, the UK and Greece, where the UK was selected in this research as the world leader in offshore wind energy.

Second, three state-of-the-art Multi-Objective Optimisation (MOO) algorithms were employed to discover optimum locations for an offshore wind farm. The 7-objective optimisation problem comprises of some of the most important techno-economic LCC factors that are directly linked to the physical aspects of each site. The results of Non-dominated Sorting Genetic Algorithm (NSGA II), NSGA III and SPEA 2 algorithms follow a similar trend, where NSGA III demonstrated its suitability by revealing more uniform and clear optimum non-dominated solutions, also known as Pareto Front (PF), because of its main design compared to the other optimisers. Based on their frequency of appearance in the PF solutions,

Seagreen Alpha, Seagreen Bravo, Teesside C, Teesside D, and the Celtic Array South West Potential development Area were discovered as the most appropriate. Since PF includes solutions from all regions, this provides the developer with the flexibility to accordingly assign costs in different development phases, as required, and to choose whether to invest the available budget on the installation or the maintenance stage of the project.

Third, in order to reveal optimum locations for UK Round 3 offshore zones and each zone individually, three different wind farm layouts and four types of turbines were considered in an 8-objective formulation, where five LCC factors are directly linked to the physical aspects and restrictions of each location. NSGA II discovered Moray Firth Eastern Development Area 1, Seagreen Alpha, Hornsea Project One, East Anglia One and Norfolk Boreas in the PF solutions. Although layouts 1 and 2 were mainly selected as optimum solutions, the extreme case (layout 3) also appeared in the PF a few times. All this demonstrates the scalability and effectiveness of the framework.

Fourth, the effectiveness of coupling MOO and Multi-Criteria Decision Making (MCDM) methods is demonstrated, so as to select the optimum wind farm Round 3 location in order to help stakeholders with investment decisions. A process on the criteria selection is also introduced, and seven conflicting criteria are considered by using the two variations of Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS) in order to rank the optimum locations that were discovered by NSGA II. From the prioritisation list, Seagreen Alpha was found as the best option, three times more preferable than Moray Firth Eastern Development Area 1.

Fifth, experts' opinions were employed in an MCDM process to select the support structure type in an offshore wind farm. For comparison, six deterministic MCDM methods and their stochastic expansion were employed; WSM, WPM, TOPSIS, AHP, ELECTRE I and PROMETHEE I in order to account for uncertainties systematically. It was shown that the methods can relate to each other and can deliver similar results. The jacket and monopile support structures were ranked first in most deterministic and stochastic approaches.

Overall, the effectiveness of the introduced research framework to meet the aim of the research is demonstrated. The framework combines a) a prototype techno-economic model for offshore wind farm deployment by using the LCC and geospatial analysis, b) MOO by using NSGA II and c) survey data from real-world experts within MCDM by using a deterministic and stochastic version of TOPSIS.

Keywords:

Decision-Making, LCC, PESTLE, Round 3, support structure, stochastic TOPSIS

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

A	Area of the wind turbine (m)
A	Pairwise comparison matrix
A^{+}	The positive ideal solution
A^{-}	Negative ideal solution
A_j	Alternative j
A_l	Alternative k
A_k	Alternative l
A^{*}_{WSM}	Weighted Sum Score
AHP	Analytical Hierarchy Process
AHP_i	Score of the i-th alternative
ANP	Analytical Network Process
BMU	Federal Ministry for the Environment, Nature Conservation and Nuclear Safety
BMWi	Federal Ministry of Economics and Technology
BSH	Federal Maritime Hydrography Agency
BWE	German Wind Association
$C(hSk)$	Concordance Matrix
C_{comm}	Commissioning of the wind turbines and electrical system Cost (£)
$C_{contingency}$	Contingency Cost (£)
$C_{D\&D}$	Decommissioning and Disposal Cost (£)
C_{decom}	Decommissioning Cost (£)
C_{eng}	Engineering Activities Cost (£)
$C_{I\&C}$	Installation and Commissioning cost (£)
$C_{I\&C\text{-}comp}$	Installation of the Components Cost (£)
$C_{I\&C\text{-}ins}$	Construction Insurance Cost (£)
$C_{I\&C\text{-}port}$	Port Related Cost (£)
C_j	Relative closeness to the ideal solution of each alternative
C_{legal}	Legal Cost (£)
$C_{monitoring}$	Monitoring Cost (£)
$C_{O\&M}$	Operation and Maintenance cost (£)
C_p	Power coefficient

$C_{P\&A}$	Production and Acquisition cost (£)
$C_{P\&C}$	Predevelopment and Consenting cost (£)
C_{postM}	Post-monitoring Cost (£)
C_{projM}	Project Management Cost (£)
C_{PTS}	Electricity Transmission Cost (£)
C_{SC}	Site Clearing Cost (£)
C_{SS}	Support Structure/Foundation Cost (£)
$C_{surveys}$	Survey Cost (£)
C_{WM}	Waste Management Cost (£)
C_{WT}	Wind Turbine Procurement Cost (£)
CAPEX	Capital Expenditure (£)
CfD	Contracts for Difference
CFD	Computational Fluid Dynamics
CI	Consistency Index
CMAES	Covariance Matrix Adaptation Evolution Strategy
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide equivalent
d_{max}	Maximal difference between the performance of alternatives
D	Wind turbine diameter (m)
$D(hSk)$	Dis-concordance matrix
D_j^+	Separation from the positive ideal solution
D_j^-	Separation from the negative ideal solution
DECC	Department for Energy and Climate Change
EEA	European Energy Association
EEG	Renewable Energy Act (translation from German)
EEPR	European Energy Programme for Recovery
EEZ	German Exclusive Economic Zone
ELECTRE	ELimination Et Choix Traduisant la REalité
Energiewende	Germany’s energy transition
EREC	European Renewable Energy Council
EMO	Evolutionary Multi-Objective
EWEA	European Wind Energy Association
f_{ij}	i-th criterion value for alternative A_j

FiT	Feed-in-Tariff
FSOWA	Fuzzy Stochastic Ordered Weighted Averaging
GDE3	Third evolution step of Generalised Differential Evolution
GIB	Green Investment Bank
GIS	Geographic Information System
GWEC	Global Wind Energy Council
HES	Hybrid Energy System
i	Index of criteria
I'	Set of benefit criteria
I''	Set of cost criteria
IBEA	Indicator-Based Evolutionary Algorithm
j	Index of alternatives
l	Set of criteria
l'	Set of criteria that belong to the concordant coalition
LCC	Life Cycle Cost
LCOE	Levelised Cost of Energy (£/MWh)
m	Total number of alternatives
MCDM	Multi-Criteria Decision Making
MCHP	Multi-Criteria Hierarchy Process
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
MOO	Multi-Objective Optimisation
n	Total number of criteria
NIMBY	Not In My Back Yard
NPV	Net Present Value
NREAP	National Renewable Energy Action Plan
NSGA	Non-dominated Sorting Genetic Algorithm
NWT	Number of turbines
OMOPSO	Optimised Multi-Objective Particle Swarm Optimiser
OPEX	Operational expenditure (£)
OSGeo	Open Source Geospatial Foundation
OWF	Offshore Wind Farm
OWPB	Offshore Wind Programme Board
$p(x)$	Preference function for evaluation of x

P	Power extracted (W)
P_R	Rated power (W)
PAES	Pareto Archived Evolutionary Strategy
PESTLE	Political Economic Social Technological Legal Environmental
PF	Pareto Front
PPA	Power Purchase Agreement
PPC	Public Power Corporation
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
r_{hj}	Performance of the i-th alternative against the j-th criterion
r_{ij}	Normalised value of j-th alternative and i-th criteria
$R\left(\frac{A_k}{A_l}\right)$	Pairwise comparison between alternative k and alternative l
RE	Renewable Energy
RES	Renewable Energy Sources
RI	Random Index
RO	Renewables Obligation
ROC	Renewable Obligation Certificate
s	Indifference for each evaluation x
$s + r$	Preference for each evaluation x
SBX	Simulated Binary Crossover
SCADA	Supervisory Control And Data Acquisition
SET Plan	Strategic Energy Technology Plan
SMPSO	Speed-constrained Multi-objective Particle Swarm Optimisation
SPEA	Strength Pareto Evolutionary Algorithm
TIC	Total Installed Capacity (W)
TLP	Tensioned Leg Platform
TOPSIS.	Technique for the Order of Preference by Similarity to the Ideal Solution
TRL	Technology Readiness Level
u	Mean annual wind speed of each specific site (m/s)
UNCLOS	Under the United Nations Convention on the Law of the Sea
VDMA	Verband Deutscher Maschinen und Anlagenbau
VEGA	Vector-Evaluated Genetic Algorithm

VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
w_j	Weight of the j-th criterion
W	Weight vector
WPM	Weighted Product Method
WSM	Weighted Sum method
ZDA	Zone Development Agreements
a_{ij}	Actual value of the i-th alternative in terms of the j-th criterion
λ_{max}	Maximum Eigen value
v_{ij}	Normalised weighted value
v_n^+	Normalised weighted value for the positive ideal solution
v_n^-	Normalised weighted value for the negative ideal solution
$\pi(a,b)$	Preference degree between alternatives a and b
ρ	Air density (kg/m^3)
Φ^+	Outgoing flow
Φ^-	Incoming flow
Φ	Net flow

1 INTRODUCTION

1.1 Background

In the last few decades, a necessity to reduce carbon emissions has been raised after concerns about the global warming effect that causes rapid changes in the environment. The awareness around the environmental impact led to further alternative ways to generate energy for more sustainable solutions. According to the 20-20-20 target on reducing carbon emissions and the new Climate Conference in Paris (COP 21) on keeping the global warming temperature below 2°C, it is important to contribute to the Renewable Energy (RE) investment growth in the UK by making the investments more attractive, information-rich and less risky [1].

Wind energy's future seems to keep growing as 18GW would be deployed by 2020 in the UK. Even after 2020, there is still a high potential to increase wind developments. Thus, there is a great need to reduce the cost of energy considerably according to [2]. It is important to identify cost reduction strategies to achieve the cost reduction goals. The future of the UK's industry size strongly depends on these goals [3]. Currently, in the first quarter of 2018, 1,716 offshore turbines are deployed in 32 offshore operational projects of an overall capacity of 6,713.520 MW [4].

Significant price increases in the overall cost of turbines, their operational and maintenance costs have a direct impact on large-scale wind projects. In general, wind energy industry is determined to lower the costs of producing energy in all phases of the wind project from predevelopment to decommissioning. The UK technology roadmap highlights that the offshore wind should be reduced below £100/MWh by 2020 and greater confidence over financial motivation is required [2]. According to [3] the costs were stabilised at £140 per MWh in 2011. Recently, the UK's Offshore Wind Programme Board (OWPB) stated that the offshore wind costs dropped below £100/MWh. More specifically, it was stated that 2015-16 project achieved a Levelised Cost of Energy (LCOE) of £97 compared to £142 per MWh in 2010-11, according to the Cost Reduction Monitoring Framework report in 2016 [5]. Recently, in 2017, Ørsted (formerly DONG Energy) guaranteed a £57.5/MWh building the world's largest offshore wind farm in Hornsea 2, according to [6].

In general, there are numerous challenges that the industry faces such as developing larger turbines, establishing effective supply chains, improving the consent procedures for new developments governmental mechanisms and support, improving grid connections and finally reducing overall uncertainty and costs etc. The most important decisions at very early stages of new investment are the selection of a profitable, cost-effective suitable offshore location and support structure type. The most important costs in an offshore wind farm can be found in [7]. The location of a wind farm and the type of support structure have great impacts on the overall Life Cycle Costs (LCC). Overall, appropriate studies should be conducted at the early development stages of the project in order to avoid disruptions, minimise the investment risk and finally provide decision makers and developers with further options.

The Crown Estate released Round 3 leases and provided nine new considerably larger zones than Round 1 and 2; offshore wind farm zones will include up to 32GW of power capacity. The new leases encourage larger scale investment plans and bigger wind turbines. The zones were identified and selected by consultation with key stakeholders. There are many successful bidders that agreed to the Zone Development Agreements (ZDA) with the Crown Estate, who are co-investing along with the developers up to the point of consent. On top of that, the Crown Estate placed a contract manager in every zone developer's office [8]. The new zones include locations further away from the shore and deeper waters which could be more challenging [9-13]. Round 3 was released in order to provide exclusive development rights and encourage a number of multi-project zones.

The site selection crucially contributes to the financial returns of an offshore wind project, as it impacts on the access, construction, ongoing operations, maintenance and overall safety of the project [14]. Offshore wind energy costs are significantly higher than onshore because of the project size and installation.

Thus, the logistics of such a project are more complex [15]. The wind also impacts significantly on the economics of the wind farm. Therefore, there is a need to maximise the production of energy, minimise the equivalent capital and operational costs, and also consider each individual offshore site constraints. The site constraints and the overall costs are all subject to a level of uncertainty and therefore, an optimisation process is needed to achieve optimum solutions. [15].

As wind farm sizes are increasing and getting further away from the shore, installation and infrastructure costs are also increasing [16]. As mentioned above, according to the UK technology roadmap [2], actions must be taken in order to reduce the overall offshore wind costs. Through an extensive literature review, it was found that there is also a need to a new transferable and integrated methodology taking into account technical and economic factors in order to benefit the decision-making process for both academic and industrial applications. At the moment, there are several countries that are developing offshore wind plans outside Europe, as stated in [17]. The present research can be applicable to these countries, because the wind industry is in its infancy and there is increased potential for future developments.

In order to deal with the problems suggested in literature, a scalable framework was introduced, so as to reveal and select the optimal offshore location deployment and support structure in Round 3 zones in the UK by considering the interplay of the life cycle aspects at the planning stage of an offshore wind development.

The research is divided in five individual journal publications as described below. First, an extensive comparative multi-disciplinary policy review in wind energy developments both in Europe and three individual countries was implemented. A Political Economic Social Technological Legal Environmental (PESTLE) analysis, was conducted in order to investigate the wind energy sector, so as to select the most appropriate country to apply the suggested framework. PESTLE analysis offered a wider perspective of the wind energy sector in Europe, the UK, Germany and Greece, identified stakeholders while revealing opportunities and challenges in wind farm developments and served as a guide for future studies. The UK was selected in this research as the world leader in offshore wind energy.

Following the selected country, a comparative Multi-Objective Optimisation (MOO) by using three state-of-the-art algorithms (Non-dominated Sorting Genetic Algorithm II (NSGA II), NSGA III and Strength Pareto Evolutionary Algorithm 2 (SPEA 2)) was conducted in order to discover optimum locations for an offshore wind farm in the UK and verify that MOO methods could generate results when coupled with LCC. The problem consists of 7 objectives that include some of the most important techno-economic LCC factors that are directly linked to the physical aspects of each site in order to reveal the interplay between CAPEX and OPEX. The results of the algorithms follow a similar trend and based on their frequency of appearance in the Pareto Front (PF) solutions, Seagreen Alpha, Seagreen Bravo, Teesside C, Teesside D, and the Celtic Array South West Potential development Area were discovered as the most appropriate.

Next, a techno-economic optimisation based on the full LCC of an offshore wind project in the UK was conducted in order to reveal the optimum locations from selected UK Round 3 offshore zones and from each of these zone individually. In addition, in this part of the study, three different wind farm layouts were also considered in an 8-objective optimisation problem instance, which extends the previous formulation by considering disposal and decommissioning costs, that directly links the LCC to the physical aspects and restrictions of each location. The NSGA II algorithm was used in this case and Moray Firth Eastern Development Area 1, Seagreen Alpha, Hornsea Project One, East Anglia One and Norfolk Boreas were discovered in the PF solutions. On top of that, although layouts 1 and 2 were mainly selected as optimum solutions, the extreme case (layout 3) also appeared in the PF.

A framework is introduced to select the most appropriate offshore wind farm location for deployment among the optimal locations that were discovered from the previous research. Hence, this couples the previous MOO formulation and a Multi-Criteria Decision Making (MCDM) method. A detailed process on the criteria selection is also introduced, and seven conflicting criteria are considered by using the two variations (deterministic and stochastic) of Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS) in order to rank the optimum locations that were discovered by NSGA II. From the prioritisation list, Seagreen Alpha was found as the best option.

Finally, experts' opinions were employed in a comparative study of MCDM methods under stochastic inputs in order to select the most suitable support structure type in an offshore wind farm among a list of both floating and fixed designs. For comparison, six deterministic MCDM methods and their stochastic expansion were employed in order to deal with uncertainty. The jacket and monopile support structures were ranked first in most deterministic and stochastic approaches.

Overall, the framework of this research combines a prototype techno-economic model for offshore wind farm deployment by using LCC factors, MOO and survey data from real-world experts by using a deterministic and stochastic version of MCDM.

1.2 Aims and Objectives

This research aims to develop and apply a scalable framework to reveal and select the optimal Round 3 offshore location deployment and support structure type by considering the interplay of life cycle aspects at the early stages/planning of development.

The contribution to knowledge is demonstrating the effectiveness of a framework that combines a prototype techno-economic model for offshore wind farm deployment by using the LCC and geospatial analysis, MOO by using NSGA II, survey data from real-world experts within MCDM by using a deterministic and stochastic version of Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS). Also, a criteria selection process for the implementation of MCDM methods has been devised. The outcomes are expected to provide a deeper insight into wind energy sector for future investments.

The aim will be achieved by delivering the following objectives:

1. Perform a Political Economic Social Technological Legal Environmental (PESTLE) analysis in Europe and three European countries in order to categorise the vital factors affecting the wind energy sector and to reveal opportunities and challenges in the development of wind farms.
2. Implement a prototype model based on LCC analysis and GIS in order to estimate the basic costs of an offshore wind farm by capturing the related resources, operations and geospatial aspects at the planning stage of a project.
3. Perform MOO in Round 3 offshore locations by linking the previous model to 3 state-of-the-art optimisers in order to compare the effectiveness of the optimisers, discover non-dominated solutions and reveal the interplay among conflicting objectives.
4. Extend the optimisation problem by adding constraints and investigate three different offshore wind farm layouts in order to reveal and assess cost-effective and non-dominated solutions. Also, assess the results by conducting a sensitivity analysis.
5. Link the output of the MOO to an MCDM method (deterministic and stochastic variations), in order to prioritise the previously discovered optimum solutions by considering experts' insights.
6. Compare and discuss the effectiveness of six MCDM methods applied to a reference case in order to demonstrate the suitability of the methods in a real-world problem and identify the most appropriate offshore support structure type under uncertainty.

1.3 Structure

The following pages present the outline of the framework which is a portfolio of five individual studies. Next, the results of each study are demonstrated. The conclusions include a summary and key findings, the contribution and further research.

Separately, the portfolio of the five studies follows in their original form as they were published in scientific journals.

1.4 List of publications

Throughout this research, the following publications were produced:

- Mytilinou, V.; Kolios, A.J.; Di Lorenzo, G. A comparative multi-disciplinary policy review in wind energy developments in Europe. *International Journal of Sustainable Energy* **2015**, 1-21.
- Kolios, A.; Mytilinou, V.; Lozano-Minguez, E.; Salonitis, K. A comparative study of multiple-criteria decision-making methods under stochastic inputs. *Energies* **2016**, *9*.
- Mytilinou, V.; Kolios, A.J. A multi-objective optimisation approach applied to offshore wind farm location selection. *Journal of Ocean Engineering and Marine Energy* **2017**, 1-20.
- Mytilinou, V.; Kolios, A.J. Techno-economic optimisation of offshore wind farms based on life cycle cost analysis in the UK. *Renewable Energy* **2018**, 132, 439-454.
- Mytilinou, V.; Kolios, A.J. A framework to select optimum offshore wind farm locations for deployment. *Energies Special Issue "Optimisation Models and Methods in Energy Systems"* **2018**, 11, 1855.

2 METHODOLOGY

A portfolio of studies to develop the framework of this research is depicted in Figure 2-1, which consists of 5 individual studies, where modules from 1 to 5 are described, and the most important aspects/findings are shown. All five parts of this work are linked together in order to form a framework that results in the optimum selection of an offshore location and support structure type in Round 3 zones in the UK. The framework of this research is depicted in Figure 2-2, where the breakdown is illustrated in modules A to H.

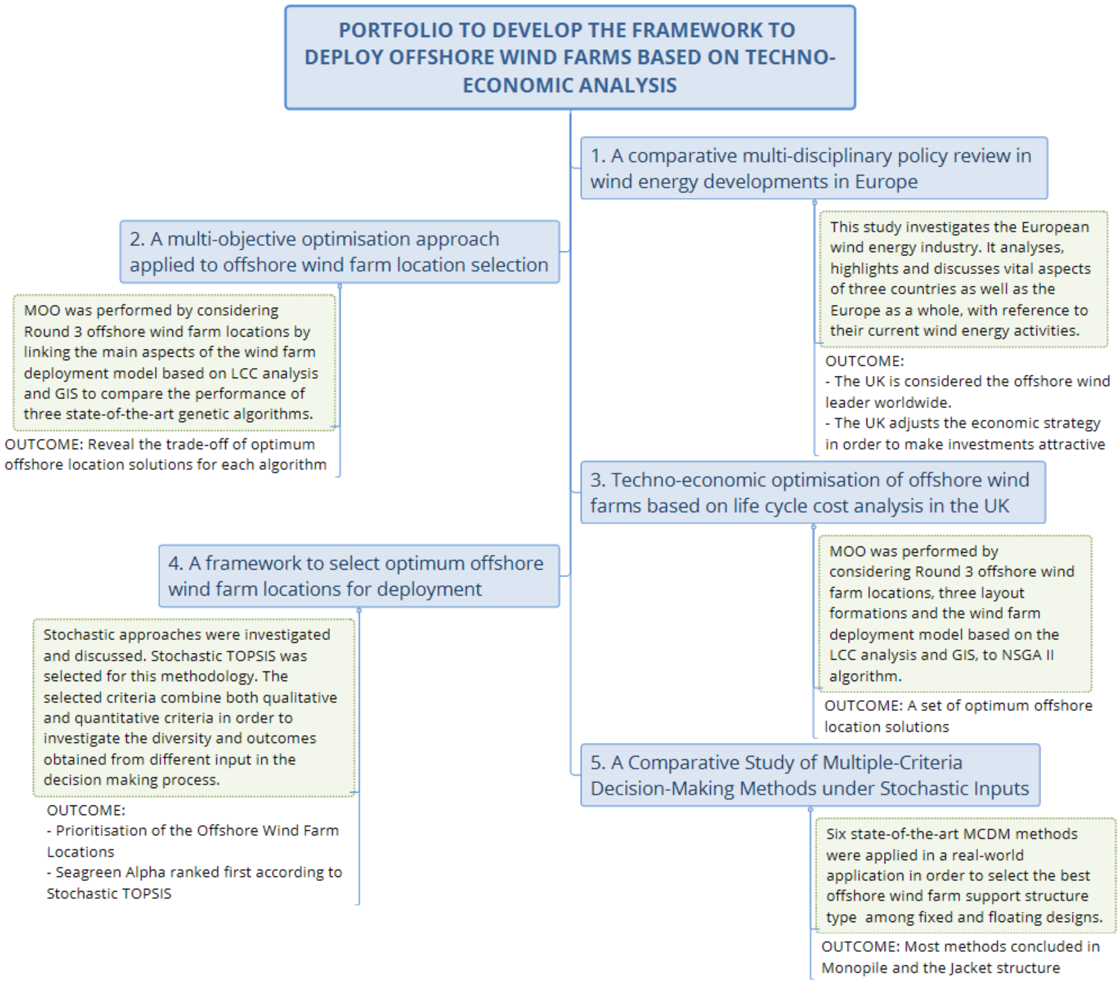

Figure 2-1 Portfolio of studies

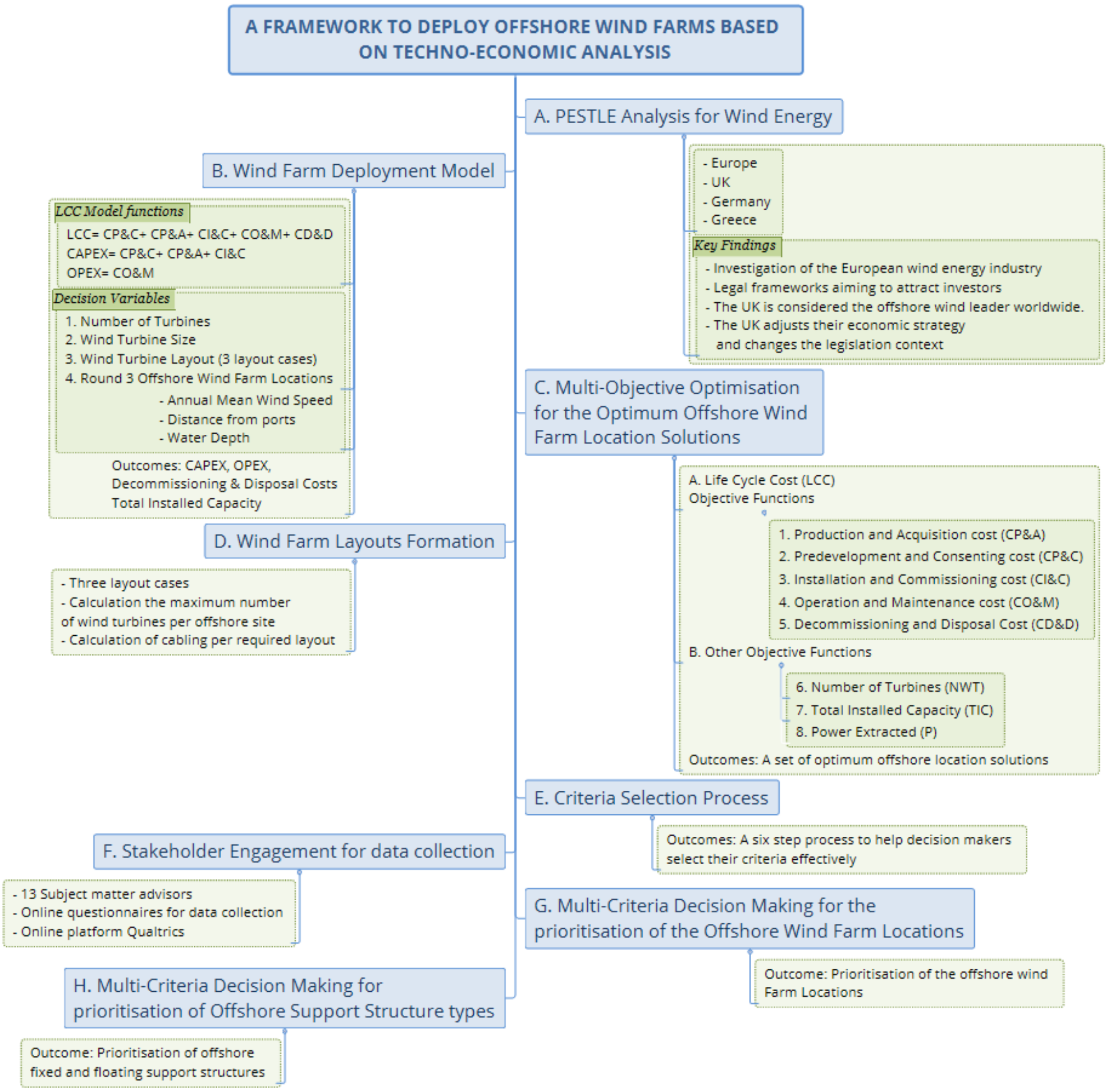

Figure 2-2 Framework outline

2.1 A comparative multi-disciplinary policy review in wind energy developments in Europe

Europe approaches a new era where opportunities for developments are becoming challenging. For that reason, the need for carefully designed, improved policies is increasing. In [18], a Political Economic Social Technological Legal Environmental (PESTLE) analysis, as shown in Figure 2-3, has been conducted in order to investigate the wind energy sector in three different European countries and the European environment, so as to select the most appropriate country to apply the suggested framework. PESTLE analysis offers a wider perspective of the wind energy sector in Europe, the UK, Germany and Greece, identifies stakeholders while revealing opportunities and challenges in wind farm developments and serves as a guide for future studies. This study is a part of the framework that refers to module 1 in Figure 2-1 and module A in Figure 2-2.

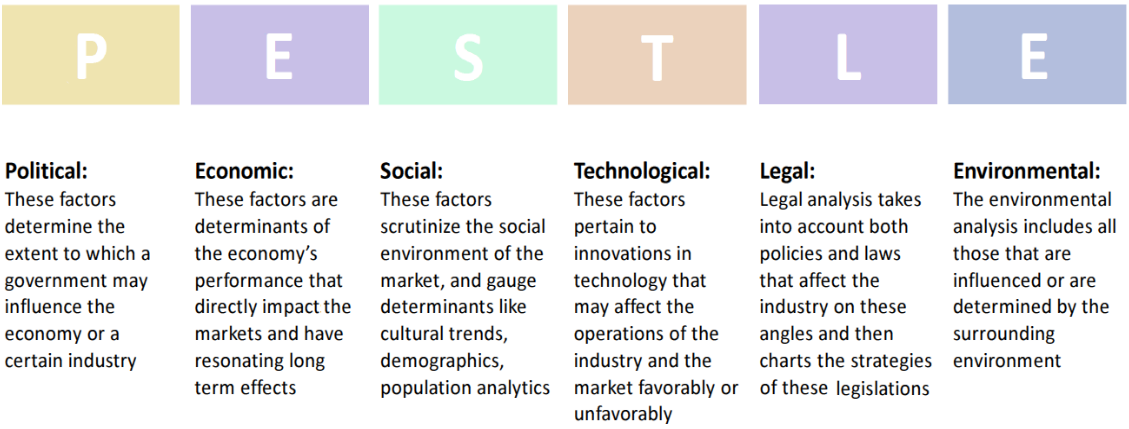

Figure 2-3 PESTLE Analysis

PESTLE analysis investigates vital aspects of the environment in which the wind industry operates. Europe has many years of collective experience regarding technology and policy insight, which could be disseminated to future developments.

The above countries were selected because of the current growth in their wind energy installations, suitability for the renewable energy systems to work, and their investment potential. Advantages and disadvantages concerning the renewable resources are presented. This study will assist in understanding the dynamics of the problem, and it could be used to provoke further research directions.

Although the European countries have all made several improvements in the areas of PESTLE, they still have to make many more over the coming years. All countries have made many improvements in their legal frameworks to try to attract investors and boost the RE sector. At the moment, Europe is considered to be a global forerunner in offshore wind energy regarding the total installed capacity. European Union countries are committed to increasing the production of electricity from RE from 10% in 2008 to 20% by 2020. In order to achieve that, the EU’s target for offshore wind installations for 2020 is 40,000 MW. According to EWEA in [19], even though the 2020 targets contain a well put forward policy guidance, there is no legislative framework to propose a plan for at least the next 30 years.

The UK’s location offers the most favourable natural resource for using wind energy [20]. Wind resources in the UK’s waters are outstanding and very suitable for wind farms. Under the United Nations Convention on the Law of the Sea (UNCLOS), nations are allowed to conduct studies or projects in the water less than 200 miles away from the mainland or halfway in waters that are less than 400 miles from other borders [20].

Currently, the UK is considered to be the world’s leader in offshore wind energy concerning the total installed capacity. Wind energy makes a substantial contribution to the UK’s energy market. Offshore wind applications are controlled by the UK government itself. However, there are many additional barriers because of the decentralised governments of Northern Ireland, Wales and Scotland that contribute to the process [20]. For all offshore installations, the government has the authority to grant permission for the application to proceed. Nevertheless, for most onshore installations, the local authorities have the leading role in the future of the projects. If an onshore wind project is bigger than 50 MW, then the central government is the one that needs to give its consent; however, the central government does not own the seabed where the offshore applications are being installed. The Crown Estate that belongs to the Monarchy is the owner of the UK’s seabed, makes a profit from all the offshore installation leases without significant taxation and at the same time supports the Treasury [20-23]. The Crown Estate owns most of the nearshore (over 50%) and offshore up to 12 nautical miles. It also owns the rights to produce electricity from the waves, wind and tides according to the Energy Act 2004 [24,25]. When the lease period given by the Crown Estate is due, the wind farm operators have the choice to repower[1] their turbines [26].

[1] to upgrade old wind turbines

According to the UK Roadmap in 2011 [2], UK's actions are based on the already scheduled arrangements, such as the financial support mechanisms for renewables, helping companies to secure investment in green infrastructure by the Green Investment Bank (GIB), and encouraging the development of new offshore wind manufacturing facilities at port sites.

As the UK's Electricity Market Reform White Paper announced, along with the UK Roadmap, in 2011, it has been decided to isolate both the Great Britain and Northern Ireland markets regarding power production, creating more investment opportunities.

During the past years, the UK has made new, ground-breaking policies to ensure the RES progress, designing policies, regarding the offshore wind applications. These are distinctive and different compared to the other countries in Europe because of the 'criteria-based' tactics to support offshore developments. The Crown Estate's role in the RE legislation, and especially the offshore wind application's developments, is vital [24,25].

Germany is considered the leader in Europe in wind power exploitation. As stated by the German Wind Association (BWE) and Verband Deutscher Maschinen und Anlagenbau (VDMA) Power systems, the onshore wind turbine market keeps expanding. Wind energy generation is estimated to grow to 45,000 MW by 2020, 65,000 MW by 2030, 80,000 MW by 2040 and 85,000 MW by 2050 [27]. The German government is planning to adopt RESs, mainly wind power, to supply the country. This would account for 80% of the overall electricity production by 2050 [28]. The energy requirements will increase to 20% by 2020 and 50% by 2050 in comparison to the 2008 levels, with 10% and 40% contribution from transportation respectively and addition of around six million electric vehicles by 2030 [29].

Among other political actions, Germany has also developed appealing investment policies for offshore wind energy farms [24]. Germany prefers to place its offshore wind turbines at a greater distance, that is, 40 km, from the shoreline, compared, for example, to the UK and Denmark at about 17 km. The country's decision to also change the depth limits stems from an attempt to preserve the land so as to maintain tourism, and retain shipping routes and fishing areas [30]; however, that causes difficulties during construction, with depths that reach 30 m next to the standard 23 m used in Europe. In addition, the weather conditions further from the shore become worse and set restrictions on the time the construction can take place. Germany aims high regarding the EU targets, but the additional RE changes have proved to be challenging.

Greece has great wind energy potential, however, the wind energy applications are underdeveloped in the country. According to [31], Greek seas meet all the essential requirements and show huge potential for offshore wind farms, especially close to the shore. Although Greece has improved many aspects of its legislation, many problems and a lack of coordination still exist. In addition, the financial instability has created an undefined and unpredictable future for the renewable energy sector. For that reason, the need for carefully designed; improved policies are increasing. Greece is a country with many islands and a long coastline with strong winds, which favour the evolution of wind energy. Unfortunately, only 13.6% of the total electricity demands of Greece comes from RESs [32]. Achieving the 20-20-20 targets is both an obligation and an opportunity for the Greek government that can guide towards energy safety, emission reduction, investment attraction, financial development and technical know-how. The legal obligations make Greece's RES market long-lasting, trustworthy and stable for potential investments.

Energy from renewables can be generated at competitive costs. The outstanding wind resources in Greece with a profile velocity that can exceed 8–11 m/s and about 2500 hours of wind in several parts of the country makes it one of the most desirable places to invest [33]. Unfortunately, according to [34], its financial crisis has caused many energy projects to be delayed or indefinitely postponed these last few years. However, the current situation is encouraging for new projects such as an interconnected system between the Greek islands. The energy market in Greece is going through some changes and is being considered as an energy hub for Southeast Europe by deregulating the production, transmission and distribution of energy, and, by starting a campaign for RESs, attracting new investment [35].

Overall, many areas have been covered with onshore wind turbines, and many more are to be installed offshore in the UK. Although in Germany most of the suitable land has already been covered and more wind installations are becoming harder to develop, the wind energy generation is still expected to grow [27]. On the other hand, Greece has considerable amounts of suitable land, but only a few wind projects have been installed. All countries have made recent changes to their RE policies in order to assist the energy market to grow and at the same time to attract investors that will eventually lead to energy independence. All EU countries are willing to meet or even go beyond the 2020 targets. Finally and most importantly, all of them still face problems on their way to energy security.

This research focuses on the UK only. The UK is considered to be the worldwide leader in offshore wind energy and the country's legal framework keeps improving and persistently moving towards new offshore plans. Offshore wind energy is investigated because it is a mature technology and shows great potential to grow in the UK.

2.2 A multi-objective optimisation approach applied to offshore wind farm location selection

Towards the deployment of a wind farm development model, a comparative study based on open-source tools, implemented in python has been created for Round 3 locations based on state-of-the-art literature shown in Figure 2-4. This was integrated into three evolutionary-based algorithms NSGAII, NSGA III and SPEA2 (selected for their performance in MOO cases and proven ability to handle the complexity of real-world problems). It is expected to assist developers and researchers at the planning stage of a wind farm by demonstrating the potential cost benefits when altering the number of turbines, turbine size and area specifications of Round 3 offshore locations. More specifically, [36] show a 7-objective optimisation problem that comprises of some of the most important techno-economic Life Cycle Cost related factors that are directly linked to the physical aspects of each site such as the wind speed, the distance from the construction ports and the water depth. By comparing the outcomes of these three algorithms, deeper insight was provided into practices to conduct planning, so as to support decision making in future investments in the wind energy sector.

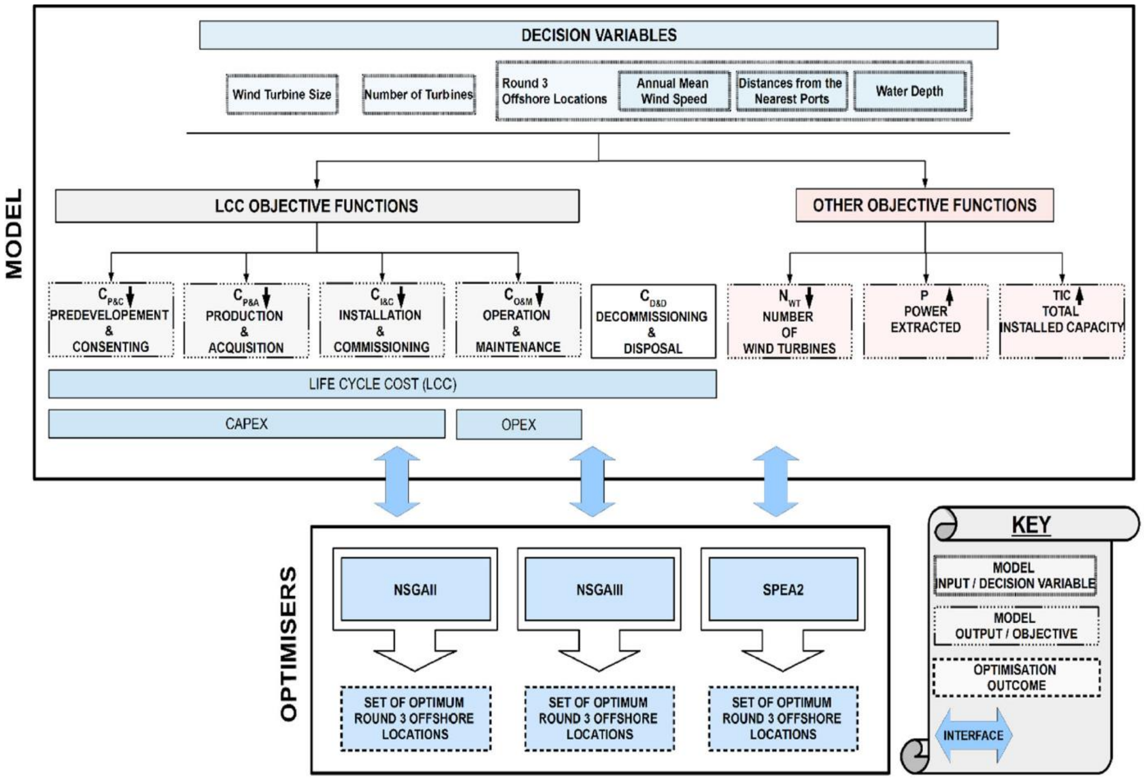

Figure 2-4 Methodology to assess the optimisers linked to the LCC

This study is a part of the framework that refers to module 2 in Figure 2-1 and modules B and C (excluding the Decommissioning & Disposal Cost calculations and the layout variables) in Figure 2-2. The Round 3 offshore wind farm zones considered for this part of study around the UK are listed in Table 2-1, which are illustrated on a map in Figure 2-5 by using QGIS.

Table 2-1 Round 3 offshore wind farm zones around the UK

Zone	Wind farm site name
Moray Firth	Moray Firth Western Development Area
Moray Firth	Moray Firth Eastern Development Area 1
Firth of Forth	Seagreen Alpha
Firth of Forth	Seagreen Bravo
Dogger Bank	Creyke Beck A
Dogger Bank	Creyke Beck B
Dogger Bank	Teesside A
Dogger Bank	Teesside B
Dogger Bank	Teesside C
Dogger Bank	Teesside D
Dogger Bank	Tranche D
Hornsea	Hornsea Project One
Hornsea	Hornsea Project Two
Hornsea	Hornsea Project Three
Hornsea	Hornsea Project Four
East Anglia (Norfolk Bank)	East Anglia One
East Anglia (Norfolk Bank)	East Anglia One North
East Anglia (Norfolk Bank)	East Anglia Two
East Anglia (Norfolk Bank)	East Anglia Three
East Anglia (Norfolk Bank)	Norfolk Boreas
East Anglia (Norfolk Bank)	Norfolk Vanguard
Rampion (Hastings)	Rampion (Hastings)
Navitus Bay (West Isle of Wight)	Navitus Bay (West Isle of Wight)
Atlantic Array (Bristol Channel)	Atlantic Array phase one
Irish Sea (Celtic Array)	Celtic Array North East Potential Development Area
Irish Sea (Celtic Array)	Celtic Array South West Potential Development Area

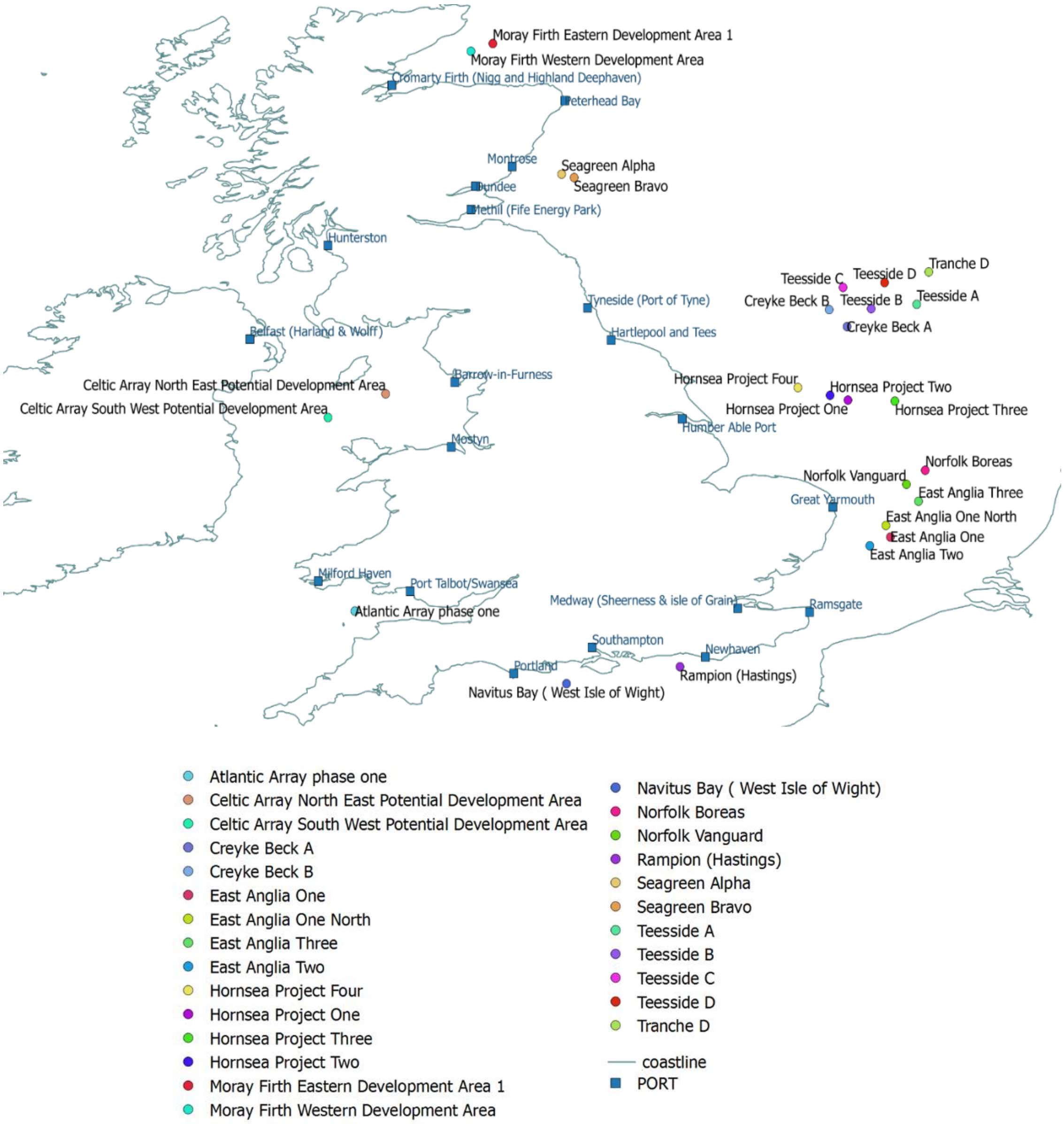

Figure 2-5 Round 3 offshore location around the UK illustrated by using QGIS

Calculating the LCC of a project is challenging. It involves all costs from the predevelopment to the decommissioning phase, and there is not a common universal reference point for wind projects. In [37], a parametric whole life cost framework for an offshore wind farm and a cost breakdown structure is presented and analysed. LCC analysis is essential for the insurers, wind farm operators and investors in order to ensure a cost-efficient long and profitable investment plan to produce power. In [37] the LCC analysis was divided into five stages of the wind project as a guideline; the predevelopment and consenting ($C_{P\&C}$), production and acquisition ($C_{P\&A}$), installation and commissioning ($C_{I\&C}$), operation and maintenance ($C_{O\&M}$), and decommissioning and disposal ($C_{D\&D}$) stage. Here, the parametric LCC analysis in [37] is used as a guideline for the economic model.

The LCC for the model is calculated as follows:

$$LCC = C_{P\&C} + C_{P\&A} + C_{I\&C} + C_{O\&M} + C_{D\&D} \tag{2-1}$$

Where $C_{P\&C}$ is the predevelopment and consenting cost, $C_{P\&C}$ is the predevelopment and consenting cost, $C_{P\&A}$ is the production and acquisition cost, $C_{I\&C}$ is the installation and commissioning cost, $C_{O\&M}$ is the operation and maintenance cost and $C_{D\&D}$ is the decommissioning and disposal cost

$$CAPEX = C_{P\&C} + C_{P\&A} + C_{I\&C} \tag{2-2}$$

$$OPEX = C_{O\&M} \tag{2-3}$$

Where CAPEX is the Capital expenditures, and OPEX is the operational expenditure. The power extracted is calculated for each site and each wind turbine respectively from:

$$P = \frac{1}{2} A C p \rho u^3 \tag{2-4}$$

Where A is the area of the wind turbine, C_p is the power coefficient, ρ is the air density and u is the mean annual wind speed of each specific site. The Total Installed Capacity (TIC) of the wind farm is calculated for every solution:

$$TIC = \mathrm{P_R} \times NWT \tag{2-5}$$

Where $\mathrm{P_R}$ is the rated power and NWT is the number of turbines.

The optimisation problem formulates as follows:

Minimise $\quad C_{P\&C}, C_{P\&A}, C_{I\&C}, C_{O\&M}, NWT, (-P), (-TIC) \quad$ (2-6)

Subject to $\quad 0 \leq \text{ site index} \leq 25$

$$0 \leq \text{ turbine type index} \leq 6$$

$$50 \leq \text{ Number of turbines} \leq 450$$

The optimisation problem has been solved by using the library platypus in python [38]

All data for the optimisation problem were acquired from the Fugro report [39], an independent provider of geo-intelligence, infrastructure and natural resources and the 4COffshore database [40], a consultancy and market research organisation that provides a global offshore interactive map and data for each wind farm and wind turbine.

4COffshore database is used by multiple scientific studies such as [41], where the authors analyse the cost of wind farm installation. The study includes data from 87 wind farms. Similarly, in [16], the authors are optimising the offshore inter array cable of an offshore wind farm considering power losses by using mixed-integer linear programming. In this study databases such as 4COffshore are used. Finally, in [42] a study that focuses on a newly developed life cycle techno-economic model is introduced by using up-to-date data from databases such as 4COffshore.

Fugro's report is also used in many scientific studies such as [43], where the data were used in order to simulate the impact of storm and surge events on offshore sandbanks. Similarly, in [44], the water surface height was determined with a GPS wave glider in Scotland. More studies that use the same datasets can be found in [45-48].

2.3 Techno-economic optimisation of offshore wind farms based on life-cycle cost analysis in the UK

The combination of a newly developed prototype framework shown in Figure 2-6 that includes economic modelling and optimisation process is assessed, so as to select the optimum offshore Round 3 location of a wind farm in the UK. A set of non-dominated optimal solutions is suggested by using the proposed framework. This part of the framework refers to module 3 in Figure 2-1 and modules B, C and D in Figure 2-2.

An optimisation formulation is presented in order to reveal optimum locations for UK Round 3 offshore zones and each zone individually. The 8-objective optimisation problem includes five techno-economic life cycle factors that are directly linked to the physical aspects and restrictions of each location, where three different wind farm layouts (including an extreme case) and four types of turbines are considered, and the optimal trade-off is revealed by using the NSGA II algorithm. The Round 3 offshore wind farm zones and sites considered for this part of study around the UK are listed in Table 2-2. The same framework was applied to all and each zone individually, which demonstrates the effectiveness of the methodology to select optimum solutions.

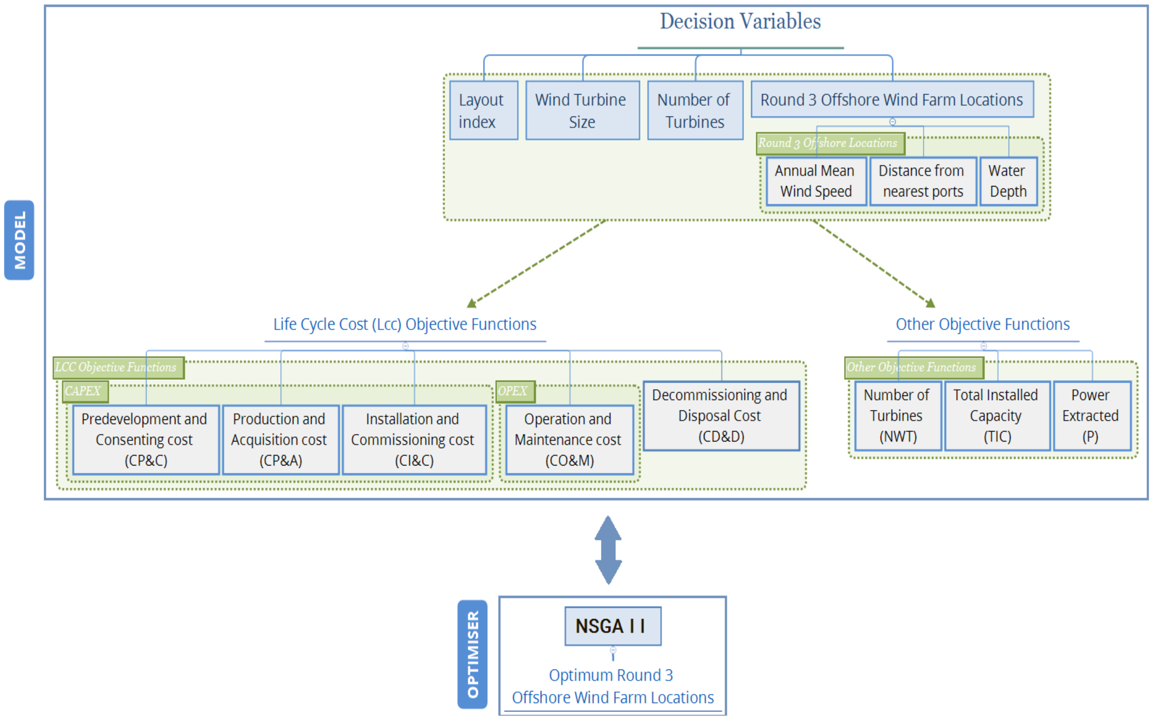

Figure 2-6 Methodology of the techno-economic optimisation

Table 2-2 Round 3 offshore wind farm zones considered

Zone	Wind farm site name
Moray Firth	Moray Firth Western Development Area
Moray Firth	Moray Firth Eastern Development Area 1
Firth of Forth	Seagreen Alpha
Firth of Forth	Seagreen Bravo
Dogger Bank	Creyke Beck A
Dogger Bank	Creyke Beck B
Dogger Bank	Teesside A
Dogger Bank	Teesside B
Hornsea	Hornsea Project One
Hornsea	Hornsea Project Two
Hornsea	Hornsea Project Three
Hornsea	Hornsea Project Four
East Anglia (Norfolk Bank)	East Anglia One
East Anglia (Norfolk Bank)	East Anglia One North
East Anglia (Norfolk Bank)	East Anglia Two
East Anglia (Norfolk Bank)	East Anglia Three
East Anglia (Norfolk Bank)	Norfolk Boreas
East Anglia (Norfolk Bank)	Norfolk Vanguard

Only a few location-selection-focused studies exist in literature, such as [49,50], but their findings and the formulation of the problems provided follow a different direction. Also, most of the layout related studies are focused on onshore wind farms. In [51], the layout optimisation considers the support structure costs and the operation and maintenance. Naturally, the offshore wind farm case is very different from the onshore, and the efficiency of the power production significantly depends on the site area and the number of turbines. Installation, operation and maintenance costs increase with the water depth, distance from the shore. More can be found in [51-54].

Most tools help optimise the energy produced at a different level relative to LCC analysis, for example through Computational Fluent Dynamics (CFD) but do not consider cost, energy or logistics trade-offs, which normally reside at a higher level regarding mathematical modelling and focus. In general, the layout among other factors assists on the maximisation of energy produced, minimisation of cost of energy and at the same time adopts the physical constraints of the site, considers the cable distances and in cases allows random positions of turbines [54].

The optimisation problem formulates as follows:

$$\text{Minimise} \quad C_{P\&C}, C_{P\&A}, C_{I\&C}, C_{O\&M}, C_{D\&D}, NWT, (-P), (-TIC) \qquad (2\text{-}7)$$

$$\text{Subject to} \quad 0 \leq \text{ site index} \leq 17$$

$$0 \leq \text{ turbine type index} \leq 3$$

$$1 \leq \text{ layout index} \leq 3$$

$$50 \leq \text{ Number of turbines} \leq \text{maximum number per site}$$

$$TIC \leq M\text{aximum capacity of sites based on the Crown Estate}$$

The study explores the cost-effectiveness of three layout concepts and reveals the non-dominated solutions for each case both for all considered locations and per Round 3 zone, which proves the effectiveness of the model. Next, the interplay between CAPEX and OPEX was revealed, and further insight of the complexity of the problem is shown through a sensitivity analysis.

The whole framework has been implemented by using Python 3. The optimisation modelling has been completed using the library platypus in python [38] and the sensitivity analysis by using the method Sobol Indices [55] by using the library SALib [56].

2.4 A framework to select optimum offshore wind farm locations for deployment

This part of the framework combines MOO and MCDM along with human expertise in real-world applications. The framework is depicted in Figure 2-7. The outcome of this step will generate deeper insight into selecting an offshore Round 3 location in the UK. Through this combination of techniques, subject-matter experts' opinion and technical/numerical issues will be linked to a framework that will provide sufficient content for a more informed decision. The insight of industry experts is combined with MOO and TOPSIS (both deterministic and stochastic variations) in order to rank and suggest the best offshore location from a set of optimum Pareto Front (PF)[2] solutions that were produced by the MOO. A process on the criteria selections is also presented by introducing important steps of the process. This part of the methodology refers to module 4 in Figure 2-1 and modules B-G in Figure 2-2.

The locations considered for this part of the study are listed in Table 2-2.

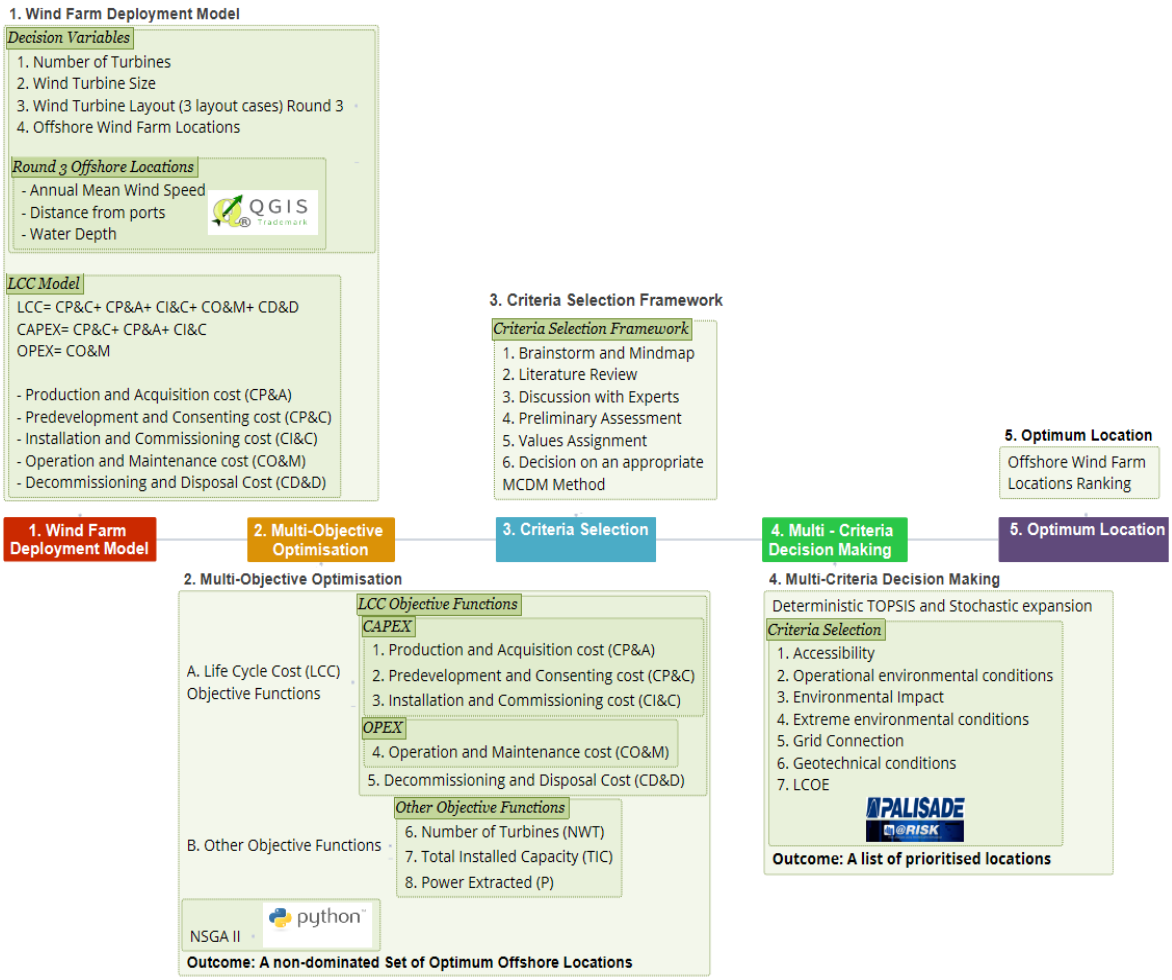

Figure 2-7 Framework to combine MOO and MCDM to select the optimum deployment locations

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[2] Pareto Front also denotes the non-dominated solutions in the trade-off of a MOO problem

The optimisation problem formulates as follows:

$$\text{Minimise} \quad C_{P\&C}, C_{P\&A}, C_{I\&C}, C_{O\&M}, C_{D\&D}, NWT, (-P), (-TIC) \qquad (2\text{-}8)$$

Subject to

$$0 \leq \text{ site index} \leq 17$$

$$0 \leq \text{ turbine type index} \leq 3$$

$$1 \leq \text{ layout index} \leq 3$$

$$50 \ \leq \text{ Number of turbines} \leq \text{maximum number per site}$$

$$TIC \ \leq \ M\text{aximum capacity of sites based on the Crown Estate}$$

In general, alternatives are selected from a wide range of options, which will be prioritised and finally ranked in a hierarchical manner. Increasing the number of criteria can overcomplicate the problem and challenge the compromise of the solutions in the final ranking. The total number of criteria in the process should be in the range of 5-9, so as to maintain the quality and credibility of the process, according to [57,58]. Certain MCDM methods cannot handle more than nine mainly because of the human perception and information processing. The criteria need to be set, so as to demonstrate the trade-offs among them in order to assist decision-makers to reflect upon, articulate and assess the alternatives accordingly. The criteria were selected based on literature and a brainstorming session with academic and industrial experts. In the session, common criteria were consolidated in order to avoid double counting and finally concluded to the ones used in the study. The criteria were selected such as to have both a manageable number and to cover all aspects but at the same time not make the data collection questionnaire too onerous. The list of criteria is shown in Table 2-3.

Table 2-3 List of Criteria

Criteria	ID
1. Accessibility	C1
2. Operational environmental conditions	C2
3. Environmental Impact	C3
4.Extreme environmental conditions	C4
5. Grid Connection	C5
6.Geotechnical conditions	C6
7. LCOE	C7

Data were collected from experts, so as to prioritise the alternatives and assess them against the seven selected conflicting criteria. In this part of the study, all selected participants in the anonymous survey were senior researchers and industry experts with at least 3 years of experience and post graduate qualifications, which also self-assessed themselves. The self-assessment expertise scores varied between 2 and 5 (with 1 being a non-expert and 5 being an expert) with a mean value of 3.8 and a standard deviation of 0.89.

If experts or researchers set values or even weights to the criteria (based on their opinion), the information that is inserted into the problem can be too uncertain and vague. That is because this type of data can never substitute the results of a study or measurements of an experiment. In MCDM, the problem is usually defined by considering most (if not all) factors that surround the case.

Although many MCDM methods can be found in literature, this study focuses on TOPSIS and its stochastic expansion. TOPSIS was selected because of its extended use in literature and the connection of the method to numerous energy related studies, such as [59,60]. Stochastic approaches of these methods are necessary in order to treat uncertainty. The deterministic variation of TOPSIS can be found in Figure 2-8 and the stochastic expansion for all MCDM methods in Figure 2-9.

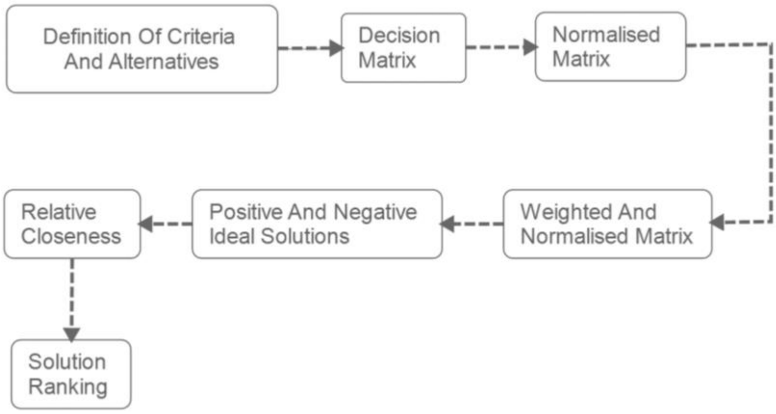

Figure 2-8 Deterministic TOPSIS process

A stochastic method can be more informative than a deterministic method because the former accounts for the uncertainty due to the varying behavioural characteristics of the target system. Deterministic methods are mainly used to describe simple, natural phenomena by physical laws and are not fit-for-purpose for large and complicated applications. Consequently, the real-world behaviour is better reflected by employing methods relevant to stochastic simulations. The latter can include the uncertainty of real-world applications, where system modelling is not trivial. Stochastic methods can increase the confidence of the decision-maker in the final results and analysis and can be more appropriate for cases where the heterogeneity of important factors is critical as the uncertainty of the considered system increases. In general, it is not feasible to obtain an analytical expression for stochastic problems, which would require more computational time and resources to deliver a satisfactory solution [61]

The Monte Carlo simulation is a particularly useful approach in stochastic modelling. It is an approach to represent the random nature of stochastic processes. The most fundamental part of such a method is the generation of random numbers as input sets, which are drawn randomly.

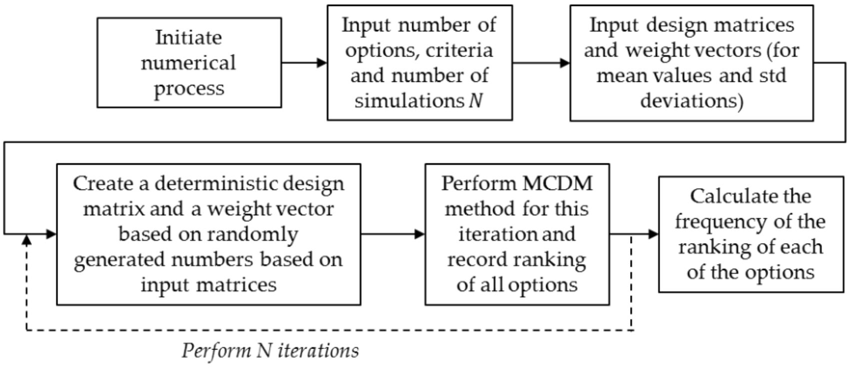

Figure 2-9 Stochastic expansion algorithm of deterministic MCDM methods

Software @Risk from Palisade was used in order to implement the MCDM part of the framework.

2.5 A Comparative Study of Multiple-Criteria Decision-Making Methods under Stochastic Inputs

An approach in [62] was proposed to combine experts' opinion through MCDM processes and stochastic inputs. A decision-making process in a real-world application has been introduced, so as to select the best offshore wind turbine support structure type. This study demonstrated the application of six different MCDM methods that are commonly used on a wide range of RE applications by the industry. This part of the methodology refers to module 5 in Figure 2-1 and module H in Figure 2-2.

Among others, decision making methods include the following; Weighted Sum method (WSM), Weighted Product Method (WPM), Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS), Analytical Hierarchy Process (AHP), ELimination Et Choix Traduisant la REalité (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), etc. According to recent developments, most of these state-of-the-art methods have been improved, modified or linked to other methods in order to support and complement other methods. Because of that, many extensions are currently available. Several MCDM methods base their techniques on weighted averages, priority setting, outranking, fuzzy principles and even combinations of them.

WSM, WPM, AHP, TOPSIS, PROMETHEE, ELECTRE methods are applied to a real-world problem for a relatively large-scale wind turbine (such as 5.5 MW) that is considered to be installed at 40-m water depth by considering 10 conflicting criteria in order to suggest the best support structure type out of 10 both fixed and floating alternatives of an offshore wind turbine under stochastic inputs as listed in Table 2-4.

Table 2-4 List of Alternatives and Criteria

List of Alternatives	List of Criteria
A1 Jacket	A Compliance/Max Displacement of Rotor
A2 Tripod	B Dynamic Performance
A3 Monopile	C Design Redundancy
A4 Suction Bucket	D Cost of Maintenance
A5 Jack-up	E Cost of Installation
A6 Spar	F Environmental Impact
A7 Barge	G Carbon Footprint
A8 TLP	H Certification
A9 Semi-Submersible	I Likely Cost
A10 Tri-floater	J Depth Compatibility

Stochastic input data will allow Monte Carlo simulations to perform numerous iterations of analysis in order to quantify results and identify the number of cases where the optimum solution will prevail. Expanding MCDM stochastically can be seen in Figure 2-9. Software @Risk from Palisade was used in order to complete this part of the framework.

3 RESULTS

3.1 A multi-objective optimisation approach applied to offshore wind farm location selection

By comparing the outcomes of the three state-of-the-art genetic algorithms described in module 2 in Figure 2-1 and also illustrated in modules B and C (excluding the $C_{D\&D}$ and the layouts) in Figure 2-2, a further insight is provided into the practises to conduct planning to support decision making in future investments. The results follow a similar trend for all algorithms. The Seagreen Alpha, Seagreen Bravo, Teesside C, Teesside D, and the Celtic Array South West Potential development Area were suggested to be the most appropriate solutions because of the high percentages in the frequency graph illustrated in Figure 3-1, as discovered by the algorithms.

The optimum solutions in the PF include all Round 3 locations, which is valuable information at the planning stage. More specifically, it provides the developer with the flexibility to make a choice assigning costs in different development phases, as it is convenient for the project, and to choose whether to invest the budget on the installation or the maintenance stage of the project.

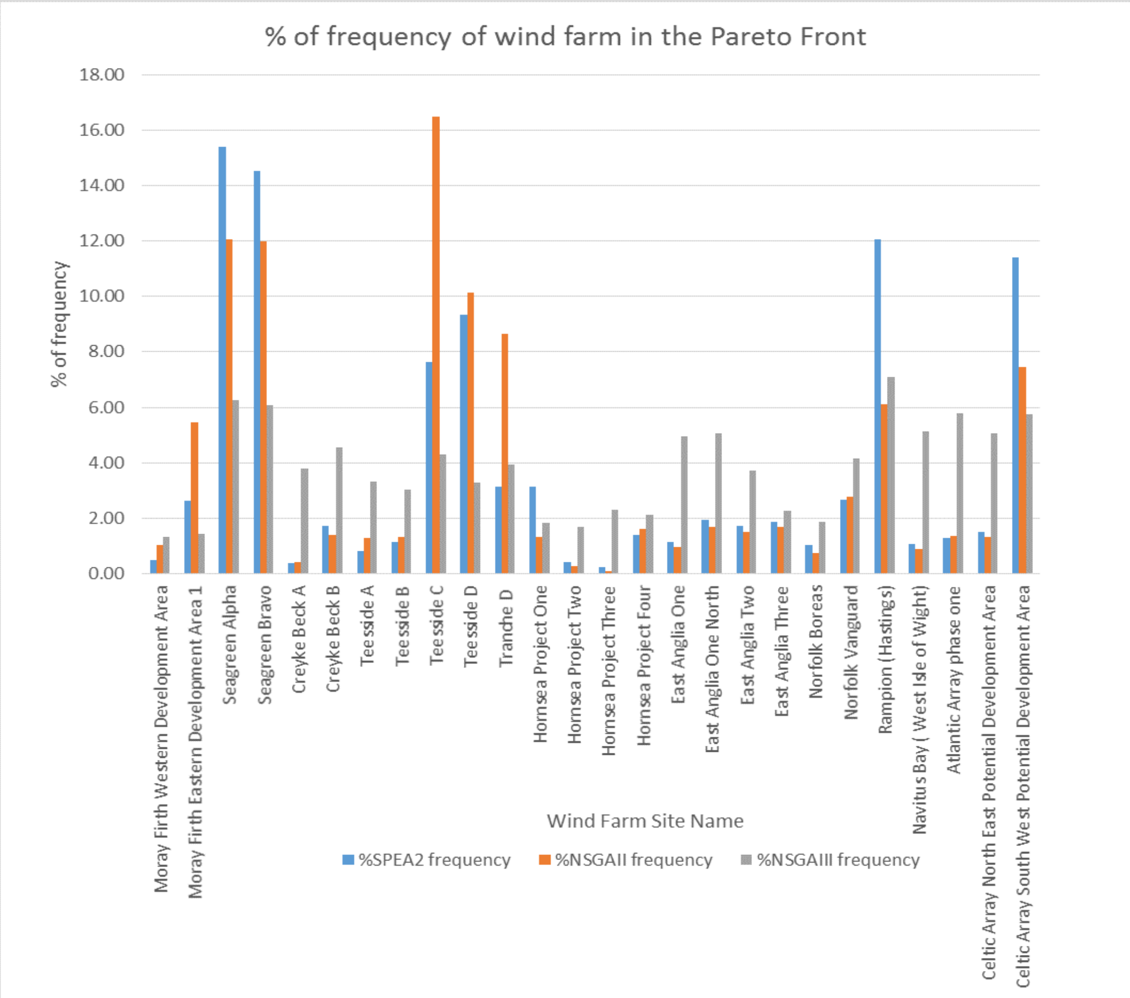

Figure 3-1 %of frequency of each site from the PF solutions from SPEA2, NSGA II and NSGA III

3.2 Techno-economic optimisation of offshore wind farms based on life-cycle cost analysis in the UK

In module 3 in Figure 2-1 and modules B-D in Figure 2-2, one of the layouts was discovered fewer times in the PF, and its solutions are more cost-effective. Overall, Moray Firth Eastern Development Area 1, Seagreen Alpha, Hornsea Project One, East Anglia One and Norfolk Boreas were finally discovered in the PF solutions. Although layout 1 and 2 were mainly selected as optimum solutions by the optimiser, the extreme case (layout 3) also appeared in the PF solutions once as shown in Figure 3-2.

Four optimum solutions were discovered in the range between £1.6 and £1.8 billion; the areas of Seagreen Alpha, East Anglia One and Hornsea Project One, shown at the bottom of Figure 3-2. Furthermore, Moray Firth Eastern Development Area 1, was found to deliver the lowest total costs per MW in Figure 3-3. The highly complex nature of the decision variables and their interdependencies were revealed, where the combinations of site-layout and site-turbine size captured above 20% of total sensitivity in CAPEX and OPEX.

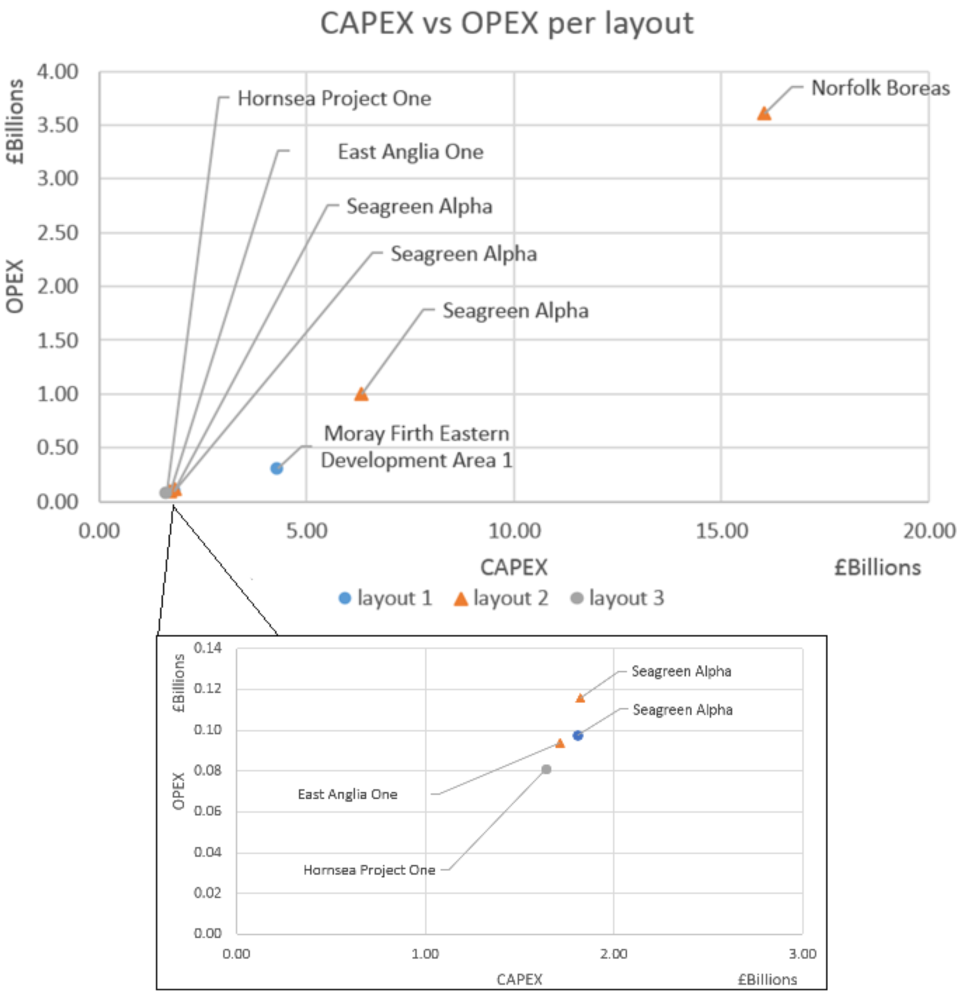

Figure 3-2 OPEX vs CAPEX for all PF solutions for layout case 1, 2 and 3 and solutions focused on the beginning of the trend of the costs

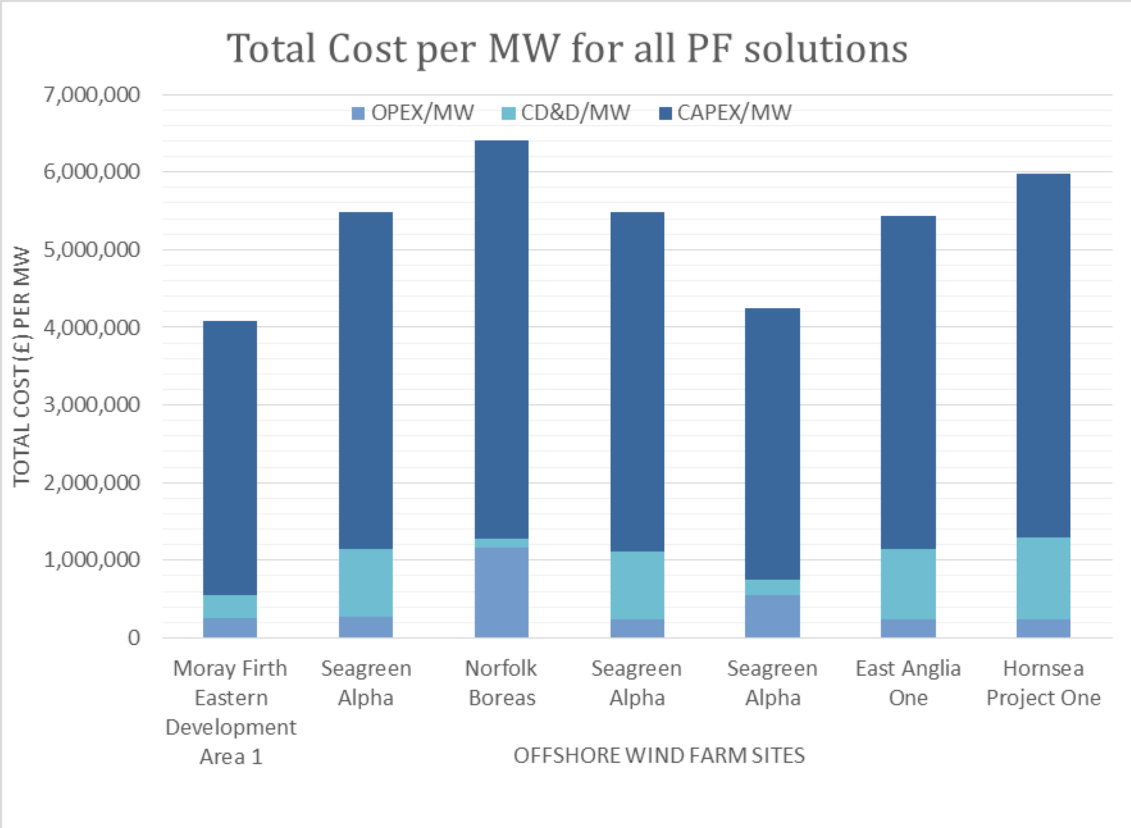

Figure 3-3 Total Cost per MW for all PF solutions

3.3 A framework to select optimum offshore wind farm locations for deployment

Next, in module 4 in Figure 2-1 and modules B-G in Figure 2-2, the PF solutions were revealed and Moray Firth Eastern Development Area 1 with 122 10MW turbines showed the lowest total costs per MW as shown in Figure 3-4. Seagreen Alpha with 259 7MW turbines follows next as the second lowest total cost solution in the PF. Nevertheless, by considering experts' input, both deterministic and stochastic TOPSIS ranked the Seagreen Alpha as the most predominant site, 3 times more preferable than Moray Firth Eastern Development Area 1, shown in Figure 3-5.

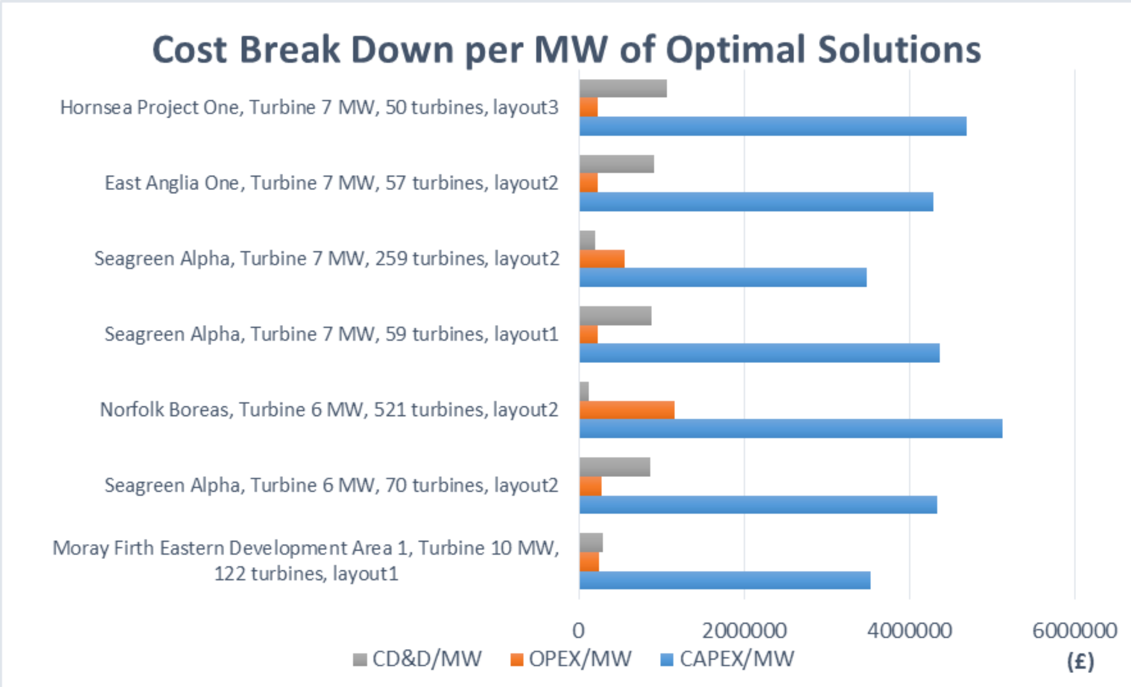

Figure 3-4 Cost break down for all PF solutions for layout cases 1, 2 and 3

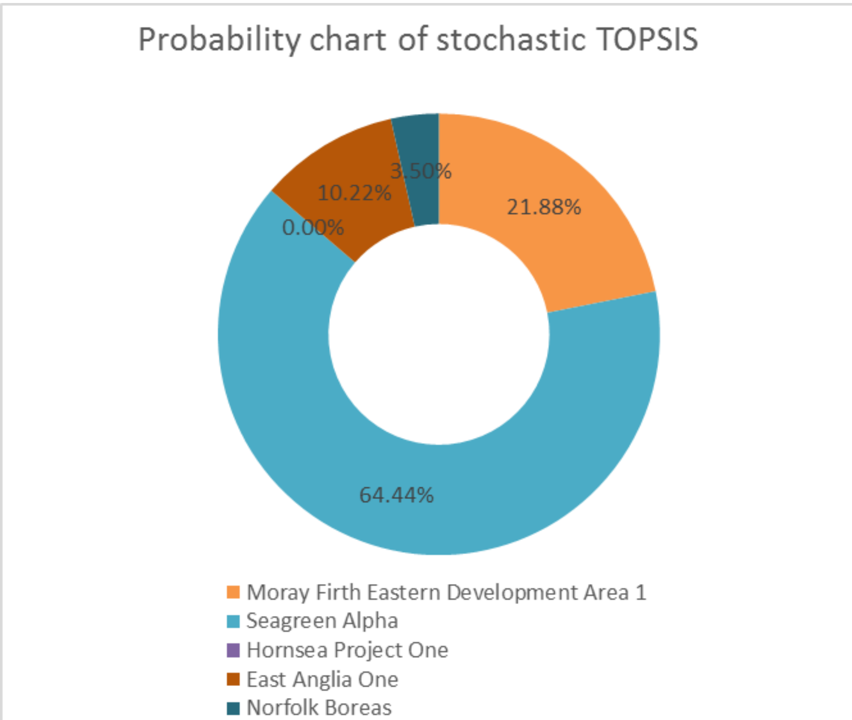

Figure 3-5 Probability chart of the stochastic TOPSIS

3.4 A Comparative Study of Multiple-Criteria Decision-Making Methods under Stochastic Inputs

Finally, in module 5 in Figure 2-1 and module H in Figure 2-2, the results showed that the MCDM methods could relate to each other and produce similar trends. The jacket and monopile support structure was ranked first in most of the methods in the deterministic approach in Figure 3-6, while the monopile was the prevailing option in most of the stochastic methods in Figure 3-7.

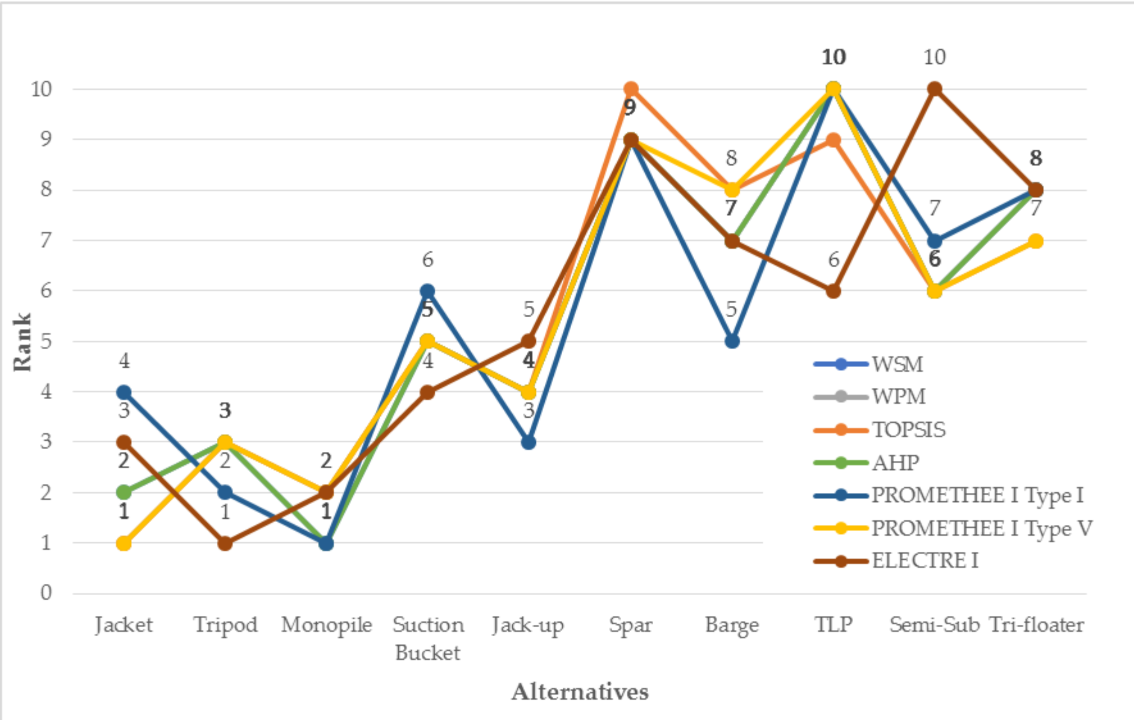

Figure 3-6 Ranks comparison for the deterministic WSM, WPM, TOPSIS, AHP, PROMETHEE I and ELECTRE I methods

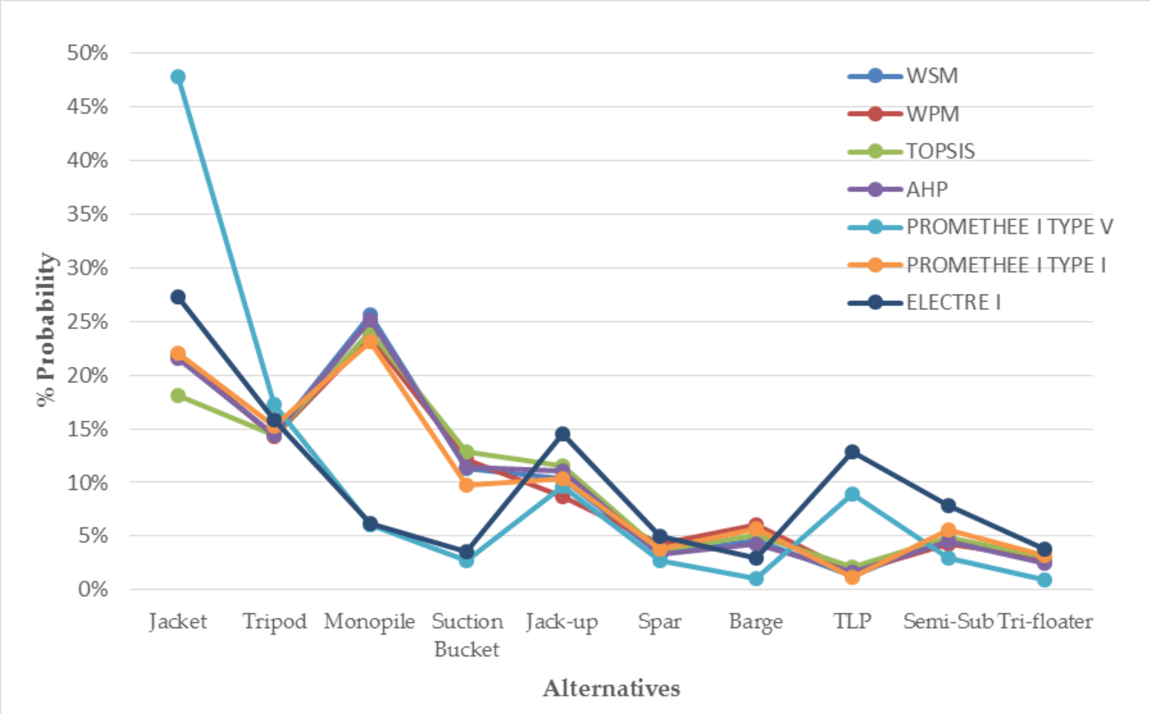

Figure 3-7 Comparative stochastic MCDM results: the probability of an alternative to score first.

4 CRITICAL DISCUSSION

The optimisation problem solved in this study revealed the optimum offshore wind farm sites in the UK. A verification of the methods was conducted by comparing different methods through comparative studies shown in modules 2 and 5, as shown in Figure 2-1. In module 2, a comparative study was conducted by using the NSGA II, NSGA III and SPEA 2 algorithms and revealed similar trends in the outcomes. Similarly, in module 5, a comparative study by using six different MCDM methods was conducted. The outcomes also revealed similar trends and results for both deterministic and stochastic.

For validation purposes, real-world data are required. However, the present techno-economic models are based on Round 3 offshore sites, which are not yet fully developed. Thus, there are no real-world data to compare the outcomes. For this reason, two approaches are suggested in this chapter.

First, all research outcomes (offshore sites) will be compared with the current development status. Second, the total costs per MW suggested in this study will be compared with the corresponding costs from similar real-world cases in the UK and literature in order to identify similarities and compare the outcomes.

First, in module 2 in Figure 2-1, six offshore locations scored higher than 10% in the frequency graph, i.e., the Seagreen Alpha and Bravo (both in Firth of Forth), Teesside C and D (both in Dogger Bank), Rampion (Hastings), and the Celtic Array South West Potential development Area, which represents the Irish Sea (Celtic Array). Both Seagreen Alpha and Bravo were consented but faced some engineering and environmental problems and developed the project accordingly to accommodate the issues [63]. Teesside C and D in Dogger Bank applications were submitted together by Forewind. Unfortunately, the projects have been cancelled according to 4COffshore [64,65]. Rampion (Hastings) is currently partially generating energy but is still under construction according to 4COffshore [66]. Finally, Celtic Array South West Potential development Area was cancelled [67].

Similarly, after including the full LCC analysis and 3 layout cases in module 3, in Figure 2-1, a new set of optimum locations was revealed. Moray Firth Eastern Development Area 1 (in Moray Firth), Seagreen Alpha (in Firth of Forth), Hornsea Project One (in Hornsea), East Anglia One and Norfolk Boreas (both in East Anglia (Norfolk Bank)) were discovered in the PF solutions. Seagreen Alpha is consented [68], Moray Firth Eastern Development Area 1 is consented [69], Hornsea Project One is under construction [70], East Anglia One is under construction [71] and Norfolk Boreas is still at concept/early planning stage [72].

Also, in module 4 in Figure 2-1, Seagreen Alpha was the final optimum solution of the overall framework and as mentioned above is consented.

Second, a comparative analysis is shown in Figure 4-1. The total modelled costs per MW (calculated in this research) suggested in modules 3 and 4 in Figure 2-1 are compared with both the corresponding costs per MW from similar real-world offshore developments in the UK and equivalent literature in order to identify similarities and compare the outcomes.

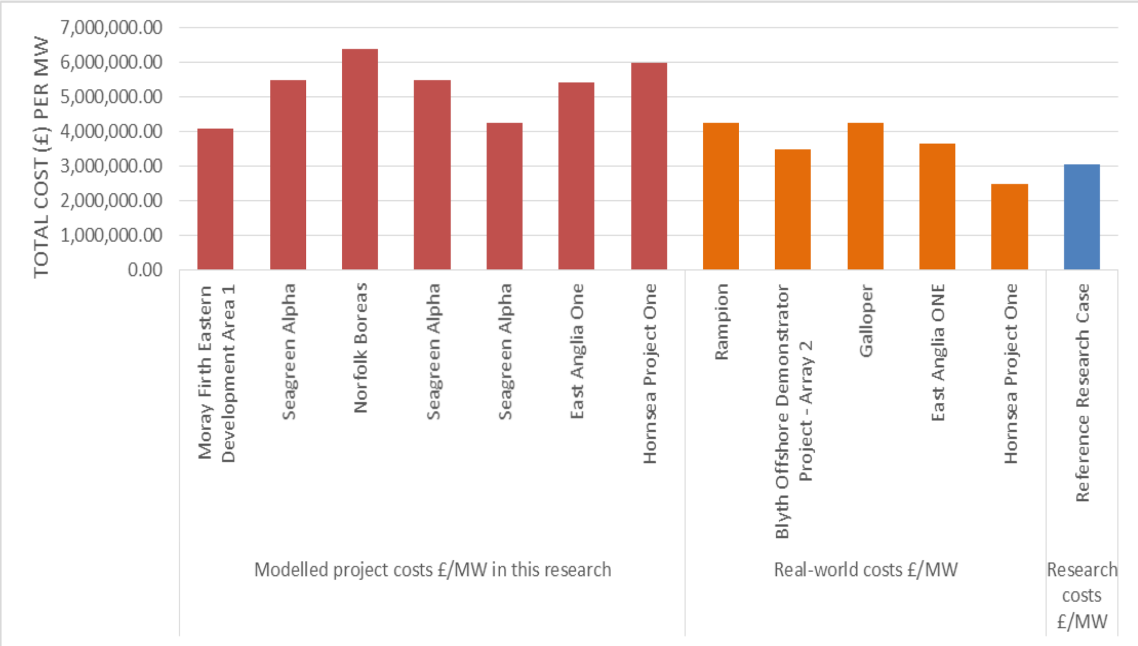

Figure 4-1 Comparison of the total cost of energy per MW among the results of this research, real-world cases and other research work

The real-world costs per MW were acquired from [37,66,70,71,73,74] and according to Figure 4-1, the results show small discrepancies with other reports and real-world data available. In general, the modelled results show higher values in most cases. These discrepancies are present because of the limitations of the framework, the LCC model formulation and the assumptions during the implementation of the LCC model, whose maturity is at “proof-of-concept” level. However, the overall costs seem to be in a comparable order of magnitude. The real-world cases are of higher technology readiness level compared to the present work. So, this level of discrepancy is justifiable for the current level of maturity of the model.

5 CONCLUSIONS AND FURTHER RESEARCH

5.1 Summary and key findings

The main purpose of this research is to assess a framework that will combine wind farm deployment model based on LCC, MOO and MCDM methods. The outcome of this research will generate additional evidence to support decision makers to select an offshore location in the UK at the planning stage of development. Through this combination of techniques, subject matter experts' opinion and technical/numerical issues will be linked into a methodology that will provide sufficient content for a more informed decision.

Key findings:

- The UK was found to be the most appropriate country for the present study because it is considered as an offshore wind energy leader, worldwide and shows great potential to grow.
- This research successfully demonstrated by example the effectiveness of the newly developed framework and delivered satisfactory outcomes for the most suitable and cost-efficient offshore wind farm Round 3 locations. A comparison has been presented among NSGA II, NSGA III and SPEA 2, which were applied to a wind energy real-world case. The optimum locations for a wind farm have been suggested by considering the significant input of the LCC analysis.
- The effectiveness of linking MOO to LCC as objective functions and comparing three different wind farm layouts in order to select the optimum solutions was demonstrated. When optimising all the regions together, in the range between 1.6 and 1.8 billion, four optimum solutions were discovered, for the areas of Seagreen Alpha, East Anglia One and Hornsea Project One. Although layout 1 and 2 were mainly selected as optimum solutions by the optimiser, layout 3 also appeared in the PF solutions.
- The sensitivity analysis demonstrated the highly complex nature of the decision variables and their interdependencies, where the combinations of site-layout and site-turbine size captured above 20% of the variability in CAPEX and OPEX. More complex interactions are expected in higher-order sets of decision variables.
- The coupling of MOO with MCDM and expert surveys was demonstrated in this paper, as a method to increase the confidence of wind energy developers at the early stages of the investment. By employing NSGA II

and two variations of TOPSIS, optimum solutions were revealed and ranked based on experts' preferences. Among the optimum solutions, Seagreen Alpha was the best option, and Hornsea Project One was the least probable to be selected.

- The effectiveness of six MCDM methods was demonstrated (i.e. WSM, WPM, TOPSIS, AHP, PROMETHEE I and ELECTRE I) along with the stochastic expansion of the methods. For the reference case study, 10 significant technical and non-technical criteria were employed to assess the optimal solution among 10 different alternatives of support structures for offshore wind turbines. The jacket structure and the monopile prevailed for most methods.

5.2 Contribution to knowledge

The contribution to knowledge is confirmed by the novelty, scientific soundness and value of the research, as detailed below. Through the introduced framework, a real-world problem has been structured and solved by recommending real-world solutions while considering experts' opinions. Throughout this process, 5 scientific journals have been successfully published.

The novelty of this research is the development and demonstration of a prototype techno-economic model and a scalable framework to improve the decision making process at the planning stage of the development of an offshore wind farm for Round 3 zones in the UK. The framework linked a parametric offshore wind farm deployment model based on LCC analysis to a genetic MOO algorithm. The results of the MOO process were combined with experts' opinion under stochastic MCDM process.

Regarding the scientific soundness of this research, experts' insights were included in the MCDM process to account for the human preference and expertise in the research. On top of that, several state-of-the-art tools and methods were included such as genetic algorithms, MCDM methods, open source software, libraries and tools. Before utilising the most appropriate MOO and MCDM methods, a comprehensive literature review and comparison analysis were conducted.

The value of the research is in the modularity, transferability, scalability of the framework. The framework is transferable to many other scientific areas, for example, the planning of new power plants both onshore and offshore or the position of floating wind/wave/hybrid devices. The revealed outcomes could benefit possible extensions of present or new Rounds of offshore wind farm zones in the future of the UK and could support decision makers to their next cost-efficient investment move. The framework or parts of it could be combined with other methods and deliver satisfactory results.

Academics could benefit by the methodology, the techniques and the stochastic expansions used in this study. The transferable framework could be used in many other scientific studies and could also be used as a baseline for other stochastic methodologies.

Investors could benefit from the decision-making of the optimum offshore site inside specific zones. The outcome of the framework could have a great impact on the decision of both the site and other aspects such as the number of wind turbines, size and layouts.

And finally, policy makers in other countries, such as South Korea and the US could benefit in a quantitative way from the framework by identifying rounds in their offshore wind energy developments considering important constrains.

5.3 Further research

The proposed framework could also be applied to other sectors to increase investment confidence and provide optimum solutions. For example, the installation of floating offshore wind and wave devices could benefit by the framework, where the optimum locations can be suggested according to cost and operational aspects of each technological need.

Currently, the cost model considers only the jacket structure as part of the optimisation problem. In the future, a new optimisation model could be implemented including different LCC calculations regarding both fixed and floating support structures that will be linked with MCDM methods following the methodology described in the previous chapters. A model to include further constraints and objectives into the problem could be implemented including policy and risk investigations.

In the future, in order to address the identified limitations, the following enhancements are recommended:

- Multiple optimisation algorithms could be combined together in order to increase the effectiveness of the optimisation search and thus reveal more and diverse optimal solutions
- More aspects could be incorporated in the framework such as wind speed distributions and a detailed layout optimisation for each wind turbine selection in order to reduce uncertainty and provide more accurate results.
- The impact of Net Present Value on the economic objectives could be further investigated in the future
- More location-related aspects could also be introduced to the framework by adding constrains from environmental factors for each offshore site, such as areas with endangered species and extreme weather conditions and excluding areas where the seabed is unsuitable for installations
- More geospatial studies are important as the seabed is not consistent for all offshore sites and that could impact the turbine layouts

The framework is scalable and transferable to other scientific areas (e.g., environmental), industry sectors (e.g., transport and telecommunications) and stages of development (e.g., execution, project control and monitoring) and could be used for improving the decision making process when it is necessary. Many studies could benefit from the above methodology. Selecting the optimum deployment location could be useful to a new onshore power plant or wave devices installation.

The present research can be transferred to offshore wind farms in other countries such as China, Japan, Taiwan, South Korea and America because they are considered the top emerging countries for offshore wind energy, as discussed in [17]. The framework could be scaled, so as to benefit these countries because their offshore wind industry is still in its infancy but there is high potential for future developments. This could further enhance the strategy and operations of public authorities to create further business development opportunities in the offshore wind energy sector.

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APPENDIX

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A comparative multi-disciplinary policy review in wind energy developments in Europe

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A comparative multi-disciplinary policy review in wind energy developments in Europe

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ABSTRACT
Over recent decades, European Union countries have committed to increasing their electricity production from renewable energy sources (RESs). Wind energy plays a significant role in a sustainable future. This paper presents a political, economic, social, technological, legal and environmental analysis. Although these countries have made many improvements in their legal frameworks aiming to attract investors and boost the RE sector, there are still challenges. The UK focuses on offshore wind energy, adjusts the economic strategy and changes the legislation context. Germany has the healthiest economic conditions, as it keeps following its initiative to design a new programme for an energy transition from conventional to RESs with emphasis on the onshore. Greece has only a few installations and much room for development but needs to make further changes in the legislation and economy so as to attract more investors in the long term. The purpose of this research is to analyse, highlight and discuss vital aspects of these countries as well as the European environment, with reference to their current wind energy activities. Ultimately, it attempts to give a wider perspective and to serve as a guide for future studies on the wind energy sector.

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PESTLE; wind energy; multi-disciplinary review

1. Introduction

Currently, wind energy is one of the fastest growing forms of renewable energy in the world. Due to the recent increase in both energy prices and dependency on fossil fuels, Europe started mapping a new energy area that favours the growth of renewable energy sources (RESs). In order to improve the worldwide energy supply and demand, the use of renewable energy is a promising direction (European Observation Network for Territorial Development and Cohesion 2011).

Clearly, the depletion of fossil fuels, in combination with environmental awareness, has pushed governments towards the exploration of alternative ways to generate energy for a sustainable future. Recently, research bodies and industrial stakeholders have centred their attention on this sector, which has turned into a fast evolving and frequently changing challenge. Several studies have illustrated the technical complexity of renewable energy developments, as can be attributed from Martin et al. (2013), Kolios, Read, and Ioannou (2016) and Kolios, Rodriguez-Tsouroukdissian, and Salonitis (2014), acknowledging the different dimensions of the problem.

The purpose of this research is to analyse, highlight, and discuss various aspects of wind energy for Europe as a whole, the UK, Germany and Greece. A comparative study of the European wind energy is performed, where the advantages and disadvantages with respect to the renewable resources are presented. To this end, a PESTLE analysis is performed. This is a framework that

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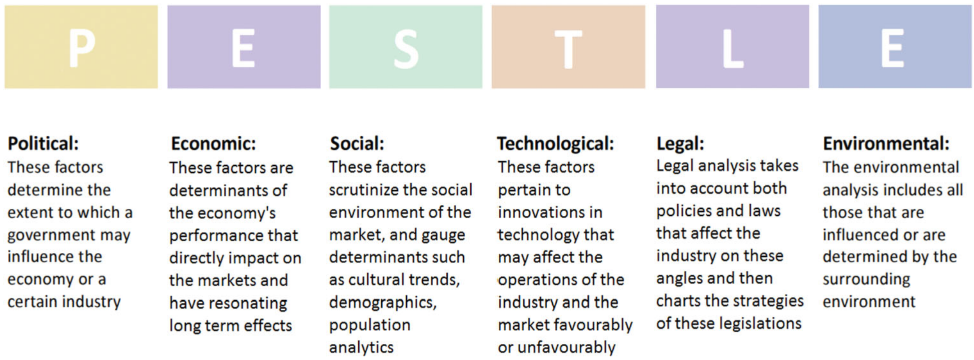

Figure 1. PESTLE analysis.

provides a wide perspective of a target-environment and consists of the following individual parts: political, economic, social, technological, legal and environmental (Figure 1). It is believed that this approach will assist in understanding the dynamics of the problem and it could be used to provoke further research directions.

The above countries were selected because of the current status in their wind energy installations, suitability for the renewable energy systems to work, and their investment potential. According to Konstantinidis, Kompolias, and Botsaris (2014), Greek seas meet all the essential requirements and show huge potential for offshore wind farms, especially close to the shore. In addition, recent financial studies including interest, grants and tax rates estimate that investment is sustainable. The UK's location on the map (BBC Weather Centre 2014) offers the most favourable natural resource for using wind energy. At the moment, the UK represents 9% of Europe's total wind energy capacity, whereas, according to the European Wind Energy Association (EWEA) statistics (EWEA 2005–15), Germany is today the top country in terms of accumulated wind energy capacity in Europe, representing 29% of the total EU capacity. The future of wind energy in the aforementioned countries is clearly very promising.

2. Developments in Europe

At the moment, Europe is considered to be a global forerunner in offshore wind energy as far as the total installed capacity is concerned. The first initiative was taken in Denmark, in the late 1980s where the introduction of Europe's first offshore wind farm took place, gathering policy insight for the next generations (Mani and Dhingra 2013). The renewable energy installations were numbered to be 72% (in terms of capacity) of the new installations throughout 2013 compared to 70% from the year before, as determined by the European Energy Association (EEA) (EWEA 2005–15). Today, there are 110.7 and 6.6 GW onshore and offshore wind energy installations in Europe, respectively. During 2013, 11,159 MW of wind power capacity was installed in the EU-28 countries. New regulations and policies in the European countries have caused wind projects to drop about 8%, since 2012. A big loss in new investments has been noticed in 2013 as a result of the fluctuating legal frameworks regarding wind energy production. Even though this affected many of the new investments, wind energy projects had 32% of the total energy capacity in 2013 (EWEA 2005–15).

European Union countries are committed to increasing the production of electricity from renewable energy from 10% in 2008 to 20% by 2020. In order to achieve that, the EU's target for offshore wind installations for 2020 is 40,000 MW. EU's status on the same installations in 2010 was only 3000 MW (European Observation Network for Territorial Development and Cohesion 2011). Looking at Europe's wind map, there are regions with significant potential for producing electricity from onshore wind power.

As reported by GWEC (2013), the offshore section is expanding its market annually. In spite of the 50% increase, which is over 1500 MW in the last few years, it is still going to be difficult for the EU to meet the 20% increase coming from renewable energy targets on time. On the other hand, Germany is expected to keep a constant rate of growth followed by Poland, Sweden, Denmark and Portugal. Although the coming years are going to be demanding, the existing legislation is still capable of supporting installations of approximately 68 GW from 2014 to 2018.

2.1. *Political*

Although wind is a vital asset for renewable energy developments, politics can influence the overall future of the wind industry. As determined by European Union's policy, a government has no absolute power on its own. The EU countries have to respect and comply with global and European politics (Kolios and Read 2013).

As defined in the Treaties and political reports, the EU's policy has to appreciate the size and population of the subsidiaries and to understand the regulation more deeply (Kanellakis, Martinopoulos, and Zachariadis 2013). As far as the energy policy in Europe is concerned, energy resources, which are enclosed within any country, do not belong to Europe but to the nation itself and Member States are ultimately in charge of their nation's energy mix (International Energy Agency 2008).

The following studies envision the political impact of wind energy in the medium term. Scotland's plan for the future is to produce 100% of their demands for electricity only from RESs by 2020 (Braunholtz 2003). The European Union's 2007 roadmap of RESs predicts that by the end of 2020 wind energy will cover over 13% of the total electricity produced and consumed in the EU (Planete-Energies an Initiative by Total 2010).

In 2007, the Strategic Energy Technology Plan (SET Plan) was agreed by the European Commission and targeted the fast growth and application of low-carbon technologies. It also strengthened industrial participation in energy R&D through European industrial initiatives. The SET Plan contains the wind energy initiatives, schemes, electricity grid, etc. In order to meet the 2020 compulsory targets, the national renewable energy action plans (NREAPs), were presented in 2009. The NREAPs specify targets for the shares of energy from RESs in transport, electricity, heating and cooling by 2020, and sufficiently evaluate the efficiency of the aims (Kanellakis, Martinopoulos, and Zachariadis 2013).

According to EWEA (2011), even though the 2020 targets contain a well put forward policy guidance, there is no legislation framework to propose a plan for at least the next 30 years. Investors face many problems for their future plans for the post-2020 policy gap. EU has to act by proposing a suitable strategy that will guide safely towards the 2050 targets in order to confront climate change.

2.2. *Economic*

The renewable energy industry has created many jobs over recent years. According to the European Renewable Energy Council (EREC 2012) studying, constructing and maintaining new installations in Europe have employed over 230,000 employees in 2005 which increased to 550,000 in 2009. However, rising electricity prices in Germany in 2012 caused many industries to close or move overseas and as a result many jobs were lost (Dohmen and Neubacher 2012). The Global Wind Energy Council (GWEC 2014) predicts that by 2020, 520,000 people will be employed in the sector. Also, by 2030 the figure will increase to 794,079 with 62% of the jobs being in the offshore sector. According to GWEC, €5.7 billion were exported relating to the wind industry alone in 2011.

Because of the energy and economic crises, the European Energy Programme for Recovery (EEPR) was created in 2009 to financially assist the overall energy sector, with emphasis on the insertion of an interconnecting infrastructure (€2.3 billion out of €4 billion overall), which promotes the investments regarding the security of energy supply. The EEPR is vital for Europe's financial rescue and also emphasises the renewable energies, financial support of the offshore wind projects, etc. (Kanellakis, Martinopoulos, and Zachariadis 2013).

Another programme, called the IEE, has been deployed to scientifically enhance the offshore grid, along with a regulatory framework for Europe. This considers aspects from policy, economic, technical and regulatory fields. The major concern is to reduce the grid connection cost when wind energy is harvested for generating electricity (Perveen, Kishor, and Mohanty 2014).

The Europe 2020 Project Bond Initiative was conceived recently and targets facilitating funds' availability for large-scale projects that are related to the infrastructure of the energy sector. Other project financing options and opportunities are complemented by the initiative between the European Investment Bank (EIB) and the EU (Kanellakis, Martinopoulos, and Zachariadis 2013).

2.3. *Social*

EU citizens are supportive concerning wind power developments. A study of public opinion has indicated that about 80% of the people living in Europe value the wind's potential and its impact on their lives (EWEA 2003, 2005–15).

A thorough study conducted in Scotland in 2003 mentioned that the residents who lived near the wind farms showed high levels of acceptance for wind energy. In fact, the survey states that Scottish people prefer that most of their electricity needs to be covered from RESs. Another study conducted in 2005 showed that the Scots are 74% certain that wind farms are absolutely essential in order to meet energy demands. When the same questions were repeated in 2010, the support from the citizens increased by 4%, which is of great significance when it is considered that wind farms had doubled by that time. At the same time, however, 59% of the people disagreed with the statement that 'the farms are ugly and a blot on the landscape' (Braunholtz 2003). That opposition against the individual projects is called the 'Not In My Back Yard' (NIMBY) syndrome. According to NIMBY, people do not like their scenery to be changed and prefer nature to stay intact where they live (Cornerstone Barristers 2013). On the other hand, Wolsink opposed the NIMBY hypothesis because it seems too simplistic, and the institutional factors are more significant (2000). An indicative survey focusing on Swedish home owners has shown that their attitude to wind energy depends on their age and earnings (Ek 2005).

Clearly, more offshore, instead of onshore, wind farms improve the electricity production because of the extremely steady wind, the usage of large power plants, larger wind farms and the reduction of any social impact (Nguyen et al. 2013).

2.4. *Technological*

Even though wind is one of the most popular renewable energy technologies, its efficiency depends on the weather conditions rather than the supply and demand (Lise et al. 2013). Wind energy technology in Europe has evolved over the years with the first offshore wind farm deployed in Denmark in 1991. Back in 1990, an individual turbine had only about a few hundred kWs compared to the offshore wind farms of today at about 1000 MW, making them comparable to a conventional power plant (Perveen, Kishor, and Mohanty 2014). In He, Li, and Gu (2010), it was claimed that offshore wind turbines are more efficient at a distance of about 50–200 m from the coast. The EU countries technologically lead with offshore wind projects up to 20 GW of capacity (Perveen, Kishor, and Mohanty 2014). New approaches adopt floating foundation turbines anchored at 60 m that resemble oil rigs, artificial islands or even an air-lifting platform which integrates aerospace and wind turbine technology (Planete-Energies an Initiative by Total 2010; Altaeros Energies 2014). In 2009, the first floating offshore wind turbine was constructed by Siemens and Statoil-Hydro in a coastal area off Karmøy, Norway. The support structures for this type of turbine give enough flexibility both for the installation and for the construction. These structures can also be easily detached from wind turbine farm systems (Perveen, Kishor, and Mohanty 2014).

London Array, the world's biggest offshore wind farm positioned 12 miles off the Kent and Essex coast, originally planned for 341 turbines units, with a total capacity of 1 GW. The produced electricity would be enough to satisfy about 750,000 homes annually (Planete-Energies an Initiative by Total 2010).

2.5. *Legal*

European legislation influenced by the European Union Treaties has illustrated the energy policies since the foundation of the EU. The original Treaties of the EU did not consider any EU intervention on energy and the foundation of the legislation regarding energy was based on: Environment (Article 175), Approximation of laws (Article 81–97), Trans-European networks (Article 154), Difficulties in the supply of products (Article 100), Research (Article 166) and External relations (various articles) (Kanellakis, Martinopoulos, and Zachariadis 2013). The Lisbon Treaty presented a fully detailed base in energy in Article 194. In an attempt to merge the Member States, this strategy was targeted to make safe and secure the energy supply in Europe's market, to encourage energy efficiency and saving, to evolve the renewables' groundwork and tie the current energy networks (Kanellakis, Martinopoulos, and Zachariadis 2013).

Failure to abide by the rules imposes large financial penalties on the target countries. A regulation has been enacted in the UK, according to Renewables Obligation (RO), where all electricity suppliers are now obliged, by law, to satisfy a fraction of their electricity needs from renewable sources. The suppliers receive a Renewable Obligation Certificate (ROC), for every MWh they generate (Ofgem 2014). The Energy Act 2008 proposed to expand the idea of ROCs. Originally, onshore wind received 1 ROC per MWh, but since 2009 this was doubled for offshore wind, which reflects the latter's higher generation cost. Wind energy receives about 40% of the total RO's income. The ROCs are the main support of the UK's wind energy, offering about 50% of the wind electricity income (Ofgem 2014).

The applicability of a Frame of Reference that monitors large-scale offshore projects with a focus on the environmental side has been analysed in Garel et al. (2014). The large knowledge gap of either positive or negative impact was the incentive to suggest a series of monitoring activities fit for purpose in order to protect the environment and develop the required knowledge. Monitoring protocols have been proposed to enhance usage, along with a set of coherent environmental indicators.

2.6. *Environmental*

The capability to derive the optimal location of RE installations has been presented by employing land analysis (Kraemer et al. 2013). By using meteorological analysis, which is used to calculate the target supply, the approach can be applied for the whole European territory and can predict potential RES locations. The results revealed that for wind energy, the coastline is one solution. Also higher capacities require a large interior space. Therefore, the future of RE will be influenced by the location. This can be particularly useful when targeting high capacities of RE in terms of planning and other feasibility studies.

The most severe challenges to wind energy are the visual and acoustical impacts on the surrounding areas. In the study performed in Maffei et al. (2013), wind farms were visualised to target individuals by using immersive virtual reality techniques in order to realise the implications of distance from the turbine and noise, that is, the number of the former along with their noise sources, and the turbines' colour. Among these factors, distance was considered to be the most important. Although these statements were deduced by simulations, the capability to perform experiments is still required to validate the aforementioned points.

As discussed in Lovich and Ennen (2013), the impact of wind energy to flying wildlife cannot be disregarded, as there is room for improvement. The effects of the wind energy both to the known and potential wildlife cannot be accurately estimated. The probability of bird mortality has been quantified to the number of collisions per turbine and is projected to be 0.02–0.15 every year (Perveen, Kishor, and Mohanty 2014).

According to Lindeboom et al. (2011), between the generators, in the bottom sandy area, there is no considerable effect on flora and fauna. On the contrary, the ecosystem has evolved, and presents higher biodiversity, which has led to a more balanced and stable equilibrium among species. Multi-objective optimisation studies in terms of environmental cost of the production of wind energy and benefits to society are a promising future direction. However, they cannot address every single problem and so far have not delivered the expected results (Lovich and Ennen 2013).

3. Developments in the UK

Wind energy makes a substantial contribution to the UK. An energy production of 15.5 TWh, in 2011, is equivalent to the power demand of 4.7 million homes. Today, there are more than 615 wind projects related to wind energy in the UK and, as indicated in Scottish Power Renewables (2013), there are 4375 onshore and 1075 offshore turbines with a capacity of 7177 and 3653 MW, respectively. In 2013, new 1883 MW installations were deployed, adding up to 10,531 MW by the end of 2013 (EWEA 2005–15). Industry projections foresee around 8 GW of capacity installed by the end of 2016, followed by a further increase of 18 GW by 2020. By that time, offshore wind is expected to supply 18–20% of the UK's power every year (Scottish Power Renewables 2013).

3.1. *Political*

The ongoing discussion around environmental and economic issues has pushed the UK to take action in order to reduce the country's greenhouse gas releases. The government decided to become involved in the generation of electricity by using RESs, which will expand the country's activity in the energy sector (Jones and Eiser 2010). In 1992, the Department of Energy was closed down and the privatisation of both gas and electricity companies followed. The Department of Energy and Climate Change (DECC) was launched in 2008, which was considered a new and revolutionary beginning regarding the country's energy targets, especially the offshore wind energy (Toke 2011).

The government's positive attitude towards RESs came from both the concerns of energy dependency from other countries and the government's commitment to Europe's legislation. The UK's aim is to take advantage of the infinite renewable resources that the country has in order to achieve energy security. The UK seems capable of achieving the EU's targets and is very likely to exceed the 20% of electricity from RESs by 2020. On top of that, the Devolved Administrations set some goals at a domestic level, too; the Scottish government set a 100% electricity generation goal coming completely from RESs by 2020. Northern Ireland Executive set a 40% goal for electricity and 10% heat coming from RESs. Finally, the Welsh government announced that they will be able to double their current status of RES electricity by 2025 (Department of Energy and Climate Change 2011).

Britain has one of the largest and fastest evolving offshore wind projects in Europe, some of them installed in Wales and Scotland. In the beginning, offshore wind energy was not well accepted by industry because of the problems it faced with unclear environmental legislation. As soon as the policy was reformed, the UK became the offshore wind forerunner around the world (Boyle 2007; Mani and Dhingra 2013). A comparative policy support in the offshore wind energy section in some European countries can be found in Green and Vasilakos (2011). The electricity produced from both offshore and onshore wind energy is enough to power millions of households (Department of Energy and Climate Change 2011).

Offshore wind applications are basically controlled by the UK government itself. However, there are many additional barriers because of the decentralized governments of Northern Ireland, Wales and Scotland that contribute to the process (Toke 2011). Another, very important, difference is that in all of the cases of offshore installations, the government has the authority to give permission in order for the application to proceed. Nevertheless, for most onshore installations, the local authorities have the leading role for the future of the projects. If an onshore wind project is bigger than 50 MW, then central government is the one that needs to give its consent; however, the central government does not own the seabed where the offshore applications are being installed. The Crown Estate that belongs to the Monarchy is the owner of the UK's seabed, makes profit from all the offshore installation leases without significant taxation and at the same time supports the Treasury (Newell and Paterson 2010; Toke 2011; Kern et al. 2014; The Crown Estate 2015).

Unfortunately, a very recent announcement has confirmed the Conservative Party's strategy to stop subsidies for new onshore wind energy projects. The already installed and authorised-to-be-installed capacity at the moment is thought to be enough for the country to reach the EU's 2020 energy targets. On top of that, local communities will play a key role and onshore wind farms will not be authorised without their permission. New policies are following to secure the above facts; the new actions will be applied from May 2016. Following that, many problems have been starting to show after the government's position, including the continuous criticism by the RE industry (Shankleman 2015).

3.2. *Economic*

According to the UK Roadmap (Department of Energy and Climate Change 2011), UK's actions are based on the already scheduled arrangements, such as the financial support mechanisms for renewables, helping companies to secure investment in green infrastructure by the Green Investment Bank (GIB), and encouraging the development of new offshore wind manufacturing facilities at port sites. As the UK's Electricity Market Reform White Paper announced, along with the UK Roadmap, it has been decided to isolate both the Great Britain and Northern Ireland markets regarding power production, creating more investment opportunities.

In addition, the reform will attempt to reduce the consumer's costs (Department of Energy and Climate Change 2011). The UK has established the ROCs to regulate and monitor the operation and use of RESs. However, when they demonstrate having fewer ROCs they have to pay a penalty to a buy-out fund, which covers any administration costs and pays off the rest of the suppliers that met their commitments (Ofgem 2014). Hence, even better conditions will be provided by the government to manage the ROC market. Large firms are in a better position than individuals. Major electricity companies (e.g. E.ON, RWE, Scottish Power, Scottish and Southern Electricity and Centrica) and international ones (DONG, Vattenfall, Siemens and Statcraft) either possess or will acquire wind farms (Toke 2011).

Construction date and RO can affect the type of ROC and the rate of £/MWh, respectively. To be more precise, the offshore wind applications installed until 2014 are worth two ROCs and when an ROC is almost finished at about 70%, then a profit of £100 per MWh is given to the ROC which is added to the total wind power market sale and regularly fluctuates, that is, £40–80 per MWh between 2006 and 2010, which translates into £140–180 per MWh for offshore operators. The rates are beyond the equivalent ones in Germany, where the Feed-in-Tariff (FiT) is €15/kWh, set against this apparently higher UK tariff is uncertainty about the income stream (Toke 2011).

The UK uses mixed information from the market by combining tradable certificates and electricity as a remuneration policy. The compensation rate for the UK is 17.7 ct/kWh and is considered to be constant throughout an entire period so as to reflect nominal prices (Prässler and Schaechtele 2012). The FiT scheme is mainly responsible for the growth of small wind markets in 2012. During the same year, 37 MW were installed, among which the range between 15 and 100 kW was popular. The rate of FiT for the same market was €0.207/kWh (Gsänger and Pitteloud 2014).

The UK government has a broad plan to make wind energy even more appealing. By 2020, an industry Task Force is to be established to set up directions and actions that will reduce the cost of offshore wind electricity to £100/MWh. This will be partly supported by the government for a period of four years to reduce the cost of offshore wind electricity (Department of Energy and Climate Change 2011).

Finally, RenewableUK has indicated that the employment rate in both the marine and wind energy sectors has risen to 74% in relation to the same statistics in 2010. The offshore industry claims that 61% more positions will become available in 2014 (RenewableUK 2014). In many cases, supporters have requested some warranties that would assist the beginning of private sector investment after the discussions that mentioned about 70,000 new positions and a 60-billion aid by 2020 (Kern et al. 2014).

3.3. *Social*

Even though RESs support UK's targets, there are still project delays or cancellations due to people's reactions (Jones and Eiser 2010). There are a few organisations that are concerned about the offshore wind developments in the UK and the programmes initiated by the government. However, these programmes are supported by some organisations such as the Royal Society for the Protection of the Birds, Greenpeace and the WWF, which continue their campaigns for offshore wind installations (Toke 2011).

Implicit issues regarding onshore developments are summarised in Jay (2010), concerning aesthetics and tourism, mostly at a local level. However, as discussed in Toke (2005) and Haggett and Toke (2006), there were no more oppositions about the close-to-land and offshore installations compared to the bigger onshore wind farms.

As stated in Gray, Haggett, and Bell (2005), locals are not as much interested in fishing around the coastline any more. The dangers of fishing near offshore wind farms are those of fishing nets causing problems. Fisheries, in some coastal societies, face many problems because of the occupation of the most profitable waters. Although ships and ferries can easily change their course, in reality this would involve additional costs. Indicatively on the West of Duddon Sands, where an offshore wind farm was being installed, the project developers had to negotiate a pay-off to shippers. Similar to ships and yachts, recreational boating companies have reported minor complaints (Toke 2011).

3.4. *Technological*

Wind resources in the UK's waters are outstanding and very suitable for wind farms. Under the United Nations Convention on the Law of the Sea or UNCLOS, nations are allowed to conduct studies or projects in the water less than 200 miles away from the mainland or halfway in waters that are less than 400 miles from other borders. The grid infrastructure in the UK is maintained by the National Grid that secures the electricity supply that is able to manage 40 GW of the offshore wind energy, which can be translated as 30% of the UK's electricity production (Toke 2011).

The largest offshore wind park in the world is Walney Park in the UK at 367 MW, which was installed in 2012. The second largest is the Thanet offshore wind development at 300 MW. London Array is considered to be the biggest project under construction, currently at 630 MW. In order to accomplish this project, the Crown Estate allowed London Array Ltd to proceed with a 50 year lease for both the location and the cable path to the shore (London Array Limited 2014). The turbines of the first part of the project are rated at 3.6 MW with a 120 m of rotor diameter and a 87 m of hub height (London Array Limited 2014).

The case of the North Hoyle offshore wind park, installed at about 8 km from the shore, in the UK, is special because of the low recorded availability on the energy performance of the plant. After one year of operation, the availability was recorded at 84%. Several issues, such as generator faults, caused unexpected maintenance and shut down. It is important to mention that turbine failure (66%), bad weather conditions (17%), construction activities (12%) and scheduled maintenance (5%) were responsible for the long downtime periods (Kaldellis and Kapsali 2013). Even lower availability is reported in the Barrow offshore wind park, 8 km away from shore at 67% in 2006–2007. The main problems were failures of the rotor cable, turbine failures and limited accessibility to the site due to large waves in the sea during that particular period (Kaldellis and Kapsali 2013).

3.5. *Legal*

During the past years, the UK has made new, ground-breaking policies to ensure the RES progress, designing policies, regarding the offshore wind applications. These are distinctive and different in relation to the other countries in Europe because of the 'criteria-based' tactics to support offshore developments. In fact, Britain's offshore plans will be based on consumers' opinions of the growth of prices caused by these plans (Toke 2011). In the UK, the Offshore Wind Farm (OWF) operators are responsible for connection to the grid. According to contemporary regulation, the UK obliges the electrical transmission system and the farm to be separate, which forces the operators to pay transmission charges so they can be connected to the grid (Prässler and Schaechtele 2012).

The country's policy has encouraged further both offshore projects and other technologies because of the improvements in the RO, where at first it was only developed at one level to apply to all renewables. In 2008, this strategy changed, because it was realised that offshore wind technology could not fit inside the earlier policy. Following that, the UK government announced the new FiTs plan for small, up to 5 MW, renewable applications starting from 2010. In addition, the UK focused on marine studies so as to discover alternative forms of suitable offshore wind projects, while designating certain areas as Natura 2000 sites (Toke 2011).

At the moment, the current energy bill suggested by the government includes a mechanism that is called the Feed-in-Tariff with Contract for Difference or FiT CfD. This mechanism will be part of the legislation that supports Electricity Market Reforms that aim to increase energy-related investments. The reason behind CfD and why it is included in the FiTs framework is that generators that sell energy to the suppliers are assured for a steady-rate period of 15–20 years. This is crucial for new investments, as they need an extended period of time for their investment to return profit. The DECC's intention is to replace the RO in the Spring of 2017 and to eventually terminate it in 2037 (Good Energy 2015; The Green Age 2015).

The Crown Estate's role in the RE legislation, and especially the offshore wind application's developments, is vital. The Crown Estate owns most of the near shore (over 50%) and offshore up to 12 nautical miles. It also possesses the rights, among others, to produce electricity from the waves, wind and tides according to the Energy Act 2004 (Mani and Dhingra 2013; The Crown Estate 2014). When the lease period given by the Crown Estate is due, the wind farm operators have the choice to repower their turbines (Mee 2006).

3.6. *Environmental*

There are serious concerns about the wildlife in the environment around the wind farms. Most of the environmental impact of a wind turbine has to do with noise, shadow flicker, electromagnetic waves, fauna and flora, bird feeding locations, sediment movement, disturbance of wildlife, interference with migration of fish, etc. (Phylip-Jones and Fischer 2013). As far as the noise impact is concerned, Great Britain's legislation allows the noise to be only 5 dB above the normal and average dBs in a region (Katsaprakakis 2012).

There are locations classified as Natura 2000, under the EU Birds and Habitats Directive, with conflicting interests. Some react negatively to the Natura 2000 in the UK, because of the large amount of land that they usually occupy. More problems have been reported near the shore, and some further out to sea. Because of the Natura 2000, special measures had to be taken to approve sizeable wind parks, which have raised concerns about the industry's plans (Toke 2011; Kern et al. 2014). Even though there is enough evidence of wildlife disturbance by the wind turbines, there is another way that the environment can coexist with the RE technologies; Mee (2006) studies the suitability of aquaculture in offshore wind farms from the industry's point of view.

4. Developments in Germany

Germany is considered the leader in Europe in wind power exploitation with installed capacity of 3238 MW up to 2013; by the end of 2013 the overall capacity had reached 33,730 MW (EWEA 2005–15).

As stated by the German Wind Association (BWE) and Verband Deutscher Maschinen und Anlagenbau (VDMA) Power systems, the onshore wind turbine market keeps expanding. Wind energy generation is estimated to grow to 45,000 MW by 2020, 65,000 MW by 2030, 80,000 MW by 2040 and 85,000 MW by 2050 (Wallasch, Rehfeldt, and Wallasch 2011).

4.1. *Political*

Germany signed up for the greatest emission reduction within Europe at the 1997 Kyoto Summit and was also the first to present the FiT that promises the lowest cost for electricity from RESs entering the country's grid. The FiTs are the main support mechanisms in Germany and have a fixed value per electricity unit, which is offered to the operators for a predefined period (Prässler and Schaechtele 2012; McKenna, Hollnaicher, and Fichtner 2014). When the Renewable Energy Act (EEG) took effect in 2000, the electricity produced by RESs was given a higher priority to access the network infrastructure, than was originally stipulated. After the nuclear disaster in Fukushima in 2011, it was decided that 8 of the 17 reactors in the country would shut down and gradually stop the rest by 2022. Germany's energy transition ('Energiewende') will determine the future of the country. The Federal Ministry of Economics and Technology (BMWi) and Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) have taken the initiative to work on the energy issues (Stegen and Seel 2013).

The German government is planning to adopt RESs, mainly wind power, to supply the country. This would account for 80% of the overall electricity production by 2050 (McKenna, Hollnaicher, and Fichtner 2014). The energy utilisation will increase to 20% by 2020 and 50% by 2050 in comparison to the 2008 levels, with 10% and 40% contribution from transportation respectively and an addition of around six million electric vehicles by 2030 (Stegen and Seel 2013).

The government has decided to compensate for the grid delays in order to give motivation to the industry to continue with new projects, as stated in the EEG. Consequently, that has had a negative effect, both increasing the cost of electricity from the consumer's side, as well as extending payment periods at a low rate or short payment periods at a higher rate to companies. In any case, companies would receive a 'sprinter' bonus for turbines erected before 1 January, 2016 (Stegen and Seel 2013). The German Exclusive Economic Zone (EEZ) has prearranged every offshore wind project while the Federal Maritime Hydrography Agency (BSH) gives the final permit to let the installations proceed (Phylip-Jones and Fischer 2013). Wind installations deployed less than 12 nautical miles from land that require the German government's permission, while beyond this threshold the government has to consent (Building Federal Ministry for the Environment, Nature Conservation and Nuclear Safety 2013; Mani and Dhingra 2013).

4.2. *Economic*

About 60% of the recently installed capacity is located in the central and southern regions of the country. Regardless of the fact that wind energy is particularly developed in these areas, the north continues as a secure and stable choice for the onshore part of wind energy, covering over 40% of the market (German Wind Energy Association (BWE) 2014). Out of the 51% of Germany's total installed RES capacity, 40% is owned by individuals and 11% belongs to farmers. The other 6.5% of capacity is owned by E.On, RWE, EnBW and EWE, four of the largest market stakeholders (Nolden 2013).

The head of Germany's Monopolies Commission openly agreed that a tsunami of costs was approaching German citizens (Frankfurter Allgemeine Politik 2012). New technologies and larger capacities being manufactured are affecting electricity charges and relocation costs. The extra renewable power charges are included in consumers' electricity bills. In Germany and some other countries (France and Denmark), the FiTs are aligned, with respect to each country's laws and legislations. As soon as the FiTs period is due, the produced electricity is being sold in the energy market at an economic price (Prässler and Schaechtele 2012). The EEG offers three different services regarding onshore wind installations which are a first five year 0.0893 €/kWh FiT, a 0.0487 Euros/kWh non-time-dependent tariff and lastly an extra 0.0048 Euros/kWh for the turbines that started operating earlier than 1 January, 2015 (Stegen and Seel 2013).

In the manufacturing part of the industry, the market is governed by eight companies that in 2012 generated 97% of the country's capacity. Enercon was the largest firm in Germany with a 42% share of the total capacity followed by Vestas with 27%, GE Energy, Nordex and Repower with 7% each, Siemens with 5%, Fuhrländer with 2% and Bard Holding with less than 1% (Stegen and Seel 2013). Further every Terawatt hour of electricity produced from RESs (both wind and solar energy) creates enough income to cover the salary of 400–410 employees, whereas coal and gas occupy just 80–125 people (Jürgen 2012).

4.3. *Social*

At first, the world was thoughtful but supportive and then enthusiastic about the Energiewende, especially the anti-nuclear and environmental campaigners. Many times though, German society strongly reacted and protested about the new installations in the wind energy section (Wolsink 2000); however, there is no proof to validate an actual NIMBY syndrome. Public reaction and opposition can be categorised as follows: first, a positive approach to the wind installations but, concurrently, opposition to letting the projects take place in their neighbourhood; second, the opposition to any wind energy application whether in people's neighbourhood or not; and third, a lack of trust in RES technology in general. Germany agreed to legally restrict the place and the height of the wind turbines in order to reduce the trouble they cause to people who live near the wind farms, for example through noise pollution and shadow flutter (Stegen and Seel 2013).

Wind farms can cause noise pollution and light disruption, resulting in complaints. The number one priority should be the choice of location as society can cause real problems such as delays or even cancellations. In addition, the more suitable the area of the installation, the less the environmental impacts on nature (Geißler, Köppel, and Gunther 2013).

4.4. *Technological*

When at first in 2012, RWE, the primary electricity producer in Europe announced major delays in the Nordesee-Ost 288 MW offshore wind farm project and six months later, the next largest utility company EnBW stopped, for an indefinite period, the manufacturing of Hohe See, a 500 MW and €1.5 billion offshore project in the North Sea, the matter started to attract concern (Stegen and Seel 2013).

At the moment, there are 18 new wind project installations under construction at 5.3, and 18 GW more were approved in 12 EU countries, half of which were approved in Germany. After completion of the projects, the offshore wind energy capacity in Europe will reach 27 GW (Kaldellis and Kapsali 2013).

Currently, the Blue TLP is one floating type of offshore wind turbine project prototype that is in the design phase. This has already been installed in both Italy and Arcadis TLP in Germany but only for an off-grid demonstration (Perveen, Kishor, and Mohanty 2014).

According to Wallasch, Rehfeldt, and Wallasch (2011), most of the total electricity in Germany was generated at large power plants but this is anticipated to be decreased by half by 2050. New transmittance systems will be vital in order to carry the electricity from the most wind productive areas in the North to the West and South regions of Germany. In their reports in 2012, the German Energy Agency, known as dena (Deutsche Energie Agentur GmbH 2012), presented a plan to improve and expand the network which is going to cost about €11.1 billion and will help Germany's goal of 60% electricity use from RESs by 2030. Dena's plan also includes the worth of the connection to the offshore wind farms (Deutsche Energie Agentur GmbH 2012).

4.5. *Legal*

EEG, the Renewable Energy Heat Act, the Grid Expansion Acceleration Act and the Energy Economy Law are the Acts supporting the energy transition.

Among other political actions, Germany has also developed appealing investment policies for offshore wind energy farms (Mani and Dhingra 2013). First, free grid connection up to 2015 has been provided to investors that will initiate a project within the EEZ, financially supported by the state. Second, a sprinter bonus up to 2015 is offered for offshore wind energy projects to speed up their implementation. Third, a number of clusters have been identified, where offshore wind energy farms can be set up via a single cable connection, in order to facilitate grid connectivity. Fourth, the Renewable Energy Law including the FiTs has fuelled the growth of the wind energy sector and other expertise as well (McKenna, Hollnaicher, and Fichtner 2014). In general, Germany is attractive from the point of view of grid connectivity and ease of regulatory procedures.

4.6. *Environmental*

Onshore wind energy has been quickly developed over the last 20 years in Germany, therefore there are currently about 23,000 wind turbines, 796 of them built in 2012 alone. Consequently, nearly all the suitable space has been covered, including the most wind efficient coastlines in the North and Baltic Seas which has set limits for potential wind installations. Furthermore, onshore wind turbine installations face many difficulties in the early stages of their construction (Stegen and Seel 2013).

Some wind turbine operators are very optimistic regarding North Rhine-Westphalia being the most suitable location, followed by Lower Saxony, Brandenburg, Schleswig-Holstein, Rhineland-Palatinate, Bavaria and finally Baden-Württemberg for either a repower or completely new wind turbine construction (Stegen and Seel 2013). The North Sea is also considered suitable for wind installations, including the Waddense, which is in UNESCO's World Heritage list and is environmentally protected (Marencic and Frederiksen 2013). Transmission cables could be laid, but only at certain periods of the year and in particular paths.

The red kite is on the Annex I list of Europe's Wild Bird Directive (EEC/79/409) in order to prevent the decrease of their population as described in Bellebaum et al. (2013). The problem is worse in the summer when the red kite is attracted to the fauna and the area around the rotor.

Germany prefers to place its offshore wind turbines at a greater distance, that is, 40 km, from the shoreline compared, for example, to the UK and Denmark at about 17 km. The country's decision to also change the depth limits stems from an attempt to preserve the land, maintain tourism, and retain shipping routes and fishing areas (Wilkes et al. 2012); however, that causes difficulties during construction, with depths that reach 30 m next to the standard 23 m used in Europe. In addition, the weather conditions further from the shore become worse and set restrictions on the time the construction can take place.

5. Developments in Greece

Greece is a country with many islands and a long coastline with strong winds, which favour the evolution of wind energy. Unfortunately, only 13.6% of the total electricity demands of Greece comes from RESs (EWEA 2005–15). According to EWEA annual statistics, 116 MW capacity was installed in Greece in 2013. By the end of 2013, there were 1865 MW compared with the 117 MW installations and 1749 MW, cumulatively in 2012 (EWEA 2005–15).

Although the growth of the wind energy in Greece in 2012 has shrunk, new investments were made worth about €150 million. At the same time, renewable energy in total attracted new potential investments of over €2.5 billion (Greek Scientific Association of Wind Energy 2010; EXPRESS 2013). Additionally, given the number of projects that are ready for implementation, wind energy is going to evolve in the next few years; however, this is all subject to political and financial stability. There is now a great opportunity for non-European banks, export credit agencies and multilaterals to penetrate the RES projects in the country.

5.1. *Political*

After the 2009 elections, upon the establishment of a green policy, the Ministry for the Environment, Energy and Climate Change was created. The Prime Minister of Greece highlighted the importance of meeting the energy goals in Directive 2009/28/EC in a speech given in 2010 (Greek Ministry of Environment Energy and Climate Change 2014). Achieving the 20-20-20 targets is both an obligation and an opportunity for the Greek government that can guide towards energy safety, emission reduction, investment attraction, financial development and technical knowhow. The legal obligations make Greece's RES market long-lasting, trustworthy and stable for potential investments (Ministry of Environment Energy and Climate Change 2007; Greek Ministry of Environment Energy and Climate Change 2014).

Initially, the Greek government had committed legally to reach 18% but eventually raised its targets to 20%. As a plan, the government targets 40% of the country's electricity, 10% of its transportation and 20% of its cooling–heating to come from RESs by 2020 (Enterprise Greece Invest and Trade 2008). Wind electricity production is estimated to make the biggest contribution to the country's energy sector (Greek Ministry of Environment Energy and Climate Change 2010, 2014).

Greece has also embraced the NREAP or NAP for 2020 and estimates that an addition of 10,000 MW to the capacity is required to meet the goals. This will include about 7500 MW of onshore and offshore wind installations (Assimakis and Kitsillis 2012). Wind energy developments are a priority for Greece, while renewable electricity, in general, can be generated at competitive costs.

A new investment law was passed by the Greek Parliament in 2011 and introduced the terms and conditions of a new investment plan for the country, assisting either domestic or foreign stakeholders and providing appropriate motivation, depending on the sector and position of the investment (Enterprise Greece Invest and Trade 2008).

5.2. *Economic*

The outstanding wind resources in Greece with a profile velocity that can exceed 8–11 m/s and about 2500 hours of wind in several parts of the country makes it one of the most desirable places in which to invest (Kaldellis 2005). Potential investors around the globe have shown interest in the Greek financial market that will potentially bring new developments to the energy sector. Unfortunately, according to Assimakis and Zafiropoulos (2014), its financial crisis caused many energy projects to be delayed or indefinitely postponed these last few years. However, the current situation is encouraging for new projects such as renewable energy installations and an interconnected system between the Greek islands.

The main reason for unilaterally cancelling the production licences for wind energy projects with a total capacity of 260 MW is the low rate of the actual capacity additions. A second reason is related to the Development Law for supporting Private Investment for Economic Growth, Entrepreneurship and Regional Cohesion (February 2011), where the upfront payment of 25% of the granted subsidy was reduced (Papadelis and Flamos 2014)

The energy market in Greece is going through some changes and is being considered as an energy hub for Southeast Europe by deregulating the production, transmission and distribution of energy, and, by starting a campaign for RESs, attracting new investment. Investing in the Greek wind market has five very promising advantages; ample wind sources that are considered among the best in EU's countries, the priority dispatch by the system operator, the high feed in tariffs, the 20 year power purchase agreement and as stated before, the promising long-term legislation that warrants a profitable investment (Enterprise Greece Invest and Trade 2008).

On the other hand, according to Oikonomou et al. (2009) Greece is lacking in both development and investment structures, especially in tourism areas, where everything else regarding tourism is underdeveloped. The country has many other problems regarding RES projects as well. The legislation lacks detailed rules and laws about the environment. For instance, it is known that the environmental conditions are not inspected and controlled after the installation and finally, the environment is never restored. Also, an installation planning policy, which forbids the construction of wind parks, is non-existent. In addition, Greece has many limitations in its legal sector regarding the load factor of wind turbines, especially in distant or difficult-to-approach areas such as islands that own a very weak network. For example, in the Dodecanese, this factor is less than 30% which is a result of PPC instabilities in the system (Oikonomou et al. 2009). Also, the financial instability of the country during the economic crisis has created an unknown territory and the future has never been more obscure.

Changes in the legislation have accelerated the authorisation process and doubled the duration of the sale contract. However, for investments below €50 million, demands for subsidies could be filled only twice a year. Also, exploiting 'agricultural land of high productivity' is another barrier related to the development of RE. Currently, there are three main policy programmes supporting RE in place, and their impact is limited. The regulation negates any benefits and creates a huge licensing back-log. Hence, aspects regarding RES deployment are not coordinated effectively and there are several high soft costs involved (Winkel et al. 2011; Sioulas et al. 2012).

At the moment, the largest manufacturing wind companies are Enercon with a 33.1% share of the total wind installations, Siemens, which used to have more than 50% of the market share until 2000 and then lost its shares, Nordex with 15.5%, Vestas with 45.5% in 2013 and Gamesa with 5.9%. Some of the above firms have penetrated the Greek wind market and undertaken many projects (Kotsikopoulos 2014).

Currently, EDF leads the production of electricity production with 322.8 MW compared to 298.8 MW in May 2013, followed by TERNA with 277.4 MW compared to 241.5 MW in May 2013; next is Iberdrola Rokas with 250.7 MW which has remained constant since 2013, Enel Green Power with 200.5 MW which is the same as the year before and last, Ellaktor with 162.9 MW with no further development in the last year. All this amounts to a total of 1214.3 MW, which is two-thirds of the total installed capacity of the country. In the sixth place, there is the PPC (Public Power Corporation) Renewables with only 72.6 MW (Kotsikopoulos 2014).

Renewable energy projects in Greece are prioritised depending on the safety of the grid and any technical constraints, where a system operator is legally forced to use renewable energy at monitored and controlled prices. The system operator can authorise the priority dispatch along with Power Purchase Agreements (PPAs) for a period of 20 years. The offshore wind installation FiT in Greece is currently set to be €108.30/MWh, which is expected to increase by 30% upon the review of the Regulatory Authority for Energy considering the size of such an investment (Assimakis and Kitsillis 2012).

5.3. *Social*

Despite their great potential, society's broad consent negatively affects further development. In some Aegean islands local authorities, organisations and residents react to new wind applications. Consequently, only 71 MW out of the total of 900 MW is installed in the Aegean, whereas they could potentially be independent of fossil fuels (Mondol and Koumpetsos 2013). A small percentage of people are strongly against any kind of wind application, ignoring the economic value of such initiatives (Kaldellis 2005). Similar to other EU countries, a significant and concentrated size of wind turbines were installed fast in some partly restricted regions which caused tension, raised huge oppositions and even prevented a few wind projects from continuing, as stated in Kaldellis (2001).

In Crete, although a significant part (40%) of the locals have faced either visual or noise problems, they still support wind energy because of increasing environmental concerns and the limited fossil fuels that are imported in order to produce energy for the island (Katsaprakakis 2012). People in Crete have accepted very early the prospect of wind applications and since 1993 a number of wind parks have been installed – some private and some by PPC. However, in the South Peloponnese, due to the numerous wind projects planned, conflicts between central governmental and local authorities have caused many problems, actions have even been taken against people or authorities that were trying to familiarise the island inhibitants with the prospect of wind energy (Kaldellis 2002, 2005).

Diverse opinions on the operation of existing wind parks in the main regions suggest difficulties in generating electricity in the islands, particularly in the summer, because of the financial knock-on effect (Kaldellis 2005). Also, on the mainland, several new wind projects are usually built very quickly and close to each other, which causes aesthetic issues for the residents compared to the islands, where only a few wind parks are scheduled and to be constructed, progressively, beginning with a PPC initiative (Kaldellis, Vlachou, and Paliatsos 2003; Kaldellis 2004).

Noise pollution from either the aerodynamic design of the blades or the engine itself is an issue. Despite the use of new silent turbines, they are still within hearing distance, especially when the wind blows towards a residential region. The problem seems to be even worse when there is also a visual contact. The noise limit for Greece is 40 dB (Katsaprakakis 2012).

Also, rocky areas are highly preferred. In areas with high tourism such as hotel resorts or an archaeological site, that is, an area with historical and cultural interest, wind turbines are installed at least 2000 m away. Aesthetic issues can be the number of the blades in a wind turbine or even the colour it is painted (Katsaprakakis 2012).

5.4. *Technological*

Because of the technological maturity in the onshore and offshore wind sector, unsettled regulations do not discourage potential investors (Assimakis and Kitsillis 2012). New interconnection wind projects have already been installed, in the Cycladic Complex, or will be installed in Crete and the North East Aegean islands, harnessing the superior wind resources that the Aegean Sea provides. All the above projects are being referred to the National Transmission Development Plan for the periods 2008–2012 and 2010–2014 as stated in Greek Ministry of Environment Energy and Climate Change (2014). The Regulatory Authority for Energy will review and assess 36 projects with a total of 5267 MW capacity from new offshore wind installations that have been applied for and delayed or stagnated because of the many regulations and policies that finally have been simplified (Assimakis and Kitsillis 2012).

The Ministry of Environment, Energy and Climate Change has also recently approved seven wind projects with a total of 204.2 MW capacity in the periphery of Western Macedonia, Thessaly and Western Greece. The cost of these projects is estimated to bring about €245 million into the economy and to offer about 472 GWh from RESs annually which is about 1% of the electricity demand in the interconnected system (ECONEWS 2013). The first wind farm with eight wind turbines, in addition to the 1559 photovoltaic arrangements in the same area, was constructed at the end of 2013 in Messinia (PRESS 2013).

In order for a renewable project to be licensed in Greece, it has to obtain a connection offer from the grid operator in charge. Even after the connection licence there can still be many difficulties in the process. In 2010, several issues on the increase of grid capacity have been resolved and new lines of high voltage, some of which are underwater, have been opened to public tender (Greek Ministry of Environment Energy and Climate Change 2014).

An underwater cable has been installed in the Cyclades complex linking and supplying the islands of Paros, (where a diesel generator was installed by PPC), Naxos, Iraklia, Sikinos and Folegandros. The island of Ios is a small island with ideal conditions for wind energy parks (Joint European Support for Sustainable Investment in City Areas 2010). Although in Ios there are three wind turbines of 1.2 MW capacity, at the moment the grid interconnection is still inefficient and it is possible that there are going to be losses as high as about 18 GWh every year (Joint European Support for Sustainable Investment in City Areas 2010; Count of South Aegean Sea 2014). Grid expansions are planned to mitigate certain problems and to link the Aegean islands with the mainland of Greece; this work is estimated to be completed in 2020 (Assimakis and Kitsillis 2012).

Recently, a new tool has been deployed that provides information to better utilise the production of wind energy, along with the disposal of conventional plants, and has been operating in the Transmission System Operation Centre. The Hellenic Transmission System Operator has also designed Special Protection Schemes that will introduce the wind energy in certain regions. It is estimated that in the next few years, prediction tools will be more advanced and will be necessary to Transmission System Operators (Greek Ministry of Environment Energy and Climate Change 2014).

5.5. *Legal*

Greece has rearranged the Union's Renewable Energy Directive or Directive 2009/28/EC and revised it into a nationwide Law 3468/2006, also known as the RES law, where the licence and operational processes for electricity production are provided in detail. In addition, there are some parts imported by the responsible authority, such as the Ministry of Environment, Energy and Climate Change as well as the Regulatory Authority for Energy (Assimakis and Kitsillis 2012).

Despite a number of regulations being introduced to facilitate developments, bureaucracy is still a considerable barrier in the whole process. Law 3851/2010 is related to the licences required for a new RES installation and is the development of the old Law 3468/2006. Offshore wind projects are also supported. In order to install a new project that has a larger than 1 MW capacity, the following are needed: an electricity production licence, a grid connection offer, an environmental terms approval, an installation licence, a building permit and an operation licence (Assimakis and Kitsillis 2012). Generally, the authorisation process needed for a wind farm is time-consuming and can take about 6–7 years. Environmental terms are issued later and exploitation rights for the wind park will be assigned after an open public tender (Greek Ministry of Environment Energy and Climate Change 2014). Hence, the authorisation process is accelerated and simplified. Reasonable FiTs are offered. This law presents new proposals for the newly and underdeveloped offshore wind section but also takes action regarding the NIMBY syndrome. Finally, it has established an independent renewable energy office, which offers a wide range of services (Chaviaropoulos 2010).

5.6. *Environmental*

According to the Regional Planning and Urban Development publication, wind energy projects can be installed in limited regions as described in the following restrictions. The installations are allowed within a distance from main roads and railways equal to at least 1.5 times the diameter of the turbine's rotor, an 1 km minimum distance from the nearest shoreline and beach, more than 3 km away from regions registered as World Heritage sites or near monuments and archaeological or historical sites, at least 1 km from cities and villages with more than 2000 residents or hamlets with a population up to 2000, at least 1.5 km away from traditional hamlets and 500 m from the boundaries of monasteries (Ministry of Environment Energy and Climate Change 2007). According to Evans, Strezov, and Evans (2009), wind applications are expensive as an investment and maintenance, while they require a significantly large space to be installed.

Continuous long-term studies are gathering data for a better understanding of birds and how they can be affected by the presence of a wind turbine. Wildlife in general can be disturbed during the construction process of a wind farm, and the environment can also be affected, causing lack of plant life, earth disruption and possible erosion. Construction works could actually lead to loss of habitat and, indirectly, death for many species (Katsaprakakis 2012). An area can be characterised as a Natura 2000 or Special Protected Area for the protection of wildlife and in particular the endangered species living there; wind farms and applications of any kind are prohibited from being installed in those areas to ensure that nature will stay intact (Katsaprakakis 2012).

6. Discussion

In summing up the previous sections, European countries have a few things in common that are analysed below. On the one hand, after the energy dependency concerns that appeared in the UK, the country was pushed towards RESs and especially offshore wind energy, a sector in which they are considered to be world leaders. The UK's goal is to gain energy security and to achieve the EU's 2020 targets. It is critical to point out that Scotland aims to fulfil its power demands by using only RESs by 2020. On the other hand, Germany has decided to embrace further RE through an energy transition that will determine the future of that country. The transition has been put into action after the disastrous nuclear accident in Fukushima that led to the shutdown of most of the country's reactors. The events pushed Germany into taking action, starting to plan new policies and setting new targets for RE. According to the German government's plans, 80% of the total power will come from RESs by 2050. From another point of view, RE and especially wind energy has always been underdeveloped in Greece. After the Greek elections of 2009, a more serious approach to RE appeared when a new ministry was created to deal with the new green policy. Even though the country still faces many financial problems, new policies for wind energy were introduced to help the energy sector to grow. Greece, especially Aegean seas and islands, have the potential to actually become fossil-fuel independent.

In the economic sector, the UK has recently introduced the CfD mechanism in order to attract more investments. The bad news is that the newly elected Conservative government plans to stop any subsidies for new onshore wind energy farms to be developed. The FiT mechanism is still applied in Germany but many problems have been raised due to the additional RE charges that the consumers are asked to pay through their electricity bills. However, wind energy investments in Germany have easier and clearer procedures. Even though Greece improved its energy sector legislation, many cancellations still happened. There is still room for improvement in the legal and economic sectors for the years to come.

Finally, many areas have been covered with onshore wind turbines and many more are to be installed offshore in the UK. In Germany, though, most of the suitable land has already been covered and more wind installations are becoming harder to develop. On the other hand, Greece has considerable amounts of suitable land but only a few wind projects have been installed.

All countries have made recent changes to their RE policies in order to assist the energy market to grow and at the same time to attract investors that will eventually lead to energy independency. All EU countries are willing to meet or even go beyond the 2020 targets. Finally and most importantly, all of them still face problems on their way to energy security.

7. Conclusions

A PESTLE analysis has been performed in selected European countries and the whole of Europe to investigate vital aspects of the environment in which the industry of wind energy operates. Europe has many years of collective experience regarding technology and policy insight, which could be disseminated to future developments. Currently, the UK is considered to be the world's leader in offshore wind energy with respect to the total installed capacity. Also, Germany has the highest installed capacity in the EU. Finally, even though Greece has great wind energy potential the wind energy applications are underdeveloped in the country. All countries have made many improvements in their legal frameworks to try to attract investors and boost the RE sector. However, all of them face many difficulties on their way. The UK has improved its FiT mechanism but has also stopped all subsidies on onshore wind energy. Germany aims high regarding the EU targets but the additional RE charges have proved to be challenging. Finally, even though Greece has improved many aspects of its legislation, many problems and a lack of coordination still exist. In addition, the financial instability has created an undefined and unpredictable future for the renewable energy sector.

Europe approaches a new era where opportunities for development are becoming challenging. For that reason, the need for carefully designed, improved policies is increasing. European countries have more things in common than was previously thought. They have all made improvements but they still have to make many more over the coming years.

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RESEARCH ARTICLE

A multi-objective optimisation approach applied to offshore wind farm location selection

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Abstract This paper compares the three state-of-the-art algorithms when applied to a real-world case of the wind energy sector. Optimum locations are suggested for a wind farm by considering only Round 3 zones around the UK. The problem comprises of some of the most important techno-economic life cycle cost-related factors, which are modelled using the physical aspects of each wind farm location (i.e., the wind speed, distance from the ports, and water depth), the wind turbine size, and the number of turbines. The model is linked to NSGA II, NSGA III, and SPEA 2 algorithms, to conduct an optimisation search. The performance of these three algorithms is demonstrated and analysed, so as to assess their effectiveness in the investment decision-making process in the wind sector, more importantly, for Round 3 zones. The results are subject to the specifics of the underlying life cycle cost model.

Keywords Round 3 · Multi-objective optimisation · UK · NSGAII · III · SPEA 2 · Decision-making

1 Introduction

In the last few decades, a necessity to reduce carbon emissions has been raised after concerns of the global warming effect that causes rapid changes in the environment. In fact, electricity production was found to be responsible for at least 24% of the total greenhouse emitted gases, in 2013 (Lin and Chen 2013). The awareness around the environmental impact led to further alternative ways to generate energy for more sustainable solutions. According to the 20-20-20 target on reducing carbon emissions and the new Climate Conference in Paris (COP 21) on keeping the global warming temperature below 2 °C, it is important to contribute to the renewable energy (RE) investment growth in the UK by making the investments more attractive, information-rich and less risky (BEC CREW 2015).

Wind energy is one of the fastest growing forms of RE in the UK; however, since structural material prices have significantly increased over the last years, it has a direct impact on larger scale wind projects, the overall cost of turbines, and their operational and maintenance costs (European Observation 2011; Lin and Chen 2013; Mytilinou et al. 2015). The UK technology roadmap highlights that the offshore wind costs need to be reduced to £100 per MWh by 2020 and a greater confidence over financial motivations is required (Department of Energy and Climate Change 2011). The location of a wind farm and the type of support structure have great impacts on the installation costs. The most important costs in an offshore wind farm can be found in HM Government (2013).

The Crown Estate released Round 3 leases and provided 9 new considerably larger zones than Rounds 1 and 2; offshore wind farm zones will include up to 32 GW of power capacity. The new leases encourage larger scale investment plans and bigger wind turbines. The new zones include locations further away from the shore and deeper waters which could be more challenging (Department of Energy and Climate Change 2011; Renewables First 2017; The Crown Estate 2010a, b, 2013).

Decision making for offshore wind energy investment is governed by a variety of criteria as can be found in (Kolios et al. 2010, 2014, 2016; Lozano-Minguez et al. 2011; Mar-

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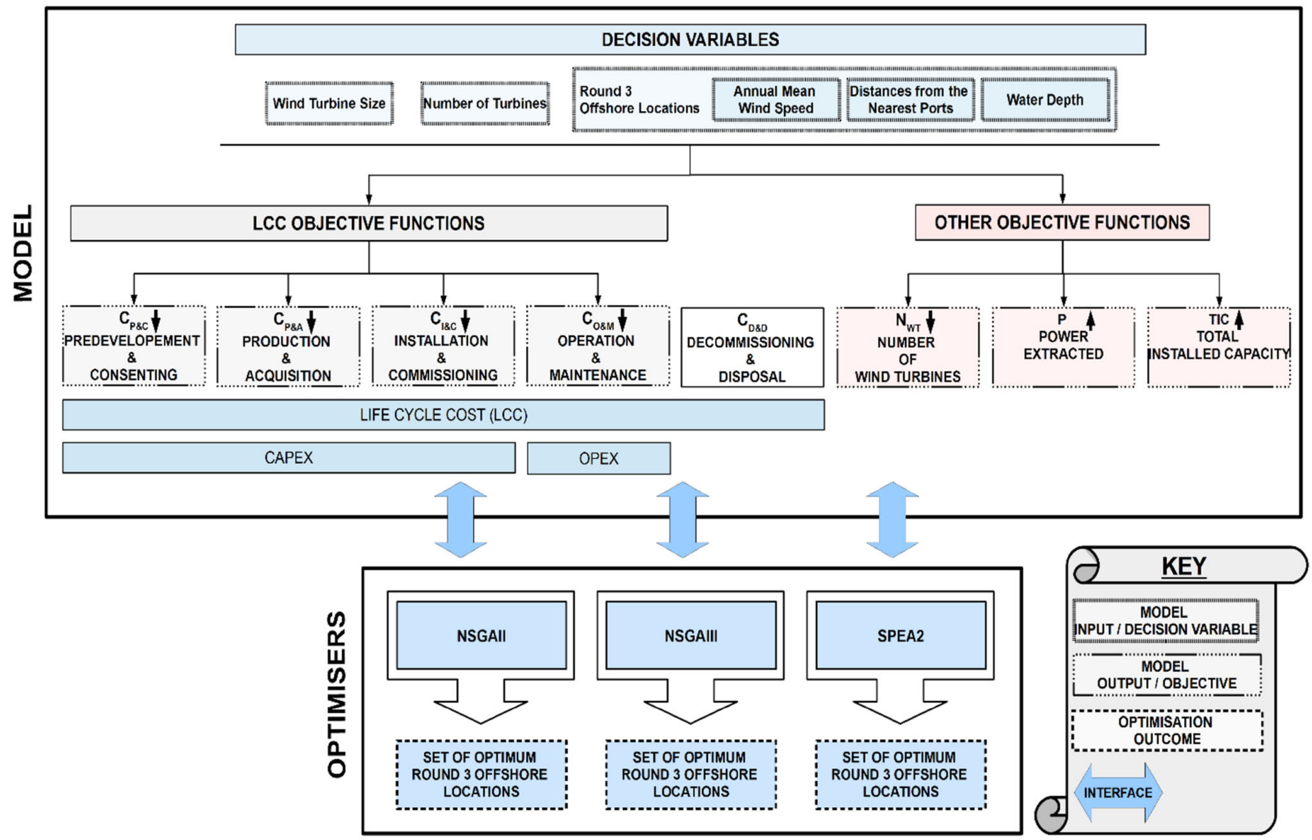

Fig. 1 Methodology layout

tin et al. 2013). One of the most important decisions arising when starting a new investment is the selection of a suitable offshore location and always requires extended effort. A methodology is proposed to help the decision-making process at these first stages of a wind farm investment considering the Round 3 zoned in the UK. Through this methodology, the location based on different physical aspects is selected.

The aim of this paper is to discover the optimum offshore Round 3 location based on financial costs and demonstrate the effectiveness of the underlying methods. The wind energy project costs associated with the design specifications of the site in conjunction with the turbine type and number of turbines should be numerically captured. This considers physical aspects unique to each offshore location, such as wind speed, water depth, and distance from appropriate construction ports, and will be modelled using life cycle cost (LCC) analysis. The best location should be discovered by considering the conflicting nature of the cost elements, so as to reduce overall cost at the early stages of a wind energy investment. Multi-objective optimisation algorithms will be coupled to the aforementioned model and used to reveal the interplay among the cost elements. To increase the effectiveness of the optimisation process and the diversity of the results, three different algorithms will be employed.

The contribution to knowledge is as follows. First, the combination of a newly developed prototype framework that includes economic modelling and optimisation process is assessed, so as to select the optimum offshore Round 3 location of a wind farm in the UK. Second, a set of non-dominated optimal solutions is suggested using the prototype framework. Both are expected to assist project developers and researchers at the first stages of the design of a wind farm.

The suggested methodology is depicted in Fig. 1. It comprises of individual modules, coupled with generic interfaces, so as to enable incremental development. Here, the physical aspects of each wind farm location (i.e., the wind speed, distance from the ports and water depth), the wind turbine size, and the number of turbines are considered, to manually select the optimum, economically efficient, and viable option (Shafiee et al. 2015).

The structure of this paper is as follows. A literature review in LCC analysis and the main phases will be explained. A description of the optimisation process and categories, and their benefits along with the most commonly used optimisation algorithms will be presented. Next, the methodology will follow. Finally, the results will be analysed and followed by a discussion. Future avenues will be drawn in the conclusions.

2 Literature review

2.1 Multi-objective optimisation

In real-world cases, multiple and conflicting objectives have to be improved simultaneously and multi-objective optimisation techniques have to be used, for example, minimising time versus energy efficiency (Branke et al. 2008).

During MOO, the decision space, the hyperplane that combines all the decision variables, is searched by evaluating the constraints and objectives. At the end of the process, a set of solutions is obtained and they are at least as many as the considered objectives. This is frequently called the Pareto Optimal Set or Pareto Front, where it is not possible to improve any objective without compromising in any of the others (Adinolfi et al. 2015).

MOO assists decision makers in appreciating the trade-off among conflicting objectives, before selecting the optimum solution for implementation, while understanding the interplay among the considered objectives. Some MOO studies can be found in Table 1.

2.1.1 SPEA

Strength Pareto Evolutionary Algorithm (SPEA) is an evolutionary based algorithm and it is also an MOO algorithm. In other words, SPEA is an Evolutionary Multiple Objective algorithm or EMO. SPEA is closely related to other evolutionary algorithms such as the NSGA, Vector-Evaluated Genetic Algorithm (VEGA), and Pareto Archived Evolution Strategy (PAES). SPEA has two versions, i.e., SPEA and SPEA 2, an extension of the former. More extensions can be found under the name SPEA+ and iSPEA. The aim of this algorithm is to locate and maintain a collection of non-dominated solutions (Pareto front) by examining thoroughly the search area by following an evolutionary procedure.

SPEA discovers and maintains a set of Pareto optimal solutions. An evolutionary process is used to investigate through the search space. During the selection process, a utility function is used, where an assessment method for dominance is combined with a density estimator. An archive of the Pareto Front is kept separately from the population of potential solutions used in the evolutionary process, thus demonstrating a form of elitism (Brownlee 2011).

SPEA 2 was selected for this work due to its suitability for MOO problems (Brownlee 2011; Nalianda 2012). SPEA is appropriate for combinatorial and continuous function MOO problems. A binary representation can be used for continuous function optimisation problems along with classical genetic operators such as one-point crossover and point mutation. In SPEA 2, the size of the archive is commonly smaller than the size of the population. It is possible to implement optimisation in calculations of density (of the revealed solutions) and Pareto dominance. More can be found in Zitzler et al. (2001).

2.1.2 NSGA

NSGA stands for non-dominated sorting genetic algorithm and it is also an MOO algorithm and an EMO. Currently, there are three versions of the code: NSGA, NSGAII, and NSGAIII, among which the last two will be considered in this study. NSGAII has been employed on a number of optimisation problems, mostly with two objectives, whereas NSGAIII is expected to be more appropriate when the number of objectives increases (Yuan et al. 2014), as in this research.

For comparison purposes, the performance of all three selected optimisers is depicted in Fig. 2, where they were applied to a benchmark test function with three objectives. Ideally, the trade-off should be as much dense and wide as possible, so as to uniformly cover the performance of the objective space. In Fig. 2, the shape of a reference problem (which was not as complex as the developed LCC) is illustrated. The application of these algorithms in the optimum selection of the wind farm location, as a class of problems, has never been attempted before. As part of the contribution to knowledge and to demonstrate by evidence the effectiveness of the optimisers to deliver non-dominated solutions in real-world modelling, all three optimisers were trialled. The optimisers were considered to compare the quality of the solutions, irrespectively of their internal functions. All algorithms can yield satisfactory results and are tested in different sectors according to the literature. Frequently, using one of them is acceptable and has delivered satisfactory results. As expected, there are advantages and disadvantages for each method, which will be investigated further below. Hence, employing all three methods will highlight the differences among them, as certain algorithms behave better in certain problems (Wolpert and Macready 1997).

The class of NSGA algorithms was selected in this study, because it is suitable for MOO problems. NSGA is appropriate for continuous function MOO problems. A binary representation of a decision variable can be used along with classical genetic operators such as one-point crossover and point mutation. A real-valued representation is recommended for continuous function optimisation problems, which consequently requires specific genetic operators such as Simulated Binary Crossover (SBX) and polynomial mutation (Deb and Agrawal 1994; Jain and Deb 2014; Nalianda 2012). The number of divisions needs to be set in the NSGAIII algorithm. The divisions are a mechanism NSGAIII uses to control the spacing of a reference point as it progresses through the loops.

Table 1 Multi-objective optimisation in RE systems

Description	Refs.	Economic modelling	Optimisation algorithms	Renewable energy
An optimisation study is conducted to find the optimum design of switching converters so as to be integrated with related renewable technologies. Multi-objective optimisation is performed with associated conflicting objectives for instance efficiency and reliability, and finally, the optimum solution is obtained among ideal options from the Pareto optimal ones	Adinolfi et al. (2015)	Includes economic aspects such as price minimisation and cost saving	Genetic algorithm NSGA II	Photovoltaic systems
A study on photovoltaic systems and electro-thermal methods was conducted. In the study, a multi-objective optimisation was suggested and applied to two conflicting objectives; the maximisation of the efficiency of the solutions from Europe and their cost minimisation	Graditi et al. (2014)	Includes cost and reliability performances	Commercial Power optimiser	Photovoltaic systems
In this study, a number of scenarios are investigated using multi-objective optimisation techniques that are applied to an electrical energy storage system investigating the connection with renewable sources	Ippolito et al. (2014)	Includes the minimization of the total electricity generation cost	Genetic algorithm NSGA II	Electrical Energy Storage system for RE systems
Yeh and Chuang are using multiple and conflicting objectives and combine them with genetic algorithms so as to find the Pareto optimal solution in a green supply chain case. In the study, four conflicting objectives and related green criteria were carefully selected such as the total cost, time etc.	Yeh and Chuang (2011)	Includes the minimization of the total cost and it consists of the product cost and transportation cost	Hybrid combination of two genetic algorithms	Green supply chain problem that also considers renewables
A methodology was created using multi-objective optimisation to maximise the energy harvested from a photovoltaic module and at the same time minimise the mass of the module-integrated converter	Mirjafari and Balog (2012)	Includes cost and efficiency objective functions	Particle Swarm Optimization (PSO)	Photovoltaic systems
The total system cost and the probability of deficiency of power supply of Hybrid Electric Systems (HRESs) are optimised using NSGA II. The HRES includes a wind turbine, a photovoltaic panel and a battery. NSGA II drives the optimisation search, but it is led by a Chance-Constrained-Programming-based method to consider RE sources uncertainty	Kamjoo et al. (2016)	Includes the total cost of the system	Genetic algorithm NSGA II	Hybrid Renewable Energy System (HRES)—includes wind turbine and photovoltaic panels

Table 1 continued

Description	Refs.	Economic modelling	Optimisation algorithms	Renewable energy
A power planning study using mixed integer non-linear multi-objective evolutionary optimisation was conducted. It presents a framework that determines the number of new generating units, the power generation capacity of them and other important aspects of a single-period generation expansion plan. The methodology is applicable to wind farms, geothermal and hydro units among others	Meza et al. (2009)	Includes Economic evaluation and risks minimising the investment and operation costs	Evolutionary programming algorithm (MEPA) based on a multi-objective genetic algorithm (MOGA)	Considers renewable generating units among others such wind farms, and geothermal and hydro units
Other references	Branke et al. (2008), Deb (2001), Karimi et al. (2017), Perkgoz et al. (2005), Sakawa et al. (2004, 2013) and Stewart (2008)			

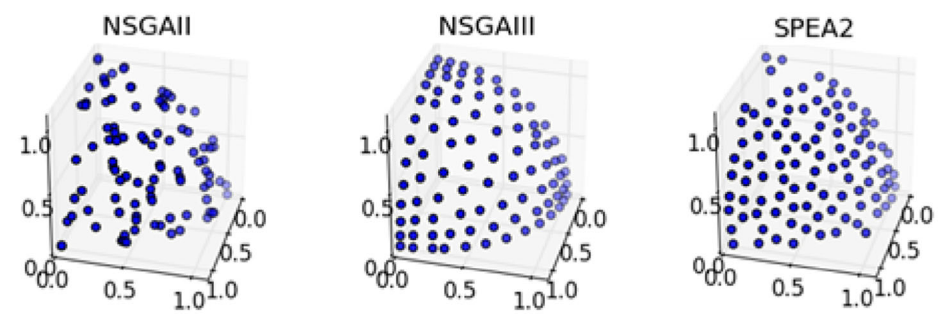

Fig. 2 NSGA II, III and SPEA (Hadka 2015) demonstrating the distribution of solutions when applied to a benchmark function with three objectives

It is suggested by Chiang (2014), Deb and Jain (2014) and Jain and Deb (2014) to use 12 divisions, where the domain of each of the many objectives is separated into regions using reference points to define normalised hyperplanes, for greater effectiveness in the discovery process.

Both optimisers are considered as the state-of-the-art multi-objective algorithms, and they are selected for this study. In general, the optimisation problem can be solved through genetic algorithms, Tabu Search, Simulated Annealing, and other Heuristic methods (Momoh and Reddy 2014). A few methods that can also be applied to this study are the following: multi-objective evolutionary algorithm based on decomposition (MOEA/D), covariance matrix adaptation evolution strategy (CMAES), the third evolution step of generalized differential evolution (GDE3), indicator-based evolutionary algorithm (IBEA), optimized multi-objective particle swarm optimiser (OMOPSO), speed-constrained multi-objective PSO (SMPSO), etc. (Hadka 2015). However, the SPEA2 algorithm has not been considered yet for that type of applications.

Evolution and genetic algorithms are used throughout the literature in many energy-related sectors. Karimi presented an approach that links a multi-objective genetic algorithm to the design of a floating wind turbine. By varying nine design variables related to the structural characteristics of the support structure, multiple concepts of support structures were modelled and linked to the optimiser. The aim is to minimise the economic costs (as a combination of the mooring system, the anchor, and the offshore floating platform) and maximise the turbine performance (standard deviation of nacelle acceleration. The Pareto Front contained a wide number of results that reflect solutions of either the single-body platforms or tension-leg platforms or multi-body platforms. In the future steps, it was suggested to optimise the levelised cost of energy and to consider a different parameterisation scheme both of which could extend to the present research (Karimi et al. 2017).

Yan suggests a methodology that includes genetic algorithms and the analytical hierarchy process decision-making method in a study related to green suppliers (Yan 2009). The design of a new optimisation algorithm is proposed in Saavedra-Moreno et al. (2011), to optimise the layout of turbines in a wind farm. New aspects were considered for the objectives, such as the shape of the wind farm, a range of costs (expressed in a benefit for investment), and orography. The optimisation algorithm is based on evolutionary algorithms and is seeded by a greedy approach, where experimental comparisons have been demonstrated.

Five different types of optimisation algorithms were used in Elkinton et al. (2008) to optimise the layout of a wind farm. As it was also mentioned in Cagan et al. (2002), solutions of higher quality can be discovered using algorithms with stochastic elements. However, these operate at a much slower speed, than the deterministic counterparts. In fact, in Elkinton et al. (2008), combining genetic algorithms with heuristics was more effective and faster than using only one of them. In this particular instance, it was suggested to use layout optimisation in small areas, or, at least, focus in good areas before launching a bigger optimisation case.

Another approach, presented in Wan et al. (2012), was used to optimise the layout of a wind farm (micro-siting optimisation: choosing the type and location of wind turbines) by considering continuous space and using particle swarm optimisation techniques. A special local search scheme was also introduced in the optimisation algorithm, to successfully speed up the process, where realistic solutions were discovered that delivered more electricity. In Papatheou et al. (2015), an evolutionary optimisation algorithm is used in the area of supervisory control and data acquisition or SCADA in a Swedish offshore wind location called Lillgrund for monitoring purposes to optimise and predict the energy production from every wind turbine in a wind farm considering related data from other wind turbines. Finally, in González et al. (2010), evolutionary algorithms are applied in a wind farm-related optimisation problem. The configuration of the layout of the turbines is optimised based on a cost model. The problem is very complex, since the optimum layout has been troubling many specialists for years. The suitability of the suggested evolutionary techniques is proven in the study.

2.2 Life cycle cost modelling

Life cycle cost was established by the Federal Energy Management Program to evaluate economically energy, water conservation, and RE projects for federal facilities. A guide was created in a handbook in Fuller and Petersen (1996), where the methodology and criteria were evaluated and presented. LCC analysis can evaluate and suggest cost reductions throughout a project's life. The outcome of the analysis can provide useful information in an investment and can direct decision making from the initial stages of a new project.

Calculating the LCC of an offshore wind project involves five stages from the predevelopment to the decommissioning phase, and there is not a common universal reference point for wind projects. In Shafiee et al. (2015), a parametric whole life cost framework for an offshore wind farm and a cost breakdown structure is presented and analysed. LCC analysis is essential for the insurers, wind farm operators, and investors to ensure a cost-efficient long and profitable investment plan to produce power.

LCC analysis gains more ground over the years because of the larger scale in wind projects. For example, Nordahl (2011) studied the advantages and disadvantages of the transition to offshore wind and proposed an LCC model of an offshore wind development. However, the study mainly centres in a simplified model and especially the operation and maintenance stage of the LCC analysis and it is suggested that there can be a further full-scale LCC framework in the future.

A study that states legal, financial, etc. related problems of wind turbines that are positioned both onshore and offshore is described in Angelakoglou et al. (2014) and involves an assessment using the LCC analysis methodology to select the best option, environmentally, energywise, and economically. Martínez et al. (2009) offer further insight in LCC analysis for a wind turbine throughout its whole life beginning from the manufacturing and installation to the decommissioning. This aims to quantify the impact of each stage along with important aspects such as manufacturing, transportation to site, and material waste.

The importance of the LCC analysis and an economic life cost-related model in three different offshore floating wind devices was presented in Laura and Vicente (2014). This study aims to develop a framework and minimise some of the most important costs in a floating type of turbine making the floating devices a more attractive investment. In the same direction, Myhr et al. (2014) also studies five different types of floating wind turbine concepts in one offshore location and compares them using LCC-related features. The water depth was found to have the most significant impact on the total cost.

According to Shafiee et al. (2015), LCC analysis includes costs calculated from several stages of the wind project such as the predevelopment and consenting ($C_{\mathrm{P\&C}}$), production and acquisition ($C_{\mathrm{P\&A}}$), installation and commissioning ($C_{\mathrm{I\&C}}$), operation and maintenance ($C_{\mathrm{O\&M}}$), and decommissioning and disposal ($C_{\mathrm{D\&D}}$) stage. Since foundations and support structures moved further towards deeper waters, Round 3 locations moved further away from the shore, and larger scale wind turbines are now becoming more common along with transportation and delays especially through vessels, the cost has been increased considerably. This study follows the LCC framework that was developed in Shafiee et al. (2015) and investigates different Round 3 offshore locations using it as common ground to select the most cost-efficient one. Through the study, the main aspects that impact the final costs are discussed.

2.3 Selecting an offshore location

To the author's knowledge, there are no studies that combine the concept of LCC with optimisation techniques with a focus on the individual LCC costs, to find the optimum offshore location for wind farm projects. Moreover, there are no studies that consider objectives based on economic figures and select the optimum Round 3 offshore location in the UK. In fact, for the selection of the location, there is very limited work accessible and with a small amount of focused and related criteria on this topic.

In the literature, many RE and location selection studies can be found, but the findings and the formulation of the problems provided follow a different direction. For example, using goal programming, the offshore location for a wind farm installation was selected in Jones and Wall (2015). The study involves Round 3 locations in the UK, while shows its flexibility to combine decision-making methods. This work shows the energy production, costs, and multi-criteria nature of the problem also considering some important factors related to environmental, social, technical, and economic aspects. The LCC analysis and their formulation into an MOO problem were not employed in the application. According to Jones and Wall (2015), multi-objective modelling techniques for both onshore and offshore wind farm are quite underdeveloped. The present study focuses on a methodology to fill this gap by linking MOO with LCC as objective functions and compares optimisation algorithms to select the optimum solution.

Another study on offshore locations is provided in Cradden et al. (2016) for an RE platform using multiple criteria and geographical information systems (GIS). A range of problems that exist around offshore RE platforms have been reviewed and a combination of criteria has been selected for the Atlantic facing shores in Europe. The potential risks were studied and it was found that the extreme weather conditions show the necessity of a compromise between the designing costs and the extra energy production. Very important factors were also the lack of ports with suitable available construction infrastructure that results in under-exploited sites, access problems, and weather window conditions, even during the summer months (Cradden et al. 2016). Although the study is very thorough, it is mostly focused on environmental, geographical, and weather issues that are out of scope because of the economic nature of the objectives and related criteria.

3 A framework for the optimisation of deployment sites for Round 3 wind farms in the UK

In Espinosa (2014) and Shafiee et al. (2015), a whole LCC formulation is provided and this study follows the steps and phases of the analysis for the optimisation problem. Assumptions and useful data in the modelling of the problem can be found in references 4COffshore (2017c), Dicorato et al. (2011), Espinosa (2014), Laura and Vicente (2014), Shafiee et al. (2015), The Crown Estate (2017) and Wind Energy The Facts (2017). Based on the previous work, a new model was developed so as to be coupled with the optimisation algorithms and drive the optimisation search.

The framework described in this section assesses the effectiveness of a suggested methodology to discover the optimum Round 3 offshore locations in the UK and improve the decision-making processes. Conceptually, the framework comprises of a model and an optimisation algorithm. The flow chart in Fig. 1 shows the optimisation model that includes seven objectives, four LCC-related objectives, described in Shafiee et al. (2015), and three additional objectives. Optimising seven objective functions at the same time, which are conflicting (from the mathematical formulation below), classifies the problem as multi-objective and it is considered rather complicated because of the interplay of the objectives and the nature of the variables.

The LCC model described in Shafiee et al. (2015) is used in this study and provided below in detail.

The LCC is calculated as follows:

$$\mathrm{LCC} = C_{\mathrm{P\&C}} + C_{\mathrm{P\&A}} + C_{\mathrm{I\&C}} + C_{\mathrm{O\&M}} + C_{\mathrm{D\&D}}$$

LCC: Life cycle cost
$C_{\mathrm{P\&C}}$: Predevelopment and consenting cost
$C_{\mathrm{P\&A}}$: Production and acquisition cost
$C_{\mathrm{I\&C}}$: Installation and commissioning
$C_{\mathrm{O\&M}}$: Operation and maintenance cost
$C_{\mathrm{D\&D}}$: Decommissioning and disposal

$$C_{\mathrm{P\&C}} = C_{\mathrm{projM}} + C_{\mathrm{legal}} + C_{\mathrm{surveys}} + C_{\mathrm{eng}} + C_{\mathrm{contingency}}$$

C_{projM}: Project management cost
C_{legal}: Legal cost
C_{surveys}: Survey cost
C_{eng}: Engineering activities cost
$C_{\mathrm{contingency}}$: Contingency cost

$$C_{\mathrm{P\&A}} = C_{\mathrm{WT}} + C_{\mathrm{SS}} + C_{\mathrm{PTS}} + C_{\mathrm{monitoring}}$$

C_{WT}: Wind turbine procurement cost
C_{SS}: Support structure/foundation cost
C_{PTS}: Electricity transmission cost
$C_{\mathrm{monitoring}}$: Monitoring cost

$$C_{\mathrm{I\&C}} = C_{\mathrm{I\&C\text{-}port}} + C_{\mathrm{I\&C\text{-}comp}} + C_{\mathrm{comm}} + C_{\mathrm{I\&C\text{-}ins}}$$

$C_{\mathrm{I\&C\text{-}port}}$: Port-related cost

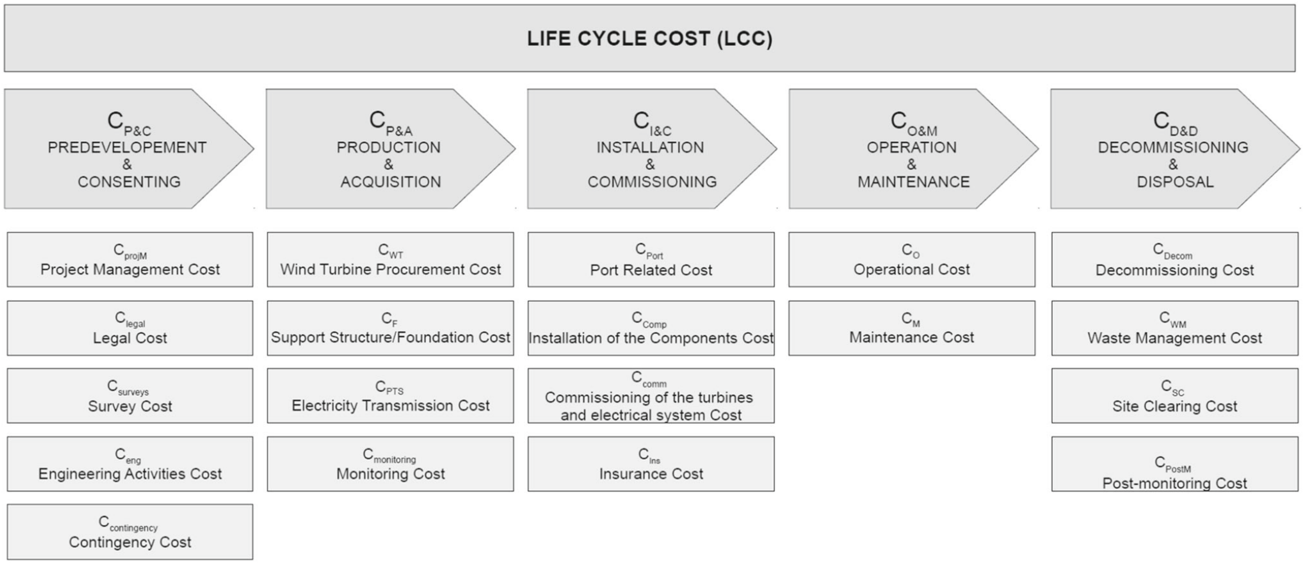

Fig. 3 Life cycle cost (LCC) break down (Shafiee et al. 2015)

$C_{\text{I\&C-comp}}$: Installation of the components cost
C_{comm}: Commissioning of the wind turbines and electrical system cost
$C_{\text{I\&C-ins}}$: Construction insurance cost

$$C_{\text{O\&M}} = C_{\text{O}} + C_{\text{M}}$$

C_{O}: Operational cost
C_{M}: Maintenance cost

$$C_{\text{D\&D}} = C_{\text{decom}} + C_{\text{WM}} + C_{\text{SC}} + C_{\text{postM}}$$

C_{decom}: Decommissioning cost
C_{WM}: Waste management cost
C_{SC}: Site clearing cost
C_{postM}: Post-monitoring cost

$$\text{CAPEX} = C_{\text{P\&C}} + \text{C}_{\text{P\&A}} + C_{\text{I\&C}}$$
$$\text{OPEX} = C_{\text{O\&M}}$$

CAPEX: Capital expenditures
OPEX: Operating expenses

More can be found in Shafiee et al. (2015).

The present study only considers the first four life cycle costs (depicted in Fig. 3) in the proposed methodology, because the aim is to understand the interplay between the CAPEX and OPEX costs to improve the decision-making process. Both these costs are considered to drive investment decisions, so as to prevent potential risks and issues when beginning a wind project by the developers.

As it is depicted in Fig. 1, the first four objectives are the costs from the LCC analysis. More specifically, the present model includes the predevelopment and consenting, production and acquisition, installation and commissioning, and finally operation and maintenance costs. The decommissioning and disposal cost is not considered at this stage. All of the cost-related objectives are minimised, as shown in Fig. 1. The mapping between the variables and the objectives that are estimated using the LCC analysis is depicted in Fig. 4. In this representation, the number of turbines, the distance from the ports, the water depth, and the power rate, which is determined by the wind turbine size shown in the specifications in Table 3, are the decision variables, as shown in Fig. 1.

The last three objectives are the number of turbines (NWT), the power that is extracted (P) from each offshore site and the total installed capacity (TIC), which are minimised, maximised, and maximised, respectively. The power extracted is calculated by the specific mean annual wind speed of each location along with the characteristics of each wind turbine both of which are considered inputs (listed in Table 2). The TIC is calculated by the number of turbines and the rated power of each of them.

The power extracted in this optimisation model is maximised and it is calculated for each site and each wind turbine, respectively, from

$$P = \frac{1}{2} A C_{\text{p}} \rho u^3$$

A: Area of the wind turbine
ρ: Air density
C_{p}: Power coefficient

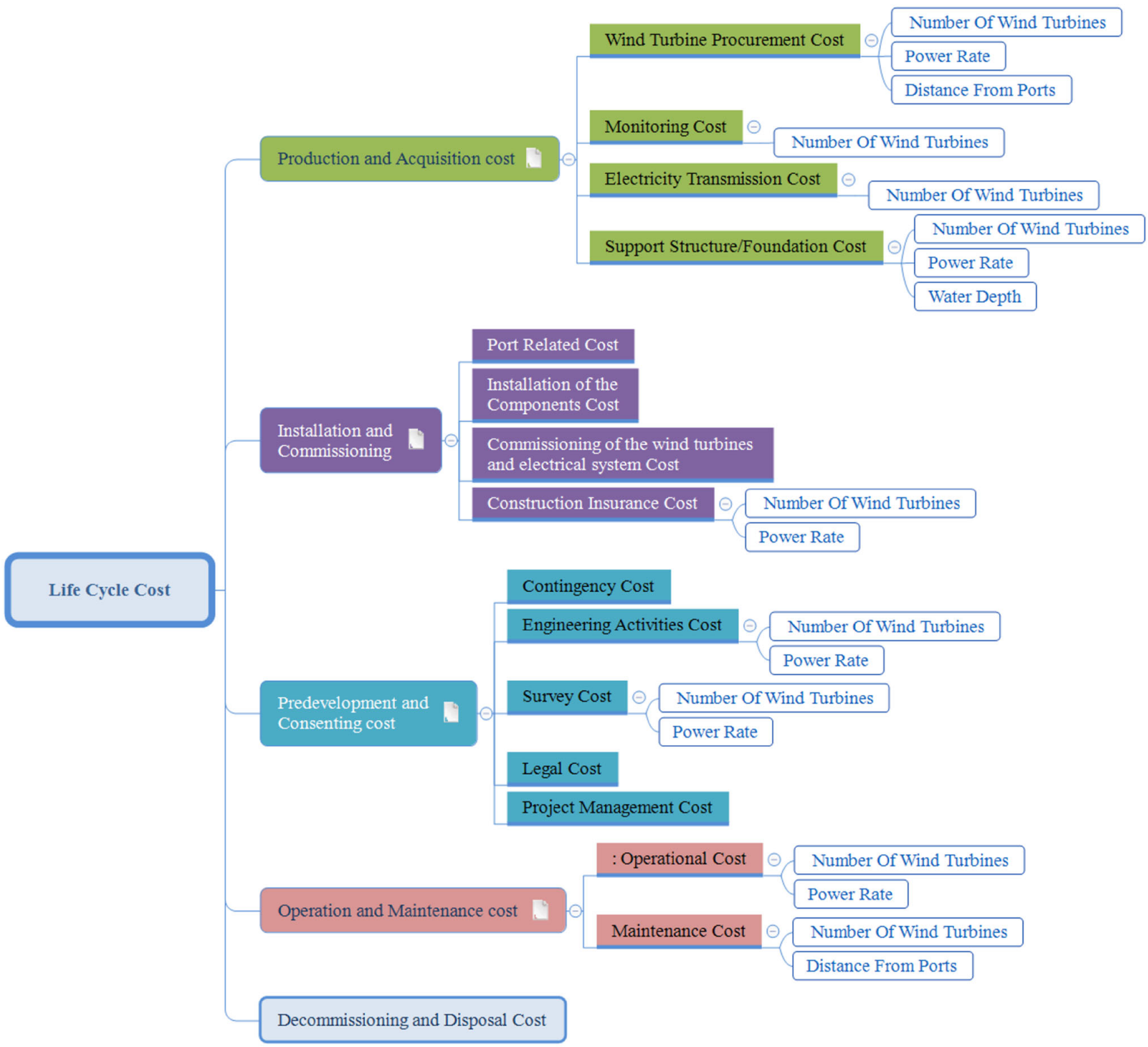

Fig. 4 Mapping the decision variables in LCC model

u: Mean annual wind speed of each specific site

The last objective of the model is the total installed capacity (TIC) of the wind farm is calculated for every solution and it is maximised:

$$\mathrm{TIC} = P_{\mathrm{R}} \times \mathrm{NWT}$$

P_{R}: Rated power

NWT: Number of turbines

For the selection of the optimum offshore wind farm location, physical aspects of each location, i.e., wind speed, water depth, and distance from designated construction ports, are considered. A list of ports was acquired from Department of Energy and Climate Change (2009), Marine Traffic Marine traffic (2017) and UK Ports Directory (2017). The list contains designated, appropriate, and sufficient construction ports that are suitable for the installation, manufacturing, and maintenance works for wind farms. New ports are agreed to be built for the conveniences of new wind farms. This study will consider only the parts and sites depicted in Fig. 5

For the distances from the ports calculation, QGIS was used. QGIS is an Open Source licensed Geographic Information System (GIS), which is a part of the Open Source Geospatial Foundation (OSGeo) (QGIS). The distances were calculated by the assumption of the nearest port to the individual wind farm, in a straight line. The specifications in Table 2 were acquired from 4COffshore (2017c); for each offshore location, a special profile was created including the

Table 2 Round 3 zones & sites and specific data acquired from 4COffshore (2017c)

Site index	Zone	Wind farm site name	Centre latitude	Centre longitude	Port	Distance from the port (km)	Annual wind speed (m/s) (at 100 m)	Average water depth (m)
0	Moray Firth	Moray Firth Western Development Area	58.097	−3.007	Port of Cromarty	123.691	8.82	44
1	Moray Firth	Moray Firth Eastern Development Area 1	58.188	−2.720	Port of Cromarty	157.134	9.43	44.5
2	Firth of Forth	Seagreen Alpha	56.611	−1.821	Montrose	72.598	9.92	50
3	Firth of Forth	Seagreen Bravo	56.572	−1.658	Montrose	91.193	10.09	50
4	Dogger Bank	Creyke Beck A	54.769	1.908	Hartlepool and Tess	343.275	10.01	21.5
5	Dogger Bank	Creyke Beck B	54.977	1.679	Hartlepool and Tess	319.949	10.04	26.5
6	Dogger Bank	Teesside A	55.039	2.822	Hartlepool and Tess	447.124	10.05	25.5
7	Dogger Bank	Teesside B	54.989	2.228	Hartlepool and Tess	380.788	10.04	25.5
8	Dogger Bank	Teesside C	55.245	1.858	Hartlepool and Tess	344.587	10.05	32
9	Dogger Bank	Teesside D	55.304	2.402	Hartlepool and Tess	405.248	10.05	35
10	Dogger Bank	Tranche D	55.429	2.982	Hartlepool and Tess	471.284	10.06	37.5
11	Hornsea	Hornsea Project One	53.883	1.921	Grimsby	242.328	9.69	30.5
12	Hornsea	Hornsea Project Two	53.940	1.687	Grimsby	217.270	9.73	31.5
13	Hornsea	Hornsea Project Three	53.873	2.537	Grimsby	310.521	9.74	49.5
14	Hornsea	Hornsea Project Four	54.038	1.271	Grimsby	173.928	9.71	44.5
15	East Anglia (Norfolk Bank)	East Anglia One	52.234	2.478	Great Yarmouth	92.729	9.5	35.5
16	East Anglia (Norfolk Bank)	East Anglia One North	52.374	2.421	Great Yarmouth	81.104	9.73	45.5
17	East Anglia (Norfolk Bank)	East Anglia Two	52.128	2.209	Great Yarmouth	74.559	9.46	50
18	East Anglia (Norfolk Bank)	East Anglia Three	52.664	2.846	Great Yarmouth	124.969	9.56	36
19	East Anglia (Norfolk Bank)	Norfolk Boreas	53.040	2.934	Great Yarmouth	143.464	9.53	31.5
20	East Anglia (Norfolk Bank)	Norfolk Vanguard	52.868	2.688	Great Yarmouth	111.449	9.56	32
21	Rampion (Hastings)	Rampion (Hastings)	50.668	−0.275	Newhaven	39.382	6.43	29
22	Navitus Bay (West Isle of Wight)	Navitus Bay (West Isle of Wight)	50.462	−1.757	Portland	77.578	9.32	42.5
23	Atlantic Array (Bristol Channel)	Atlantic Array phase one	51.336	−4.523	Port Talbot/Swansea	85.069	9.89	40
24	Irish Sea (Celtic Array)	Celtic Array North East Potential Development Area	53.961	−4.119	Barrow-in-Furness	101.749	9.86	36
25	Irish Sea (Celtic Array)	Celtic Array South West Potential Development Area	53.677	−4.875	Belfast	154.763	10.15	50.5

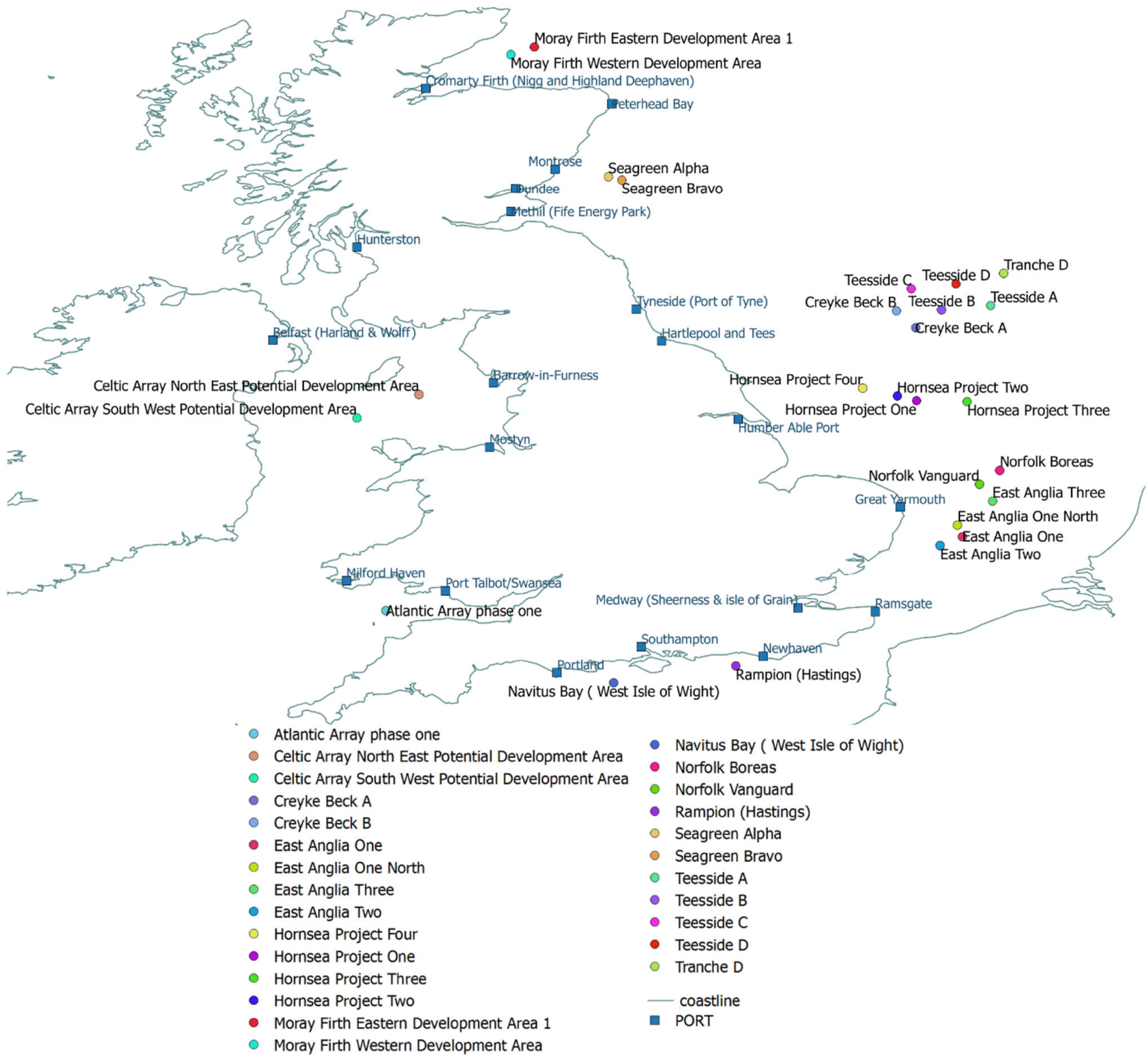

Fig. 5 Round 3 offshore location around the UK using QGIS

coordinated, the distances to the shore and port, annual wind speed, and average site water depth.

Table 2 shows among various data, the locations that each of these zones contains. Each location correlates with their specific data used in this problem.

Table 3 lists the specifications of the turbines that are considered in this study. These were extracted from reference turbines in 4COffshore (2017d).

The optimisation problem formulates as follows:

$$\begin{aligned} \text{Minimise} \quad & C_{\mathrm{P\&C}}, C_{\mathrm{P\&A}}, C_{\mathrm{I\&C}}, C_{\mathrm{O\&M}}, \mathrm{NWT}, (-\mathrm{P}), (-\mathrm{TIC}) \\ \text{Subject to} \quad & 0 \leq \text{site index} \leq 25, \\ & 0 \leq \text{turbine type index} \leq 6 \\ & 50 \leq \text{number of turbines} \leq 450, \end{aligned}$$

where the objectives are described above.

The site index and turbine-type index are specified in Tables 2 and 3, respectively. In the formulation, minimising the negative TIC and P is equivalent to their maximisation. The number of turbines was deliberately selected both as variable and as objective so as to minimise the CAPEX.

The optimisation modelling has been completed using the library platypus in python (Hadka 2015) and the selected optimisation algorithms are NSGA II, NSGA III with 12 divisions, and SPEA 2. For all the algorithms, the default implementations were employed and the stopping criteria were set to 10,000 iterations.

Table 3 Turbine specifications

Turbine type index	Rated power (MW)	Rotor radius (m)	Hub height (m)	Total weight (t)
0	10	95	125	1200.5
1	8	82	123	965
2	7	77	120	955
3	6	70	100	656
4	5	63	107	707.5
5	3.6	53.5	83.5	476
6	3	45	80	362.6

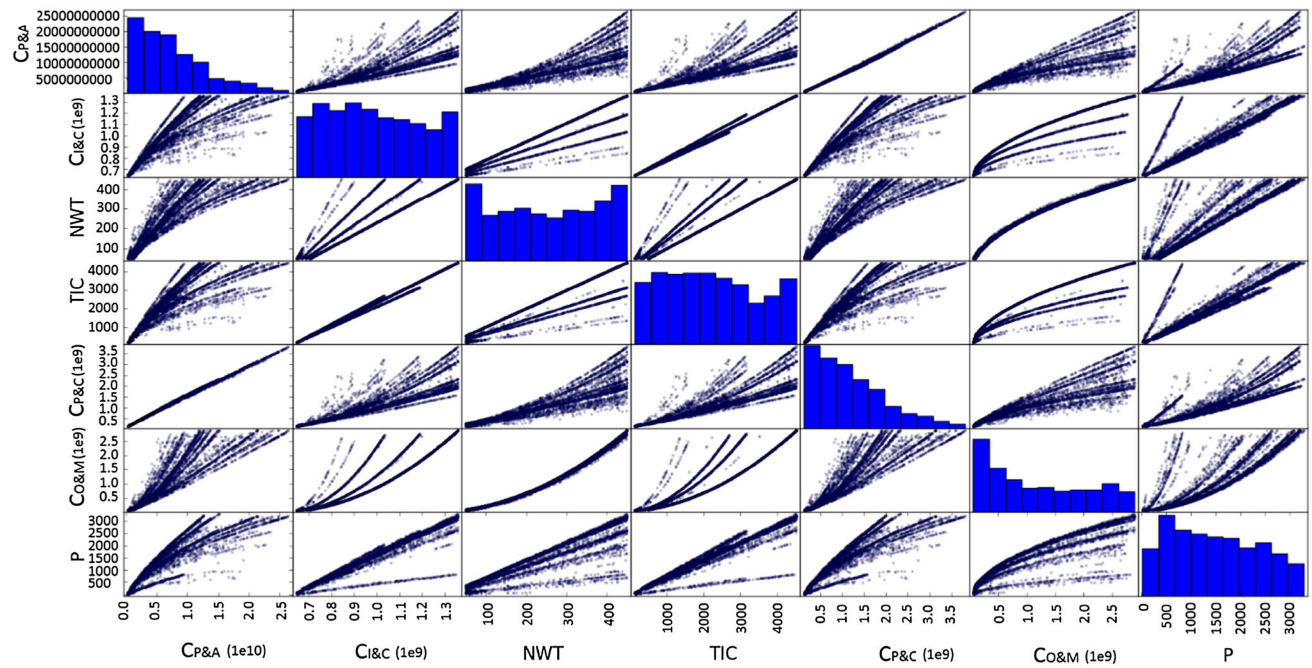

Fig. 6 Scatter plot matrix among the seven objectives, i.e., $C_{\mathrm{A\&P}}$, $C_{\mathrm{P\&C}}$, $C_{\mathrm{I\&C}}$, $C_{\mathrm{O\&M}}$, NWT, P, and TIC using NSGAII

In this study, a comparison among the pareto front solutions from each optimiser is conducted, where each optimiser delivered a non-dominated trade-off with the best possible solutions for offshore wind farm locations.

4 Results

The pareto front solutions from every algorithm and their trade-offs are presented. Although the variables are discrete in nature, the revealed trade-offs appear to be continuous. Each pareto front solution consists of the wind farm location, number of turbines (NWT), type of turbine, power extracted (P) for the specific site, total installed capacity (TIC) (i.e., the total capacity of the wind farm), and the life cycle costs (i.e., $C_{\mathrm{P\&A}}$, $C_{\mathrm{P\&C}}$, $C_{\mathrm{I\&C}}$, and $C_{\mathrm{O\&M}}$).

A scatter plot matrix was considered as the best option to visualise a seven-dimensional problem and it is depicted from Figs. 6, 7, 8, 9, 10, and 11. In Figs. 6, 8, and 10, seven objectives, i.e., $C_{\mathrm{P\&A}}$, $C_{\mathrm{P\&C}}$, $C_{\mathrm{I\&C}}$, $C_{\mathrm{O\&M}}$, NWT, P, and TIC, are illustrated, and in Figs. 7, 9, and 11, the CAPEX, OPEX, NWT, P, and TIC are also provided. This is part of the Pareto Front, as it was discovered by the optimisers. In the main diagonal of the figure, the histograms represent the concentration of points in ten buckets of equal size. All the trade-offs are continuous, which means that there is not any (discontinuous) gap in performance.

4.1 NSGA II

In Figs. 6 and 7, the revealed trade-offs demonstrate that non-dominated solutions were discovered. However, certain areas were not explored thoroughly. For instance, the plot of 'P versus NWT' illustrates that there is a strong upper limit, as expected from the nature of the model. In addition, in the same plot, it is obvious that the majority of solutions are

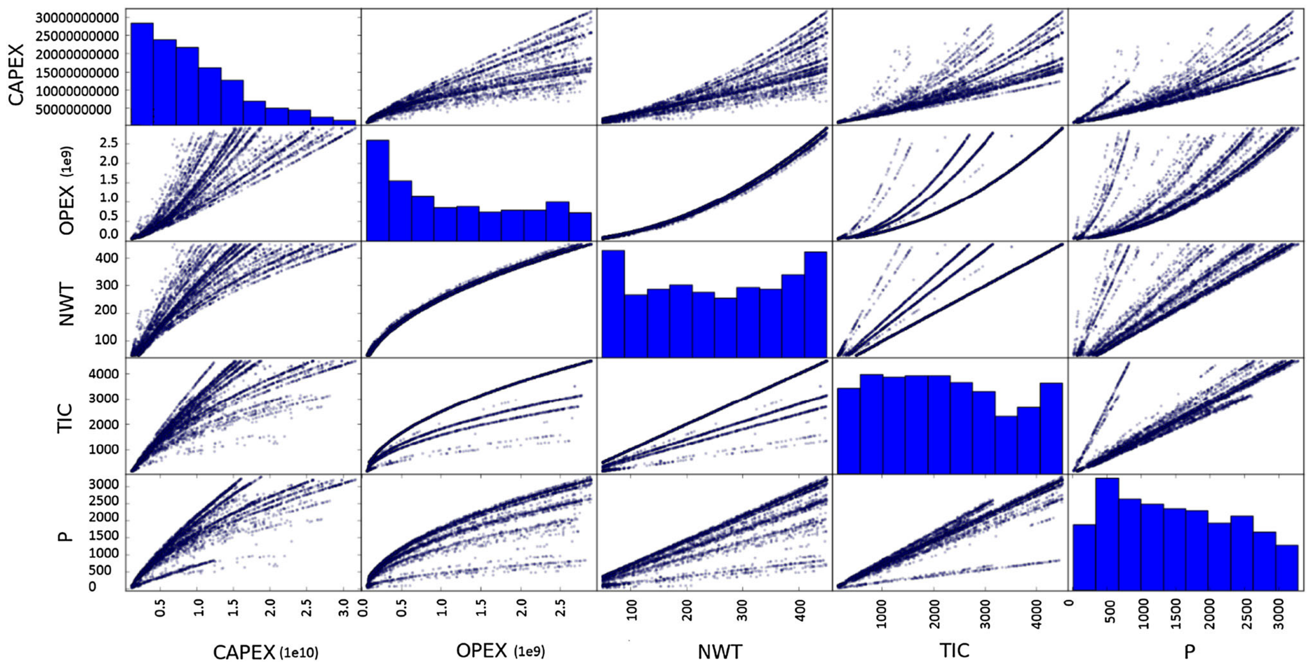

Fig. 7 Scatter plot matrix among CAPEX, OPEX, NWT, P, and TIC using NSGAII

focused on the upper bound, whereas below that, the number of points explored is scarce. This practically means that the optimiser quickly identified chromosomes with good performance and used the computational budget towards exploring along this direction. This pattern applies to most of the plots. Plots whose performance has a pattern similar to '$C_{\mathrm{O\&M}}$ versus $C_{\mathrm{I\&C}}$' also demonstrate that certain performance routes were discovered and followed throughout the optimisation search. This explains the solid legs within the swarm of solutions. The bottom area of 'P versus $C_{\mathrm{P\&A}}$' illustrates that a few areas of dominated performance (sporadic solutions) were discovered, but were not further investigated. Finally, '$C_{\mathrm{P\&C}}$ versus $C_{\mathrm{P\&A}}$', 'TIC versus $C_{\mathrm{I\&C}}$', and '$C_{\mathrm{O\&M}}$ versus NWT' vary in harmony.

By interactively investigating the results, the following behaviour was identified. Each of the legs of the plot 'TIC versus $C_{\mathrm{O\&M}}$' is linked to a particular wind turbine. Then, by varying the combination of the number of turbines and the site, a wide range of values of the cost element can be obtained. This is more obvious in the PFs discovered by NSGAIII because of the continuous points discovered for the same type of plot, whereas this would be very hard to spot in the results from NSGAII. This feature could be integrated into a process to detect any hidden performance relationships.

4.2 NSGA III

Compared to NSGAII, NSGAIII was also found to behave better when the number of objectives increases (relative to the other two optimisers), as expected by definition. Hence, the final results appear more uniform, as shown in Figs. 8 and 9. Consequently, the trade-offs for certain pairs of objectives are much more complete (in terms of the distance between any two points) and richer (in terms of a number of points within a relatively narrow area). It seems that the chromosomes covered a wider spectrum of solutions. In NSGA III, the 'NWT versus $C_{\mathrm{O\&M}}$' present the most straightforward relationship as they are approaching an exponential trend. As before, the same three combinations clearly vary in harmony. In general, this demonstrates the suitability of NSGAIII in such problems (and will be considered as the main optimiser in the next stages of the research).

4.3 SPEA2

The performance of SPEA2 is depicted in Figs. 10 and 11. Fundamentally, the same characteristics can be observed. However, SPEA2 stands between NSGAII and NSGAIII, in terms of trade-off findings. It discovered more diverse solutions than NSGAII but less diverse than NSGAIII.

5 Discussion

Optimum locations for a wind farm have been discovered using three different MOO algorithms, NSGA II, NSGA III, and SPEA 2 and using the LCC analysis, to achieve cost-efficient solutions. The results follow a consistent trend and they seem to be in relative agreement. TIC, $C_{\mathrm{P\&A}}$, $C_{\mathrm{I\&C}}$, and $C_{\mathrm{P\&A}}$ vary in harmony, as shown in Figs. 6, 8, and 10, which

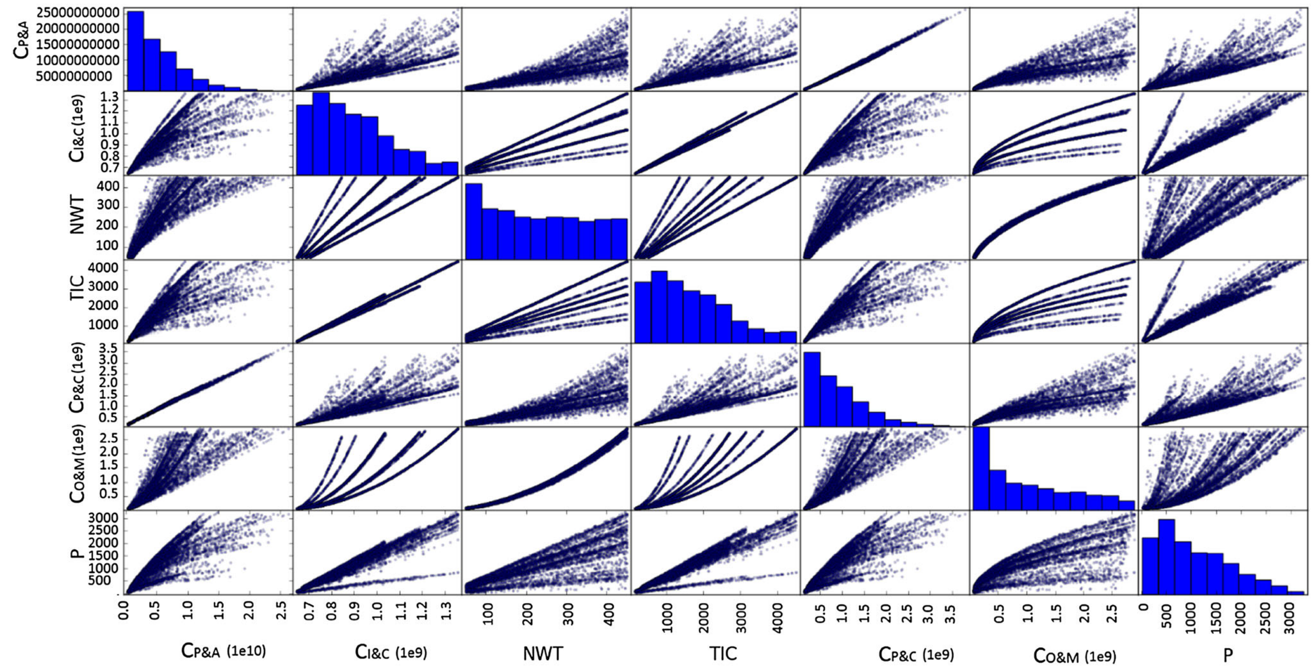

Fig. 8 Scatter plot matrix among the seven objectives, i.e., $C_{\mathrm{A\&P}}$, $C_{\mathrm{P\&C}}$, $C_{\mathrm{I\&C}}$, $C_{\mathrm{O\&M}}$, NWT, P, and TIC using NSGAIII

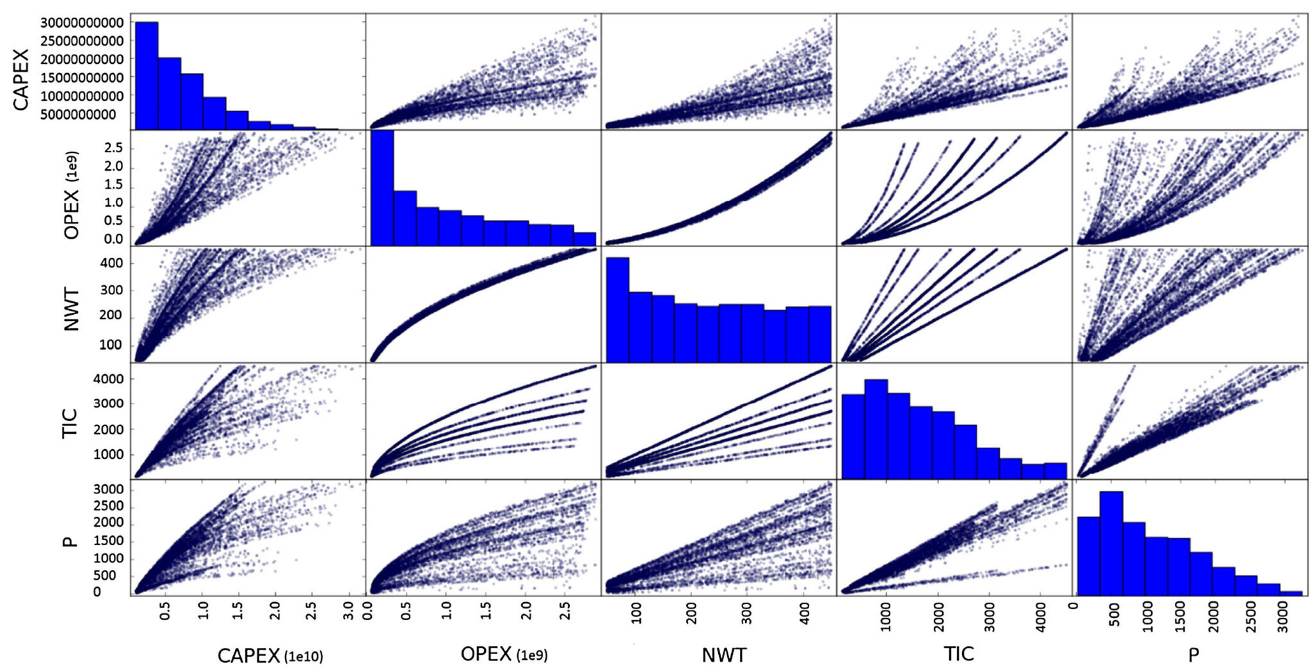

Fig. 9 Scatter plot matrix among CAPEX, OPEX, NWT, P, and TIC using NSGAIII

suggests to be compound into a single objective in the future, for simplicity. In addition, $C_{\mathrm{O\&M}}$ and NWT also vary in harmony by following a parabolic trend. In the same figures, most of the discovered solutions live at the lower end of the range of $C_{\mathrm{P\&A}}$ and $C_{\mathrm{P\&C}}$. This points out future research directions, so as to identify areas, where the performance remains constant.

In the histogram of $C_{\mathrm{O\&M}}$, many points of the optimal revealed behaviour reside at the lower bound of the range of the objective. Consequently, this is also noted in the concentration of points in the CAPEX and OPEX. This was the easiest to discover relative to the other objectives. Because the shape of the trade-offs among $C_{\mathrm{P\&A}}$, $C_{\mathrm{P\&C}}$, and $C_{\mathrm{I\&C}}$ is similar and the same holds of the trends of the histograms,

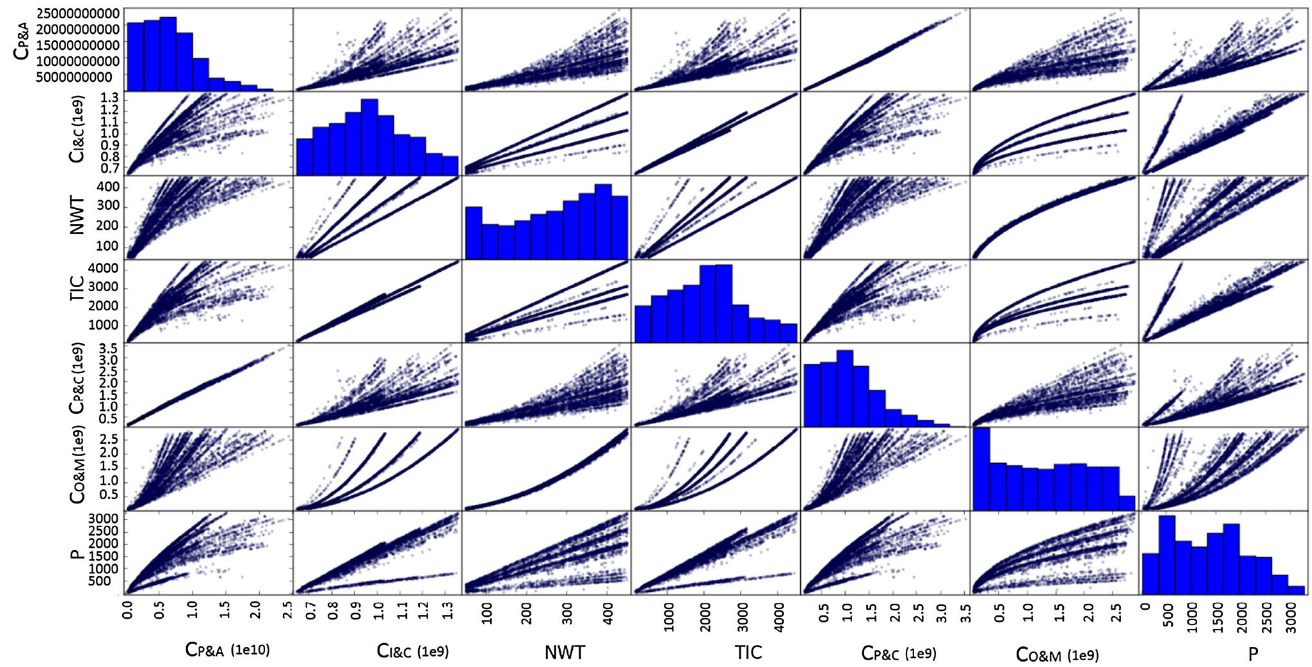

Fig. 10 Scatter plot matrix among the seven objectives, i.e., $C_{\mathrm{A\&P}}$, $C_{\mathrm{P\&C}}$, $C_{\mathrm{I\&C}}$, $C_{\mathrm{O\&M}}$, NWT, P, and TIC using SPEA2

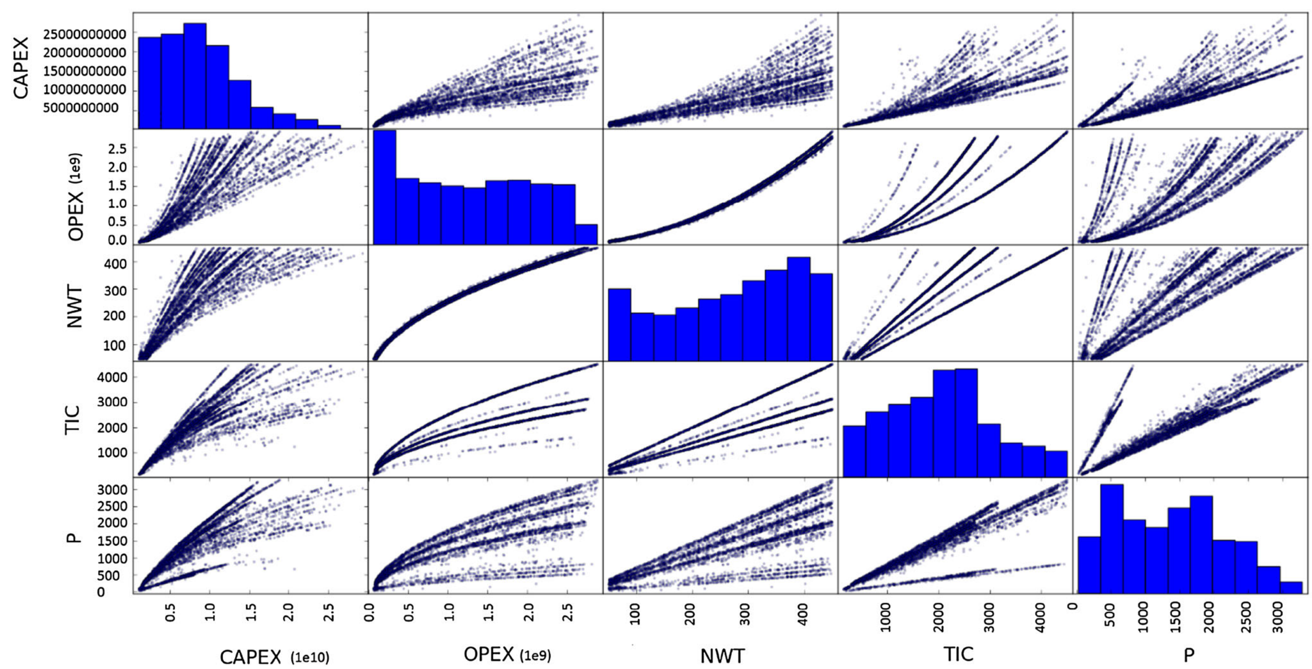

Fig. 11 Scatter plot matrix among CAPEX, OPEX, NWT, P, and TIC using SPEA2

it is sensible to consider the CAPEX objective in the future steps of the research (instead of all these three individual objectives).

In SPEA2 and NSGAII results, the sparse dots at the end of each graph represent that the method (i.e., the search patterns employed by those algorithms) has not discovered a wide range of solutions in those areas.

Several results show a relative harmony between each other and some others show the conflicting performance between the objectives. Six offshore locations scored higher than 10% in the frequency graph, i.e., the Seagreen Alpha and Bravo (in Firth of Forth), Teesside C and D (in Dogger Bank), Rampion (Hastings), and the Celtic Array South West Potential development Area, which represent the Irish Sea

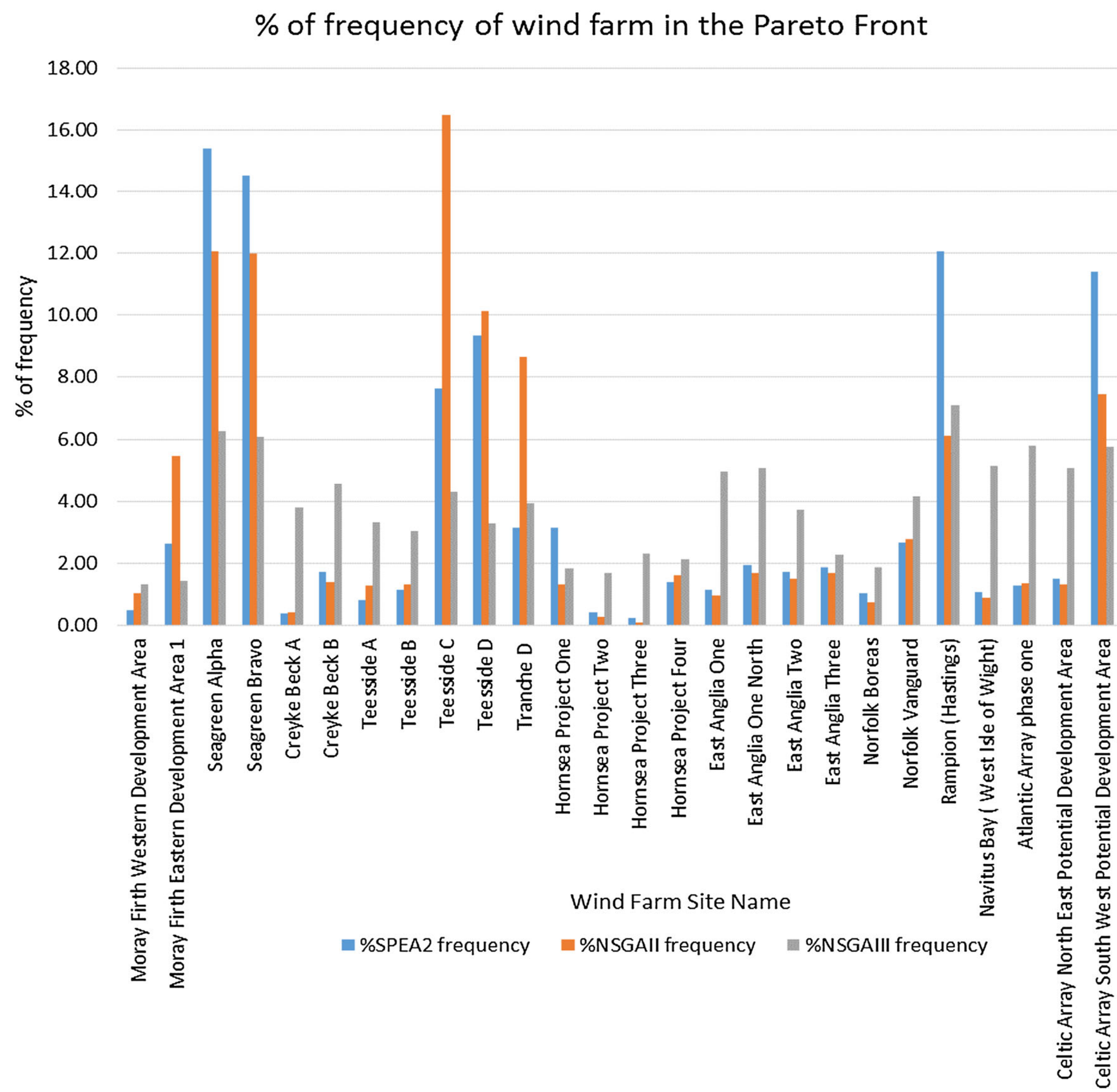

Fig. 12 % of frequency of each site from the pareto front solutions from SPEA2, NSGAII, and NSGAIII

(Celtic Array). A frequency graph has been created in Fig. 12 to summarise and depict the % frequency of each offshore location that appears in the pareto front solutions. In general, the Firth of Forth, Dogger Bank, and Irish Sea (Celtic Array) zones reached the highest score for all optimisers.

The Teesside C scored first and it is closely followed by Seagreen Bravo when using NSGAII. The Seagreen Alpha in Firth of Forth seems to have the highest scores of all when using the SPEA2 algorithm, and thus, it is considered one of the best options for a wind farm project, as it was identified by all three optimisers. Finally, Seagreen Alpha was scored first for the NSGAIII. In general, the Hornsea Projects family has been found to be suitable in only a small amount of appearances in the pareto front.

The performance of the algorithms has shown that NSGAIII demonstrated its suitability in multi-objective problems as its results appear to be more uniform and clear because of its main design, compared to the other optimisers. Therefore, the trade-offs for certain pairs of objectives are more complete, wider, and richer, in terms of a number of points. In general, the patterns of the revealed trade-off are very clear and distinct for the results from NSGAIII with 12 divisions.

The non-dominated results demonstrate that employing MOO algorithms was a sensible choice, so as to complement the process of wind farm location selection. For example, both Moray Firth Western Development Area and Seagreen Alpha were found to be in the trade-off at least once by the optimisers. For the developer, this means that it is equally cost efficient to choose either location. However, the latter has appeared significantly more frequent than the former. The developer could accordingly allocate the development

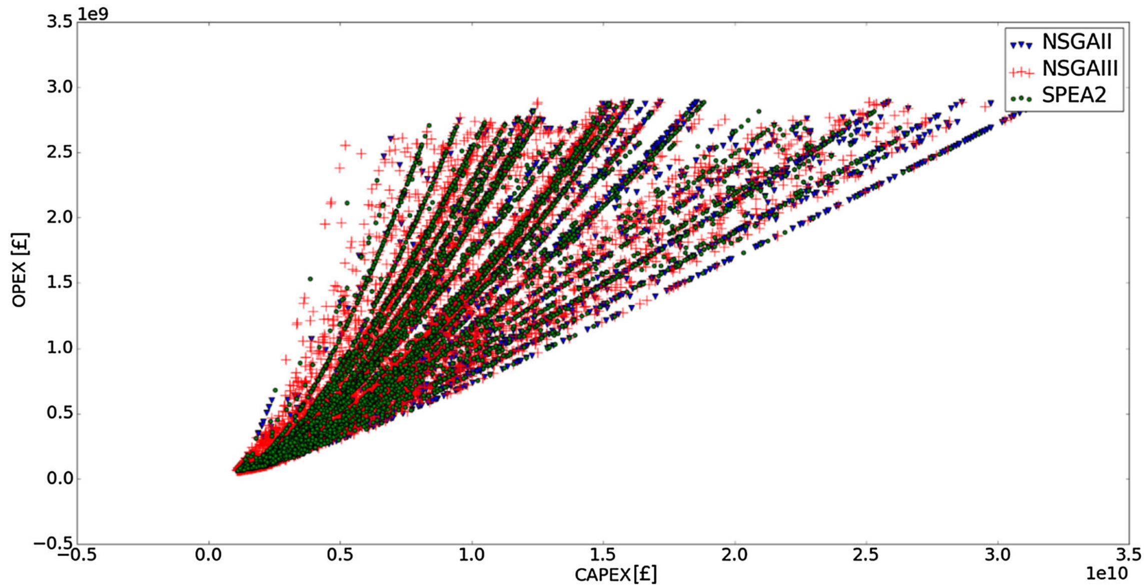

Fig. 13 Comparison of CAPEX versus OPEX using NSGAII, NSGAIII, and SPEA2

Table 4 Selected solution based on high frequency (from Fig. 12) for each algorithm

Algorithm	Site name	Turbine type (MW)	NWT	TIC (MW)	*P* (MW)
SPEA 2	Seagreen Alpha	10	148	1480	718.04
	Seagreen Bravo	6	308	1848	157.70
	Rampion (Hastings)	6	185	1110	475.86
NSGA II	Teesside C	10	402	4020	2846.06
	Seagreen Alpha	3	449	1347	685.93
	Seagreen Bravo	6	117	702	536.49
NSGA III	Rampion (Hastings)	8	261	2088	360.56
	Seagreen Alpha	10	293	2930	1994.90
	Seagreen Bravo	7	50	350	290.17

budget in different development phases, as required. More specifically, the Seagreen Alpha provides many more optimum options that are equally efficient (involving the number and type of turbines in each solution) than the Moray Firth Western Development Area, which gives the flexibility to invest more money in the installation or the maintenance stage of the project.

An application has been submitted and consented for the Firth of Forth Seagreen Alpha and Bravo, which are at the first phase of the Round 3 Firth of Forth development according to 4COffshore (2017f), RYA (2017). Both Seagreen Alpha and Bravo faced some engineering and environmental problems and developed the project accordingly to accommodate such constraints that appeared in their offshore locations (4COffshore 2017f). Teesside C and D in Dogger Bank applications were submitted together by Forewind. Unfortunately, the projects have been cancelled according to 4COffshore (2017a, 2017b). Rampion (Hastings) is currently under construction according to 4COffshore (2017e). Finally, Celtic Array South West Potential development Area was also cancelled (4COffshore 2014).

Probably, the six primary selected offshore locations have been either cancelled, consented or just submitted and only one of them is under construction, because other factors are also involved in the selection process. For example, the cancellation in all cases happened, because the Crown Estate asked the developers to revise all the terms of their agreement, while the project transitioned toward the development phase (4COffshore 2017e). Other reasons could also result in cancellation such as environmental problems, legal and procurement restrictions, etc.

By relating some of the most important techno-economic LCC factors to the physical aspects of each wind location (i.e., the wind speed, distance from the ports, and water depth), the wind turbine siz,e and the number of turbines, it is possible to discover a more cost-efficient solution. By comparing the outcomes of the three algorithms and suggesting the most suitable locations, useful insights are provided for both industrial and educational purposes in the wind sector for future investments.

In Fig. 13, the performance of each optimisation algorithm in CAPEX versus OPEX is shown. As expected, most of the solutions gather at the lower left end. NSGAII and SPEA2 discovered and followed certain trends for a particular wind turbine, as shown by the various legs in the figure. Because of the design of NSGAIII, the discovered solutions are more spread throughout the objective space.

Table 4 shows the top three locations discovered by each optimiser in terms of frequency in the Pareto Front from Fig. 12. The listed solutions were selected manually so as to demonstrate the conflicting nature of the objectives. The table numerically demonstrates the conflict among the objectives in the trade-off, for instance, comparing Seagreen Alpha and Seagreen Bravo using SPEA 2 algorithm, when the NWT increases then P decreases. In the results of the same algorithm, including Rampion (Hastings), when the NWT increases, TIC reduces (whereas previously, it increased). This demonstrates the conflicting nature of the results and non-linear relationships, which will be further investigated in the future.

From the obtained results, the average savings were calculated to assess the performance of the approach and the framework. An average savings formula was used (i.e., Average savings $= \frac{\text{Maximum cost} - \text{Average cost}}{\text{Maximum cost}}$) to calculate percentages for CAPEX and OPEX using NSGA II, NSGA III, and SPEA 2. NSGA II reached 77 and 66.7% savings for CAPEX and OPEX, respectively. NSGA III found 69.1 and 59.2% for CAPEX and OPEX, respectively. Finally, SPEA 2 shows 70.1 and 55.8% savings for CAPEX and OPEX, respectively. It appears that the optimisation approach can discover solutions with lower CAPEX deviation than OPEX. The high percentages were expected because of the large number of conflicting objectives which forces the optimisers to discover a great number of solutions in the Pareto Front.

6 Conclusions

This study successfully demonstrated by example the effectiveness of the newly developed optimisation process and delivered satisfactory outcomes for the most suitable and cost-efficient offshore wind farm Round 3 locations. A comparison has been presented among the three state-of-the-art algorithms (i.e., NSGA II, NSGA III, and SPEA 2), which were applied to a wind energy real-world case. The comparison and the useful outcomes on their performance have been illustrated and discussed. The optimum locations for a wind farm have been suggested by considering the significant input of the LCC analysis. Six sites were suggested (with the frequency of appearance higher than 10% in the parent front).

The results follow a relatively similar and consistent trend. The performance of the algorithms has shown that the NSGAIII demonstrated its suitability in multi-objective problems as its results appear to be more uniform and clear because of its design compared to the other optimisers.

The limitations of this work are related to the LCC calculations and the associated assumptions that had to be made in the development of the model. To get more accurate results, more precise data are required to validate and calibrate the LCC, which could refine the results of this work. Many data and assumptions taken for this study have been obtained and chosen from wind-related databases and crown estate reports, to reach the real-world values. However, research and surveys are important for every individual site to have more accurate inputs. Data acquisition is the hardest part as it is impossible for a developer to proceed without a project plan. Here, only one type of foundation was considered, the jacket structure. The impact of Net Present Value on the economic objectives (i.e., CAPEX and OPEX) has not been considered and will be further investigated in the future.

The revealed outcomes will have an important impact on a possible extension of the Round 3 zones in the future of the UK and will help decision makers for their next cost efficient investment move. The proposed framework could also be applied to other sectors to increase investment confidence and provide optimum solutions. For example, the installation of floating offshore wind and wave devices could be benefited by the framework, where the optimum locations can be suggested according to cost and operational aspects for each technological need.

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Techno-economic optimisation of offshore wind farms based on life cycle cost analysis on the UK

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In order to reduce the cost of energy per MWh in wind energy sector and support investment decisions, an optimisation methodology is developed and applied on Round 3 offshore zones, which are specific sites released by the Crown Estate for offshore wind farm deployments, and for each zone individually in the UK. The 8-objective optimisation problem includes five techno-economic Life Cycle Cost factors that are directly linked to the physical aspects of each location, where three different wind farm layouts and four types of turbines are considered. Optimal trade-offs are revealed by using NSGA II and sensitivity analysis is conducted for deeper insight for both industrial and policy-making purposes. Four optimum solutions were discovered in the range between £1.6 and £1.8 billion; the areas of Seagreen Alpha, East Anglia One and Hornsea Project One. The highly complex nature of the decision variables and their interdependencies were revealed, where the combinations of site-layout and site-turbine size captured above 20% of total Sobol indices in total cost. The proposed framework could also be applied to other sectors in order to increase investment confidence.

1. Introduction

According to the 20-20-20 target on reducing carbon emissions and the Climate Conference in Paris (COP 21) on keeping the global warming temperature below 2 °C, it is important to contribute to the Renewable Energy (RE) investment growth in the UK by making the investments more attractive, information-rich and less risky [1]. The UK technology roadmap highlights that the offshore wind costs need to be reduced to £100 per MWh by 2020 and greater confidence over financial motivations is required [2].

Offshore wind managed to reach 24% of the total installed power in Europe in 2015 compared to the 13% share the previous year [3]. Currently, 1716 offshore turbines are deployed in 32 offshore operational projects of an overall capacity of 6713.520 MW in the UK [4]. However, significant price increases in the overall cost of turbines, their operational and maintenance costs etc. have a direct impact on large-scale wind projects. The location of a wind farm and the type of support structure have great impacts on the overall costs [5–7].

Ensuring a long-term and profitable investment plan for investors and developers can be challenging. In many cases, both pre-consent and post-consent delays cause inconveniences. Considerable actions are mandated, on top of the development plans, for minimising investment, developing the supply chain, securing consents, ensuring economic grid investment and connection, and accessing finance [2,8]. Overall, appropriate studies should be conducted at the early development stages of the project in order to avoid disruptions and minimise the investment risk. A very important decision that appears when starting a new investment is the selection of a suitable offshore location (zone and site) and always requires extended effort from developers. The location of a wind farm and the type of support structure have great impacts on the installation costs. The most important costs in an offshore wind farm can be found in Ref. [9].

In Ref. [10], a study was conducted in order to discuss and compare the results among three state-of-the-art optimisation evolutionary and genetic algorithms (NSGA II, NSGA III and SPEA 2) and then applied to a real-world case of the wind energy sector. A set of optimum locations for a wind farm are suggested by considering only round 3 zones, which are specific sites released by

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Nomenclature

A	Area of the wind turbine (m^2)
C_p	Power coefficient
$C_{P\&C}$	Predevelopment and Consenting cost (£)
$C_{P\&A}$	Production and Acquisition cost (£)
$C_{I\&C}$	Installation and Commissioning cost (£)
$C_{O\&M}$	Operation and Maintenance cost (£)
$C_{D\&D}$	Decommissioning and Disposal Cost (£)
CAPEX	Capital Expenditures (£)
LCC	Life Cycle Cost (£)
NWT	Number of turbines
OPEX	Operational expenditure (£)
P_R	Rated power (W)
u	Mean annual wind speed of each specific site (m/s)
TIC	Total Installed Capacity (W)
ρ	Air density (kg/m^3)

the Crown Estate, where the developers can install and deploy offshore wind farms around the UK. The study considered some of the most important techno-economic Life Cycle Cost (LCC) factors that are directly linked to the physical aspects of each wind farm location such as the wind speed, the distance from the construction ports and the water depth. Optimal solutions were discovered by all three algorithms and such outcomes are expected to reveal the benefits of possible extensions of the Round 3 zones in the future of the UK and will help decision makers for their next cost-efficient investment decision.

The aim of this paper is to establish a methodology for the decision-making process at the initial stages of a wind farm investment of Round 3 zones in the UK that reveals the optimum offshore locations by considering a model that combines techno-economic factors of the LCC analysis, layout selection and location-based constraints. The revealed optimum solutions per zone and a reference selection of zones will offer flexibility at the cost budget assignment phase of the wind farm development and is aligned with the reduction of the cost of energy at less than £100 per MWh. It is also expected that the differences among three suggested wind farm layouts will be explored by considering the conflicting nature of the cost elements. The outcomes will provide further insight into wind energy sector for future investments.

The contribution of this work follows. First, as illustrated in Fig. 1, it proves the effectiveness of the developed framework that links the economic modelling of the LCC analysis to an optimisation method, where the solutions comprise of wind farm layouts, offshore Round 3 locations in the UK, number of turbines and turbine size. The interplay between CAPEX and OPEX will be revealed through multi-objective optimisation and quantified based on each decision variable through sensitivity analysis. This study assists project developers and researchers at the first stages of the development of a wind farm in order to select an optimum, economically efficient and viable option.

The remaining structure of the paper consists of a literature review on LCC analysis, turbine layout optimisation, wind farm location selection and cost related frameworks in the offshore wind energy sector. Next, the methodology of the present study will follow. The non-dominated results for all zones and each zone individually will be analysed and discussed. Future avenues will be drawn in the conclusions.

2. Literature review

2.1. Offshore wind farm location selection

The UK has released 3 Rounds of offshore wind farm sites for leasing. The 3 Round divisions appeared because of the administrative licensing process adopted by the UK and reflect the development of offshore power collection and transmission systems. In Round 1, the developments were small (up to 90 MW) and with up to thirty turbines each and near the shore (less than 30 km away from the shore). Round 2 sites were released later and contained larger projects up to 500 MW and a bit further away from the shore (up to 90 km). Finally, Round 3 is currently undergoing planned installations up to 1000 MW and 300 km distance from the shore [11]. When the Crown Estate released the new Round 3 offshore wind site leases, they provided nine new considerably larger zones that include up to 32 GW of power capacity. The new leases encourage larger scale investments and consequently bigger wind turbines. The new zones include locations further away from the shore and in deeper waters which could be more challenging [2,8,12–14].

The Round 3 zones are the following; Moray Firth, Firth of Forth, Dogger Bank, Hornsea, East Anglia (Norfolk Bank), Rampion (Hastings), Navitus Bay (West Isle of Wight), Atlantic Array (Bristol Channel) and Irish Sea (Celtic Array). Every zone consists of various sites and extensions. In this study, the five first zones in the North Sea are investigated. The selected zones provided a group of sites. These groups were selected as a reference case in order to prove the present methodology that provides results for both overall and individual zones.

Each location faces similar challenges; deep waters or high distances from the shore, etc. For example, Dogger Bank offers some advantages because of its shallow waters and high wind speed (above 10 m/s). It also offers economies of scale. However, it faces marine environmental issues and long distance from the shore and thus the ports, which has a costly impact [15]. The Round 3 offshore zones and sites are shown in the following Fig. 2.

In literature, only a few location-selection-focused studies can be found but the findings and the formulation of the problems provided follow a different direction. Goal programming was used in Ref. [16] in order to obtain the optimum offshore location for a wind farm installation. The study involves round 3 locations in the UK and discusses its flexibility to combine decision-making. The work shows the energy production, costs and multi-criteria nature of the problem while considering environmental, social, technical and economic aspects.

A study on offshore locations for a RE platform by using multiple criteria and Geographical Information Systems (GIS) is provided in Ref. [17]. Issues around offshore RE platforms have been reviewed and a combination of criteria has been selected for the Atlantic facing shores in Europe. Potential risks and trade-offs between designing costs and energy production were discovered. Factors such as the lack of construction ports that results in under-exploited sites, access problems and weather window conditions, even during the summer months were provided. The study is mostly focused on environmental, geographical and weather issues.

Similarly, a study for the optimum selection of wind turbines was conducted in Ref. [18] by considering cost-effective criteria and especially the cost of energy and the local wind conditions. The study demonstrates the need for a framework to deal with such challenging problems where a decision is necessary. In Ref. [19], a selection method of the optimum access point for offshore wind farms in China is suggested by using multi-objective optimisation and a comprehensive weight decision-making method, Analytic

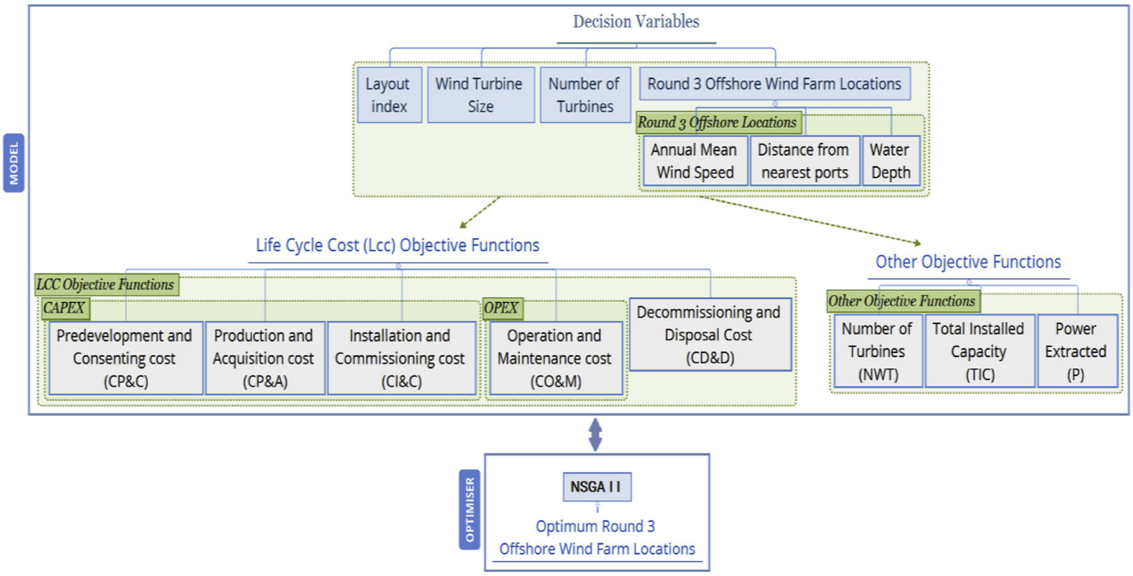

Fig. 1. Framework outline.

Hierarchy Process (AHP). The study selects the optimum access point in a power grid for an offshore wind farm which is integrated into the onshore power system. Although similar methods were employed, none of these studies shows a focus on the location selection for renewable installation employing life cycle cost factors.

2.2. Life cycle cost analysis

The LCC analysis can evaluate costs and suggest cost reductions throughout a project's whole life. The outcome of the analysis can provide deeper insight into an investment and can impact on direct decision making from the initial stages of a new project [20]. LCC analysis gains more ground over the years because of the larger scale in wind projects. For example, the advantages and disadvantages of the transition to offshore wind and a LCC model of an offshore wind development were proposed in Ref. [21]. However, the present study mainly focuses on a simplified model and especially the operation and maintenance stage of the LCC analysis and it is suggested that there can be a further full-scale LCC framework in the future. More studies can be found in Refs. [22–28].

Calculating the LCC of a wind farm and especially an offshore wind project can be very challenging. It involves many cost phases from the predevelopment to the decommissioning phase, and there is not any common universal reference point for wind projects. In Ref. [29], a parametric whole life cost framework for an offshore wind farm and a cost breakdown structure is presented and analysed. LCC analysis is essential for the insurers, wind farm operators and investors in order to ensure a cost-efficient long and profitable investment plan to produce power. In Ref. [29] the LCC analysis was divided into five stages of the wind project as a guideline; the predevelopment and consenting ($C_{P\&C}$), production and acquisition ($C_{P\&A}$), installation and commissioning ($C_{I\&C}$), operation and maintenance ($C_{O\&M}$), and decommissioning and disposal ($C_{D\&D}$) stage.

There are limited studies that combine the concept of LCC analysis with MOO. There are no studies that consider objectives based on economic figures in order to select the optimum Round 3 offshore location in the UK. In fact, for the selection of the location, there is very limited work accessible and with a small amount of focused and related criteria on this topic. The present study focuses on all five components of the LCC costs in Ref. [29]. It also considers three different cases of turbine layouts based on the theory behind the positioning and an extreme case, in order to find the optimum offshore location for wind farm projects. This study also provides optimum location solutions both in the overall Round 3 zones and individual location solutions per Round 3 zone.

2.3. Genetic algorithms

NSGA stands for Non-dominated Sorting Genetic Algorithm and it is also a MOO algorithm and an Evolutionary Multi-criterion Optimisation (EMO). Currently, there are three versions of the code; NSGA, NSGAII and NSGAIII [30]. This research employs the NSGA II algorithm because of its suitability for this type of MOO problems with many objectives as discussed in Ref. [10].

The design of a new evolutionary based optimisation algorithm is proposed in Ref. [31], in order to optimise the layout of turbines in a wind farm. The shape of the wind farm, a range of costs and orography were included. Five different types of optimisation algorithms were used in Ref. [32] in order to optimise the layout of a wind farm. Higher quality solutions are expected to be discovered by using algorithms with stochastic elements. Combining genetic algorithms with heuristics was more effective and faster than using one of them.

In Ref. [33], the authors optimised the layout of a wind farm (micro-siting optimisation: choosing the type and location of wind turbines) by considering continuous space and by using particle swarm optimisation techniques. A special local search scheme was also introduced in the optimisation algorithm to successfully speed up the process. Finally, evolutionary algorithms are applied to a wind farm optimisation problem in Ref. [34]. The configuration of the layout of the turbines is optimised based on a cost model. The suitability of the suggested evolutionary techniques is proven in the study. More can be found in Refs. [35–37].

2.4. Wind farm layouts

Layout optimisation is a significantly complex problem and is governed by many trade-offs. The problem is usually solved by

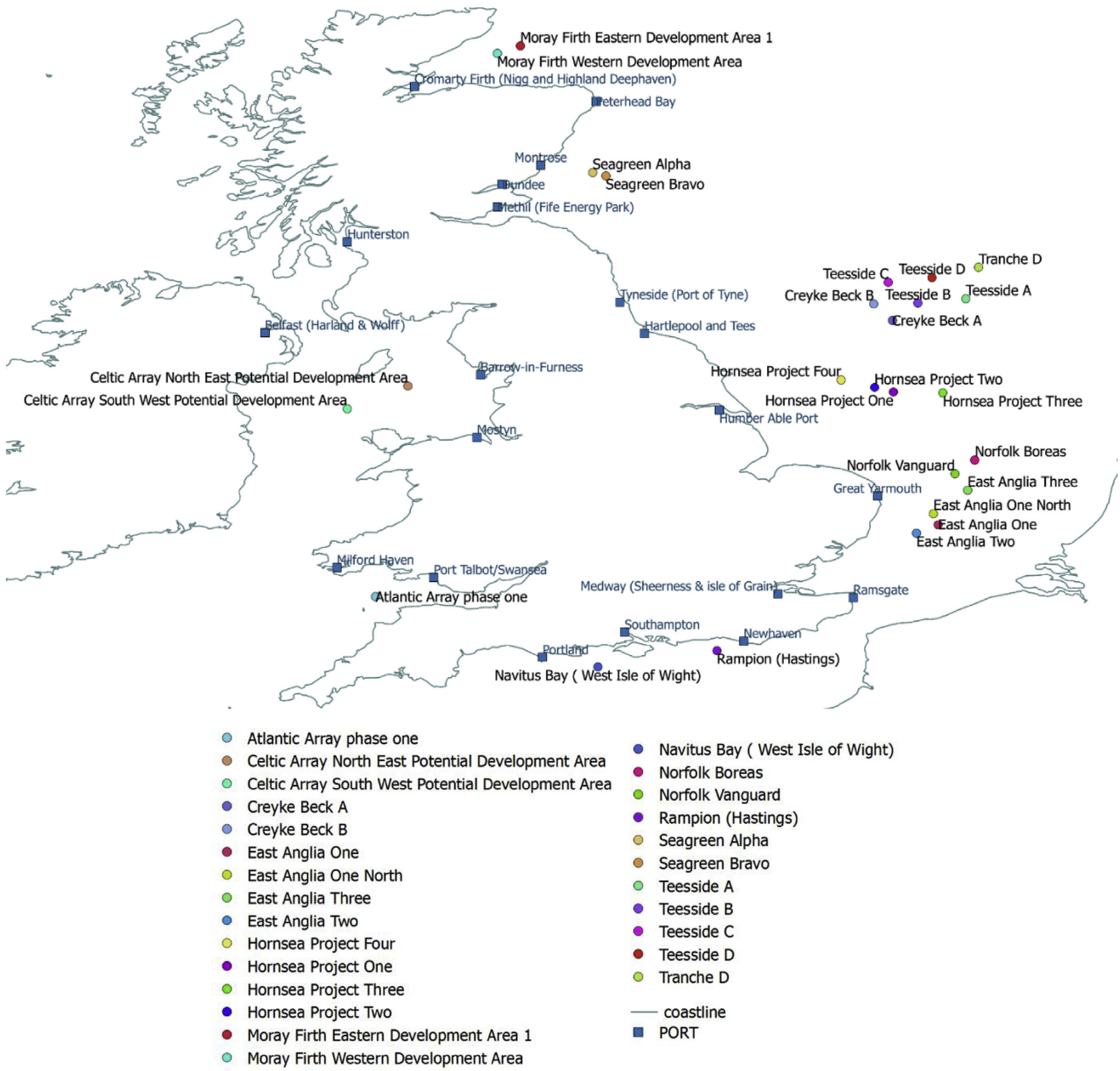

Fig. 2. Round 3 offshore location around the UK by using QGIS.

using layout optimisation processes that position the turbines accordingly in order to reduce/minimise the wake effect and, at the same time, to increase/maximise the produced power [38,39]. Wind turbines are usually placed in groups in order to efficiently transform wind energy to electricity and reduce installation and maintenance costs at the same time. However, although cost reduces by grouping turbines, the power extracted from them is considerably decreased. Turbulence or wake effect created by each turbine can affect the ones that are at their wake and thus many studies aim to reduce these wake effects in order to maximise the produced power, especially at large scale offshore farms. In order to achieve the optimum positioning, identical rows and large distances between turbines or irregular positioning yield better power production and profit [3,39]. When optimising the layout, minimising the distance between turbines reduces the cabling costs but increases the wake effect, which minimises energy generation [40].

The problem with multiple wake effects in a wind farm is the wind speed deficit, which depends on the nearest turbines. At a large scale, though, the phenomenon is not fully comprehended. Many studies in the aerodynamic sector are focused on this effect and their results show disagreements among the studies and real large-scale wind farms, where the wake effect is the most relevant and appears to have a heavy impact [39,41]. The methodology behind layouts is the basic theory of the rule of thumb. According to the rule, the prevailing theory, wind turbines are usually placed 5–9 times the rotor diameter at the dominant-for-the-location wind speed direction and 3–5 times the diameter vertical to the previous mentioned dominant wind speed as shown in Fig. 3. Other studies use even ten times the diameter between the rows and seven times along the rows.

The number and the size of the turbines to be installed are determined by the size of the investment and also depend on each other (number of turbines vs turbine size). Bigger turbine size is usually preferred because the cost and the energy production are usually proportional to its nominal power. Therefore, the net profit from each turbine is also proportional to its nominal power. However, sometimes even if it is more sensible to employ large-scale turbines, the price of smaller turbines might be considerably lower [39].

The first study to consider the layout optimisation was [42]. A wind farm site modelled with 100 possible squares and their centres as points for the position of the turbines in order to ensure the validity of the Jensen model where each square side is five times the diameter of the turbine (5D) [43,44]. In Ref. [45], a multi-objective genetic algorithm is employed on an island in the Aegean sea. The maximisation of the energy extracted and the minimisation of the cost is provided. The study assumes the wind direction stable and the wind speed constant. The minimum space between turbines is considered as eight times the diameter of the turbine (8D) in the prevailing wind direction and only two times the diameter at the crosswind direction (2D). The Pareto Front (PF) solutions of this study provided the optimum configurations, the total power produced, cost and number of turbines. Although the cost and the number of turbines are optimised, no economic model or LCC was presented. The study focuses mostly on the wake effect.

The layout optimisation problem is addressed throughout the literature in many scientific publications. However, the studies do not consider the construction and logistics in the calculations. To the best of the authors' knowledge, in literature LCC analysis and three different offshore layout cases were never linked before to a MOO formulation in order to conclude to the optimum wind farm location. The offshore wind farm selection is studied by each developer individually and never has a framework appeared in order to guide researchers and decision makers, so as to make informed and low-in-risk decisions.

3. A framework for the optimisation of deployment sites for round 3 wind farms in the UK

The LCC analysis of a project is always challenging. It involves

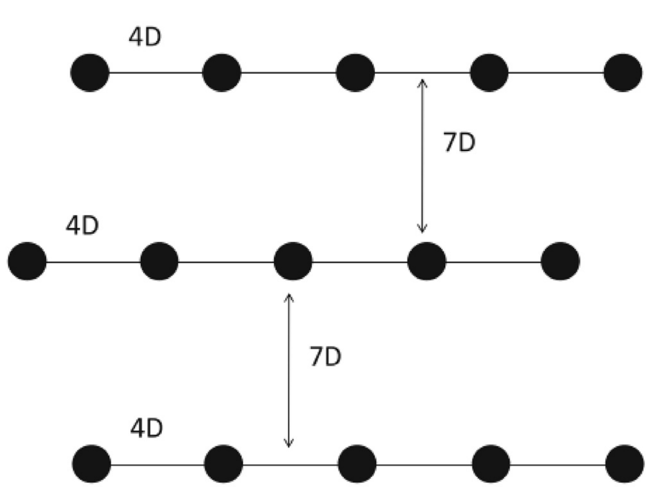

Fig. 3. Wind farm layout as introduced in Ref. [39].

stages from the predevelopment to the decommissioning phase. In Refs. [29,46], a whole LCC formulation is provided and this study integrates these phases into the optimisation problem, as shown in Fig. 4. Assumptions and related data in the modelling of the problem can be found in the following references [26,29,46–50]. Based on the previous references, a new model was developed, so as to be coupled with the optimisation algorithm and drive the optimisation search. The LCC model described in Ref. [29] is used as a guideline in this study and its structure is provided below in detail. The type of foundation that was considered in the LCC model in the present work is the jacket structure.

The LCC, CAPEX and OPEX represent the Life Cycle Cost, Capital expenditure and Operational expenditure, respectively and they are calculated as follows. The individual costs are the following; $C_{P\&C}$ is the Predevelopment and Consenting cost, $C_{P\&A}$ is the Production and Acquisition cost, $C_{I\&C}$ is the Installation and Commissioning cost, $C_{O\&M}$ is the Operation and Maintenance cost, and finally, $C_{D\&D}$ is the Decommissioning and Disposal Cost.

$$LCC = C_{P\&C} + C_{P\&A} + C_{I\&C} + C_{O\&M} + C_{D\&D}$$

$$CAPEX = C_{P\&C} + C_{P\&A} + C_{I\&C}$$

$$OPEX = C_{O\&M}$$

The framework described in this section is suggested in order to assess the effectiveness of the suggested methodology to discover the optimum location from a selection of Round 3 offshore locations in the North Sea, in the UK. Conceptually, the framework comprises of a model and an optimisation algorithm, also shown in Fig. 1. Fig. 5 shows the framework with the extension of a decision making phase and links to the other phases.

The optimisation problem includes eight objectives; five LCC-related objectives, as described in Ref. [29], and three additional objectives. Optimising eight objective functions at the same time, which are conflicting (from the mathematical formulation above), classifies the problem as many-objective and it is considered rather complicated because of the interplay of the objectives, the nature of the variables and the nature of the constraints.

For the selection of the optimum offshore wind farm location, physical aspects of each location, i.e., wind speed, water depth and distance from designated construction ports, are considered. A list of ports was acquired from Refs. [51–53]. The list contains designated, appropriate and sufficient construction ports that are suitable for the installation, manufacturing and maintenance work for wind farms. New ports are agreed to be built for the conveniences of new wind farms. However, this study assumes that the list below contains a selection of currently available ports around the UK.

Table 1 was acquired from Ref. [49], for each offshore location a special profile was created including the coordinates, the distances to the shore and port, annual wind speed and average site water depth. Among various data, Table 1 shows the locations that each of these zones contains. Each location correlates with their specific data used in this problem.

For the distances from the ports calculation, QGIS was used. QGIS is an Open Source licensed Geographic Information System (GIS), which is a part of the Open Source Geospatial Foundation (OSGeo) [51]. These distances were calculated under the assumption that the nearest port to the individual wind farm is a straight line. In this study, the distances represent the route of the ships and impact the overall costs. The real shipping routes were not considered and for this reason, a simplification of the real routes was assumed instead. The straight lines were calculated by using QGIS because of simplicity of the approximation and to demonstrate the proof-of-concept. The estimated metrics were integrated

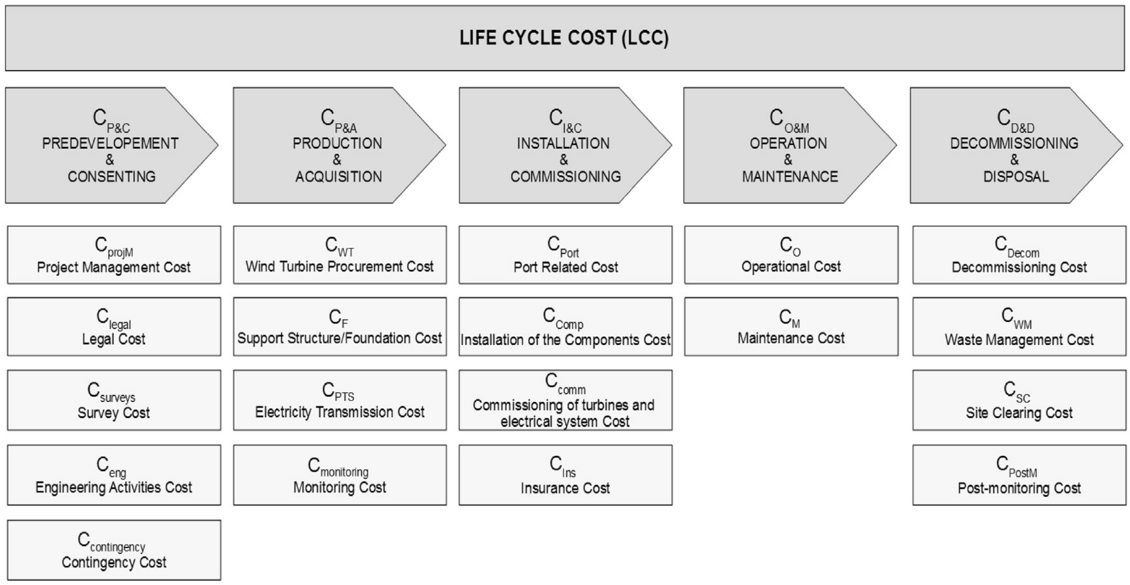

Fig. 4. Life Cycle Cost (LCC) break down [29].

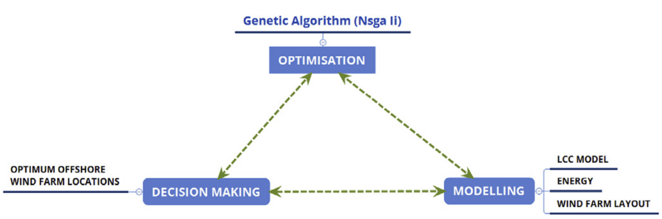

Fig. 5. Framework for the layout and location selection optimisation.

into the configuration settings of the whole LCC.

The lower and upper limits of a theoretical array layout will be compared and contrasted to an extreme case. More specifically, in the lower limit case (3–5 layout), the horizontal and vertical distance between turbines is 3 and 5 times the rotor diameter, respectively. In the upper limit case (5–9 layout), 5 and 9 times the rotor diameter were considered horizontally and vertically. In the extreme case (10–18 layout), the horizontal and vertical distance between turbines is 10 and 18 times the rotor diameter. All cases are depicted in Fig. 6. The present work focuses on the optimisation of offshore wind farm locations considering the maximum wind turbine number that can fit in the selected round 3 locations according to three different layout configuration placements. The wind farm is oriented according to the most optimal wind direction (South West) as investigated and mentioned below. The maximum number of turbines is determined by considering types of reference turbines of 6, 7, 8 and 10 MW, whose specifications are listed in Table 2. The three layout cases are depicted in Fig. 6 and listed in Table 3, where D is the diameter of each turbine. According to the topology capacity and the three layout cases, the calculated maximum number of turbines is listed from Table 5 and Tables 6 and 7(in Appendix A), and all this is integrated into the model.

In Fig. 7, the example of Moray Firth zone (which includes Moray Firth Western Development Area and Moray Firth Eastern Development Area 1) shows the positioning of the turbines considering layouts 1, 2, 3 and turbine sizes.

The wind rose diagrams provided the prevailing wind direction, which sets the layout orientation. All wind farm sites were discovered to have dominant southwestern winds followed by western winds. For that reason, the orientation of the layouts is assumed to be southwestern (as the winds are assumed to blow predominantly from that direction). The wind rose graphs for each offshore site are acquired from Ref. [52].

The QGIS maps of the offshore sites were acquired from the official Crown Estate website [53] for QGIS and AutoCAD. The wind speeds, the wind rose graphs and the coordinates of each location were obtained by FUGRO and 4COffshore [49,52].

The first five objectives of the MOO problem are the costs of the LCC analysis. More specifically, the present model includes the predevelopment and consenting, production and acquisition, installation and commissioning, operation and maintenance and finally decommissioning and disposal costs. All the cost related objectives are minimised.

The last three objectives are the number of turbines (NWT), the power that is extracted (P) from each offshore site and the total installed capacity (TIC), which are minimised, maximised and maximised, respectively. The power extracted is calculated by the specific mean annual wind speed of each location along with the characteristics of each wind turbine both of which are considered inputs (listed in Table 1).

The power extracted in this optimisation model is maximised and it is calculated for each site and each wind turbine respectively from:

$$P = \frac{1}{2} A C p \rho u^3$$

where A represents the area of the wind turbine, Cp is the power coefficient, ρ is the air density and u is the mean annual wind speed of each specific site. The wind speeds used in the calculations were assumed to be the same for each turbine and for each location. This simplification was used in order to demonstrate the effectiveness of the methodology as a proof-of-concept.

The last objective of the model is the TIC, which is calculated by the number of turbines and the rated power of each of them.

Table 1
Round 3 zones & sites and specific data acquired from Ref. [49].

Site Index	Zone	Wind farm site name	Centre Latitude	Centre Longitude	Port	Distance from the port [km]	Annual wind speed [m/s] (at 100 m)	Average Water Depth [m]
0	Moray Firth	Moray Firth Western Development Area	58.097	−3.007	Port of Cromarty	123.6	8.8	44
1	Moray Firth	Moray Firth Eastern Development Area 1	58.188	−2.720	Port of Cromarty	157.1	9.4	44.5
2	Firth of Forth	Seagreen Alpha	56.611	−1.821	Montrose	72.5	9.9	50
3	Firth of Forth	Seagreen Bravo	56.572	−1.658	Montrose	91.1	10	50
4	Dogger Bank	Creyke Beck A	54.769	1.908	Hartlepool and Tess	343.2	10	21.5
5	Dogger Bank	Creyke Beck B	54.977	1.679	Hartlepool and Tess	319.9	10	26.5
6	Dogger Bank	Teesside A	55.039	2.822	Hartlepool and Tess	447.1	10	25.5
7	Dogger Bank	Teesside B	54.989	2.228	Hartlepool and Tess	380.7	10	25.5
8	Hornsea	Hornsea Project One	53.883	1.921	Grimsby	242.3	9.6	30.5
9	Hornsea	Hornsea Project Two	53.940	1.687	Grimsby	217.2	9.7	31.5
10	Hornsea	Hornsea Project Three	53.873	2.537	Grimsby	310.5	9.7	49.5
11	Hornsea	Hornsea Project Four	54.038	1.271	Grimsby	173.9	9.7	44.5
12	East Anglia (Norfolk Bank)	East Anglia One	52.234	2.478	Great Yarmouth	92.7	9.5	35.5
13	East Anglia (Norfolk Bank)	East Anglia One North	52.374	2.421	Great Yarmouth	81.1	9.7	45.5
14	East Anglia (Norfolk Bank)	East Anglia Two	52.128	2.209	Great Yarmouth	74.5	9.4	50
15	East Anglia (Norfolk Bank)	East Anglia Three	52.664	2.846	Great Yarmouth	124.9	9.5	36
16	East Anglia (Norfolk Bank)	Norfolk Boreas	53.040	2.934	Great Yarmouth	143.4	9.5	31.5
17	East Anglia (Norfolk Bank)	Norfolk Vanguard	52.868	2.688	Great Yarmouth	111.4	9.5	32

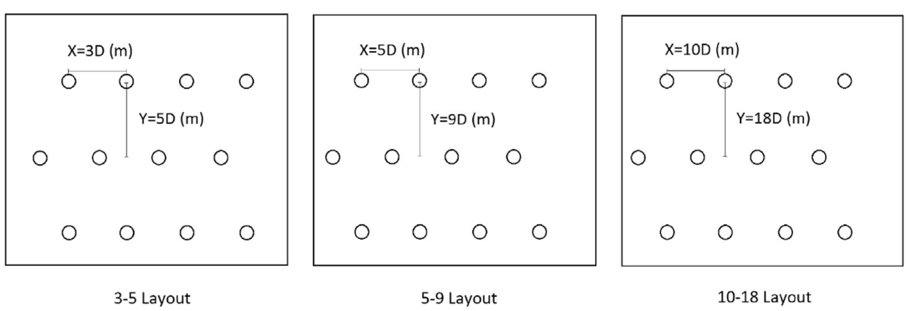

Fig. 6. Demonstrating different layouts, where D corresponds to the diameter of the turbine.

Table 2
Turbine specifications.

Turbine Type Index	Rated power (MW)	Rotor Radius (m)	Hub Height (m)	Total Weight (t)
0	10	95	125	1580
1	8	82	123	965
2	7	77	120	955
3	6	70	100	656

Table 3
Layout specification.

Layout name	X separation	Y separation
3-5 layout	3D	5D
5-9 layout	5D	9D
10-18 layout	10D	18D

$$TIC = P_R \times NWT$$

where P_R represents the rated power and NWT is the number of turbines.

The optimisation problem formulates as follows:

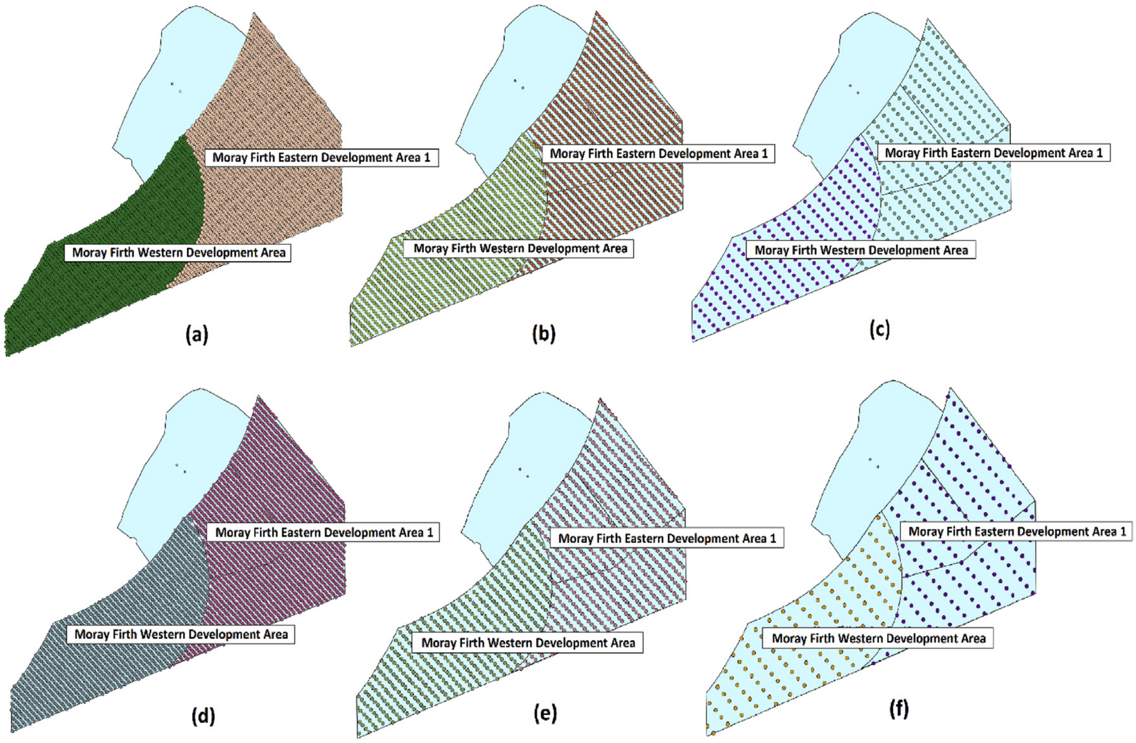

Fig. 7. Moray Firth zone. Maximum number of wind turbines placed according to 3–5 layout, 5–9 layout and 10–18 layout for the case of 10 and 6 MW turbine. In (a) Moray Firth, 6 MW turbines positioned in 3–5 layout, (b) Moray Firth, 6 MW turbines positioned in 5–9 layout, (c) Moray Firth, 6 MW turbines positioned in 10–18 layout, (d) Moray Firth, 10 MW turbines positioned in 3–5 layout, (e) Moray Firth, 10 MW turbines positioned in 5–9 layout, (f) Moray Firth, 10 MW turbines positioned in 10–18 layout.

$$
\begin{array}{ll}
\text{Minimise} & \mathrm{C_{P\&C}},\ \mathrm{C_{P\&A}},\ \mathrm{C_{I\&C}},\ \mathrm{C_{O\&M}},\ \mathrm{C_{D\&D}},\ \mathrm{NWT},\ (-\mathrm{P}),\ (\mathrm{TIC}) \\
\text{Subject to} & 0 \leq \text{site index} \leq 20, \\
 & 0 \leq \text{turbine type index} \leq 3 \\
 & 1 \leq \text{layout index} \leq 3 \\
 & 0 \leq \text{Number of turbines} \leq \text{maximum turbine number per site} \\
 & TIC \leq \text{Maximum capacity of Round 3 sites based on the Crown Estate}
\end{array}
$$

Although the maximum numbers of turbines have been estimated by using QGIS, the maximum capacity allowed per region was also considered, as specified by the Crown Estate in Table 4. Both Crown Estate maximum capacity limitation per zone and a maximum number of wind turbines that can be placed in each zone's sites were considered as constraints in the optimisation problem. These were selected because of the possibility that the constraints might overlap in an extreme case scenario. Therefore, both constraints were added to the problem in order to secure all cases.

Table 4
Maximum capacity of Round 3 wind farms, specified by the Crown estate.

Zone	Capacity MW
1. Moray Firth	1500
2. Firth of Forth	3465
3. Dogger Bank	9000
4. Hornsea	4000
5. East Anglia	7200
6. Rampion	665
7. Navitas| Bay	1200
8. Bristol Channel	1500
9. Celtic Array	4185
TOTAL CAPACITY	32715

For the estimation of cabling length, which is required to calculate parts of the LCC related to the spatial distribution of the wind turbines in the wind farm, the minimum spanning tree algorithm is used. The location of the turbines is treated as a set of vertices of a graph and the cabling represents the edges that connect the vertices. Given a set of vertices, which are separated by each other by the different layout indices, from Fig. 6, the minimum spanning tree connects all these vertices without creating any cycles, thus yielding minimum possible total edge length. This represents the minimum cable length of the particular layout.

The whole framework has been implemented by using Python 3. The optimisation modelling has been completed using the library platypus in python [54] and the sensitivity analysis using the method Sobol Indices [55] by using the library SALib [56].

Also, the physical features of the site cannot allow turbine installation in all parts of the seabed. Also, the assumption that the offshore sites can host up to a maximum number of turbines was introduced without considering any site investigations or initial capital cost.

4. Results and discussion

The LCC model described in the methodology was used in the optimisation problem and 8 objectives were included in the process by utilising the NSGA II algorithm according to Fig. 1. The outcomes show trade-offs between important factors such as CAPEX vs OPEX and the total costs for each solution individually. By applying the framework described above, the optimal recommendations for deploying an offshore wind farm are produced. First, the available sites are selected along with the specifications of each site. Also, a range of wind turbines is selected along with their specifications. Both of the above are used as an input to the LCC. Next, the configuration settings of the optimisation function are specified and the optimisation algorithm runs by utilising the aforementioned LCC.

First, the results from all locations (from all five zones) are provided and illustrated in Figs. 8 and 9, accordingly. Second, the results for each zone individually are provided and illustrated below from Figs. 10–14. Each case includes the results from all layouts for comparison. A new simulation was performed for each zone, from scratch; a zone can include for example 2 locations (Moray Firth Zone), 6 locations (East Anglia Zone), etc. All results shown and discussed are equally optimal solutions, according to the Pareto equality.

4.1. Location selection for all layouts for 18 locations (5 round 3 zones)

Here, the results include all 18 locations acquired from the five selected Round 3 zones. The comparison includes CAPEX versus OPEX costs and total costs, as shown in Figs. 8 and 9. Overall, for all layouts, the solutions from the trade-off according to CAPEX and OPEX are shown in Fig. 8. All layouts were found to deliver optimal solutions, where the 10–18 layout was found only once with few turbines. In the range between £1.6 and £1.8 billion of total cost, 4 solutions were discovered, for the areas of Seagreen Alpha, East Anglia One and Hornsea Project One.

The breakdown of all costs is depicted in Fig. 9 by normalising the total cost per MW of installed capacity (throughout the lifecycle of the project). Norfolk Boreas seems to include the highest total costs per MW compared to the rest of the sites. The gap between the highest and lowest cost solutions is approximately £2 million per MW. On average, CAPEX per MW is ten times larger than OPEX per MW, while OPEX per MW and $C_{D\&D}$ per MW are comparable in size.

4.2. Location selection for all layouts per round 3 zone

Here, the same methodology was applied to each zone individually from the five selected Round 3 zones, the trade-offs

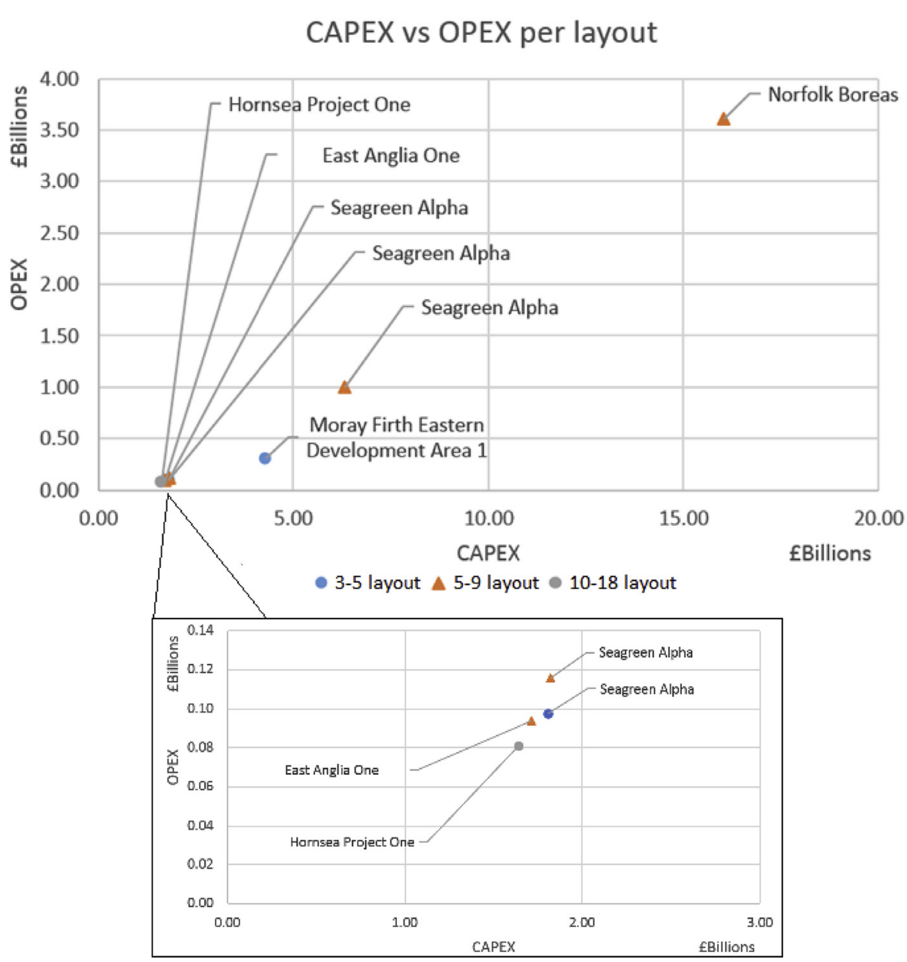

Fig. 8. OPEX vs CAPEX for all PF solutions for all layout cases and solutions focused on the beginning of the trend of the costs.

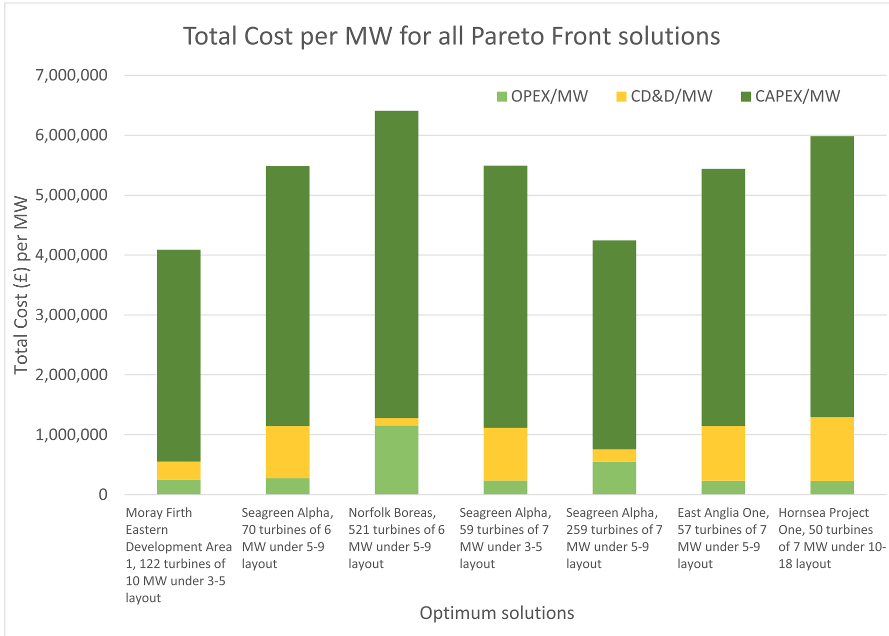

Fig. 9. Total Cost per MW for all Pareto Front solutions.

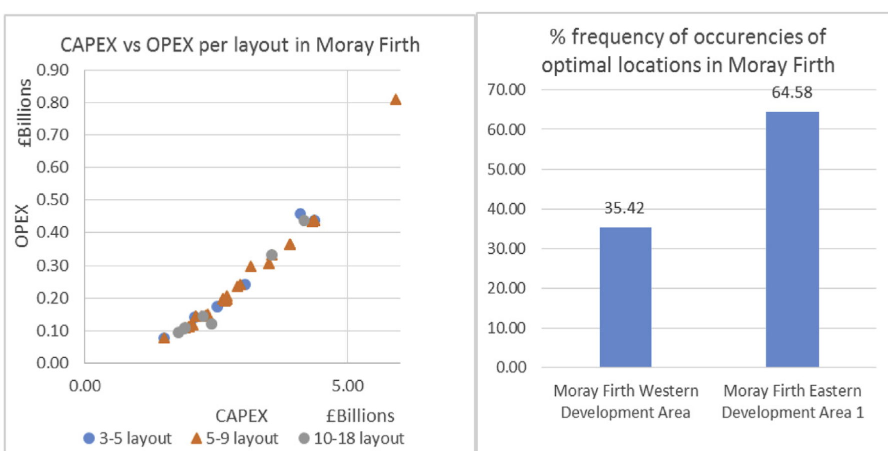

Fig. 10. (a) Comparing OPEX vs CAPEX for the zone of Moray Firth for all layout cases and (b) % of frequency in the PF front for the zone of Moray Firth and all layout cases.

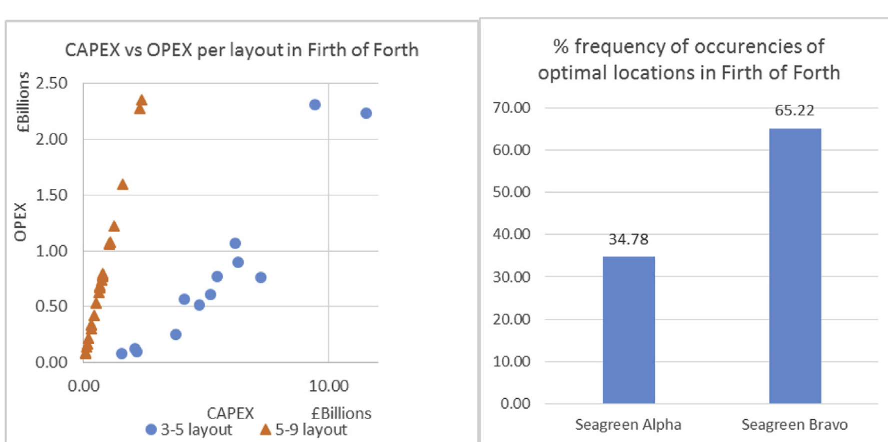

Fig. 11. (a) Comparing OPEX vs CAPEX for the zone of Firth of Forth for all layout cases and (b) % of frequency in the PF for the zone of Firth of Forth and all layout cases.

between CAPEX and OPEX and the relative frequency in the PF solutions are shown from Figs. 10–14.

For Moray Firth, the trade-off between CAPEX vs OPEX appears more concentrated, as shown in Fig. 10(a) where CAPEX and OPEX vary together irrespectively of the considered layouts, which suggests that the sites present a similar performance for different layouts. In one extreme case, the 5–9 layout is far from the cluster of points. The revealed solutions for this zone present the lowest costs in terms of CAPEX and OPEX. In the aggregated frequency, in Fig. 10(b), in Moray Firth, Moray Firth Eastern Development 1, the gap appears almost twice as much as Moray Firth Western Development Area.

The solutions of Firth of Forth follow different trends per layout in the CAPEX vs OPEX trade-off, in Fig. 11(a), where it is also shown that for the 3–5 layout, OPEX develops much faster than CAPEX as the costs increase. The opposite holds for 5–9 layout. The clear separation of layouts, where the performance of CAPEX vs OPEX for 5–9 layout seems to vary linearly, which indicates that the choice of layout is more important in Firth of Forth compared to all other cases. The 10–18 layout was not found in this case. In the frequencies, the optimum results Seagreen Bravo appears almost twice as much as Seagreen Alpha in Fig. 11(b).

The detailed analysis for Dogger Bank is similar to the analysis for all the regions, performed in the above section. As shown in Fig. 12(a), only 3–5 and 5–9 layouts were selected and three solutions from 3 to 5 layout appear at the bottom left corner. This site is the most expensive in terms of CAPEX and OPEX. Then, in Fig. 12(b), Creyke Beck B gathered the highest percentage of non-dominated solutions. Also, Teeside C, Teeside D and Tranche and 10–18 layout were not selected by the optimiser in this case.

The 5–9 layout seems to be the most frequent in Hornsea, as shown in Fig. 13(a). A few solutions from 10 to 18 layout appear at the bottom left corner and there is a discontinuity in the optimal results, which proves the ability of the optimiser to reveal solutions in a small region of optimal performance and distant regions. Fig. 13(b), Hornsea Project Three and Four present similar frequencies. Hornsea Project Two was not selected by the optimiser.

In East Anglia, most optimal solutions are of 3–5 layout, as shown in Fig. 14(a). Relative to the other cases, the percentages of frequency demonstrate little discrepancy, as shown in Fig. 14(b) which means that all of them can be selected by developers. 10–18 layout was not selected by the optimiser. The discontinuity in the results for 3–5 layout between approximately £12 billion and £30 billion in CAPEX demonstrates the gap in the attainable trade-off.

Regarding the frequency of revealed solutions, one can notice 3 clusters. The first cluster, in terms of highest percentage, includes two areas that were equally visited by the NSGAII. The second cluster comprises of three areas that were visited by 13.33%. The last cluster includes a single location, which had been visited half of the times of the previous cluster.

4.3. Sensitivity analysis

For the purposes of the sensitivity analysis, the levels of 80, 100, 120, 150 were utilised for population size and 2, 3, 4, 5 were utilised for the tournament selection of the algorithm. The quality of the discovered trade-offs was assessed by employing the hypervolume indicator of the points in the trade-off as shown in Ref. [57] (also provided by platypus library), where the reference point was a high dimensional point from the trade-off with the most extreme and dominated value for each component of the reference point. Each combination of population size and tournament selection was executed for ten times and the respective variance was calculated for each set, whose results are listed in Table 5.

The results of the hypervolume calculation varied between the order of magnitude of 10^{57} and 10^{59}. According to this range, the value of variance is consistently negligible, which suggests that the selection of the aforementioned settings for NSGA II does not impact on the operation of the algorithm and its ability to reveal an optimal trade-off. The results of this study, presented in Subsections 4.1 and 4.2, were produced by using the population size of 100 and tournament selection of 2, based on authors' experience.

Following the dissimilarities in the trade-off of the cases analysed above, a sensitivity analysis has been performed to further investigate the diverse behaviour. The overall sensitivity of decision variables and their pairwise sensitivity are depicted in Figs. 15 and 16, respectively, by calculating Sobol indices. In a sensitivity analysis, Sobol indices explain the importance of an input factor on the variance of the output. Consequently, ST, S1 and S2 correspond to total order sensitivity index, first order and second order sensitivity index (i.e. corresponds to pairwise sensitivities between variables), respectively.

According to Fig. 15, all variables have high ST index. Here, the categorical variables are treated as integers. Hence, the absolute value will be considered for this sensitivity analysis. The confidence interval for S1 is less than 10%, which shows that the sample size is sufficient to deduct conclusions and the absolute value of S1 is too

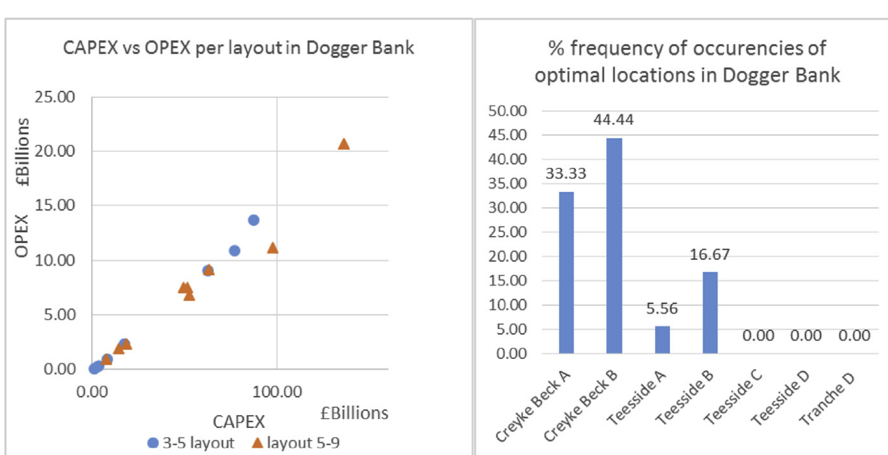

Fig. 12. (a) Comparing OPEX vs CAPEX for the zone of Dogger Bank for layout case 1 and 2 and (b) % of frequency in the PF for the zone of Dogger Bank and both layout cases 1 and 2.

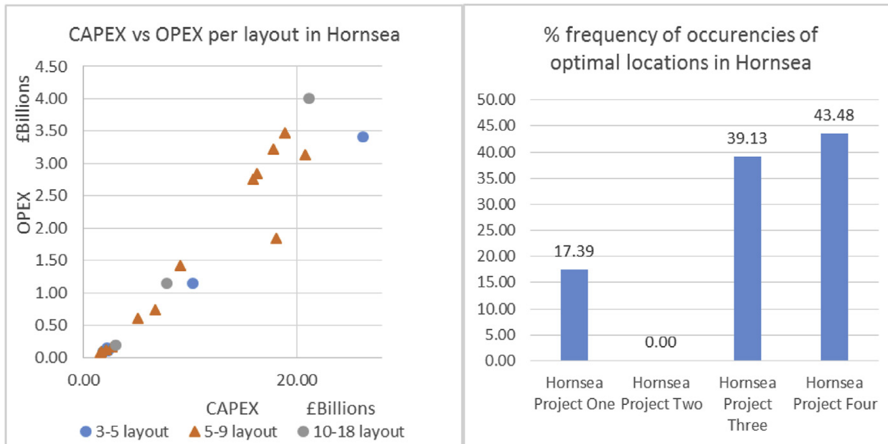

Fig. 13. (a) Comparing OPEX vs CAPEX for the zone of Hornsea for all layout cases and (b) % of frequency in the PF front for the zone of Hornsea and all layout cases.

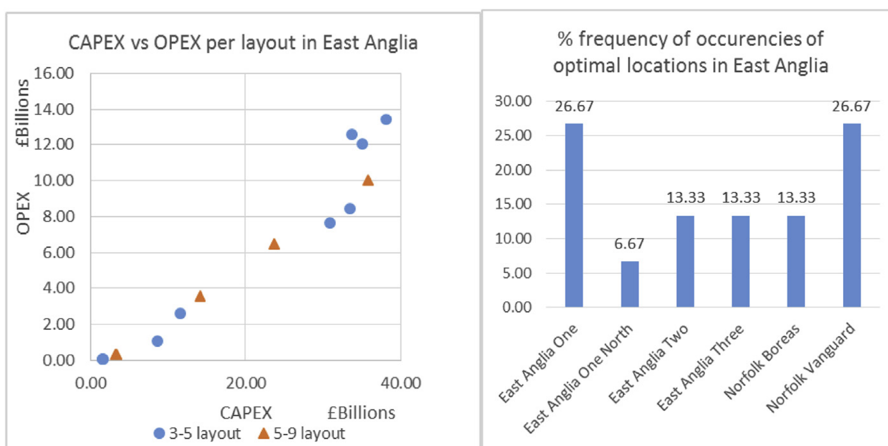

Fig. 14. (a) Comparing OPEX vs CAPEX for the zone of East Anglia for all layout cases and (b) % of frequency in the PF front for the zone of East Anglia and all layout cases.

Table 5
Variance of hypervolume indicator, through statistical sensitivity analysis, by altering the configuration parameters of NSGA II.

Population size	Tournament			
	2	3	4	5
80	1.172723	1.345013	0.988865	1.40078
100	0.955844	0.975384	0.976562	1.451503
120	1.070043	1.109467	0.94458	0.826054
150	0.734528	1.031415	0.979032	1.138782
200	0.63721	1.013199	0.714002	0.861545

low, which means that varying a single variable at a time has little impact on CAPEX and OPEX. S2 in Fig. 16 provides deeper insight and verifies the complexity of the problem. For the S2 index, more samples are required to accurately identify the interactions among the variables. The combination of the site and the layout is the most powerful pair to cause a change both for CAPEX and OPEX. Then, the site and the turbine size is the second most powerful combination to cause a change to both CAPEX and OPEX.

It is important to note that the sample size for the current modelling in the framework has more than 20,000 samples, which has captured a fraction of the total sensitivity. The investigation of

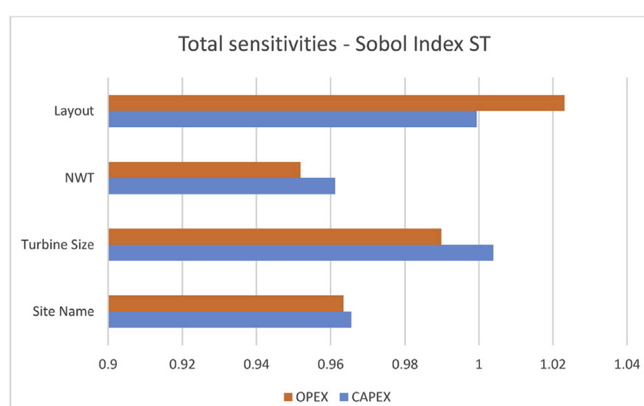

Fig. 15. Total sensitivity based on Sobol indices.

higher orders of Sobol indices could be explored in the future, so as to reveal the importance of the combination of more inputs. Negative sensitivities shown in Fig. 16 could be addressed by acquiring additional samples. Hence, it is expected that the combination of multiple input changes at the same time could more

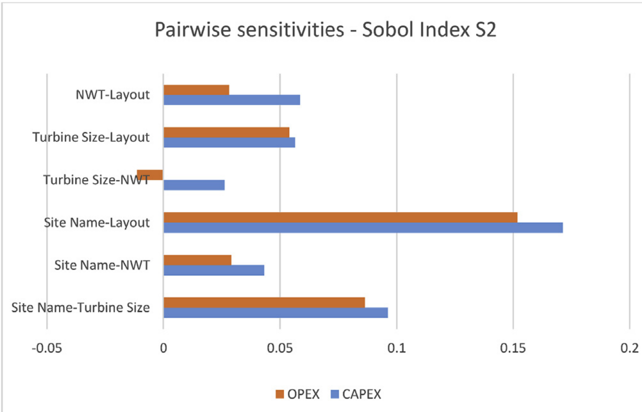

Fig. 16. Pairwise sensitivity.

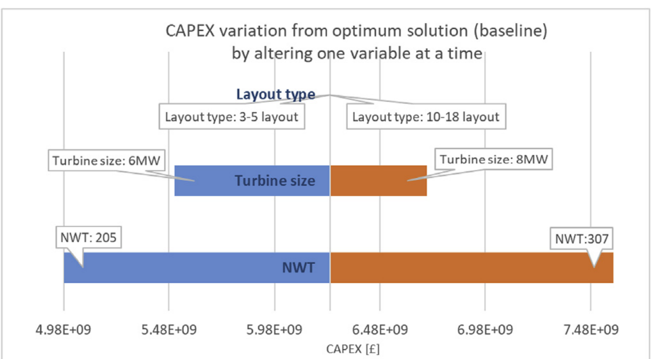

Fig. 17. CAPEX variation from optimum solution (baseline) by altering one variable at a time.

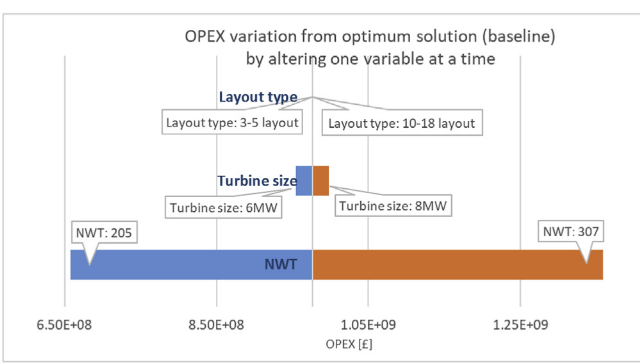

Fig. 18. OPEX variation from optimum solution (baseline) by altering one variable at a time.

drastically affect CAPEX, OPEX and the remaining objectives. Potentially, changing the modelling could consider a wider range of inputs to provide a deeper insight into the original problem, but this would increase the computational cost.

In order to illustrate the above abstract observation, a demonstration of the sensitivity of the problem is provided below. More specifically, a reference case was selected among the optimum solutions revealed above for which the decision variables changed one at a time. The solution that was chosen is in Seagreen Alpha under 5–9 layout with 259 turbines of 7 MW. By considering the previous solution as the baseline, the number of turbines varied by 20% (±20%), the layout type changed to 3–5 layout and 10–18 layout, and finally the turbine type changed to 6 MW and 8 MW, as shown in Figs. 17 and 18, for CAPEX and OPEX, respectively. Clearly, the number of turbines causes the greatest change, whereas a change in the layout yields such a little change that is very hard to notice.

5. Conclusion

This study demonstrated the effectiveness of a methodology by linking MOO with LCC as objective functions and comparing three different wind farm layouts in order to select the optimum solutions. The results provided greater insight into the decision-making process to develop an offshore wind farm through optimisation techniques by considering different wind turbine layouts, number of turbines, Round 3 locations in the UK and turbine size.

Trade-offs between the CAPEX and OPEX were revealed and further investigated by conducting a sensitivity analysis. When optimising all the regions together, in the range between 1.6 and 1.8 billion, four optimum solutions were discovered, for the areas of Seagreen Alpha, East Anglia One and Hornsea Project One. Although 3–5 and 5–9 layouts were mainly selected as optimum solutions by the optimiser, 10–18 layout (i.e., the extreme case) also appeared in the PF solutions a few times. When optimising 5 zones separately, Moray Firth Eastern Development area 1 was mostly chosen in Moray Firth and Seagreen Bravo in Firth of Forth. The results of optimisation in East Anglia were the most balanced, which recommend that all sites are equally appropriate to be selected. In Hornsea, Hornsea Project Two was never selected in the PF. In Dogger Bank, Creyke A and B amount for 77% of the optimum solutions, whereas Teeside C and D, and Tranche D were never selected. The sensitivity analysis demonstrated the highly complex nature of the decision variables and their interdependencies, where the combinations of site-layout and site-turbine size captured above 20% of the variability in CAPEX and OPEX. Higher-order interdependencies will be investigated in the future.

The revealed outcomes will have an important impact on a possible extension of the Round 3 zones in the future of the UK and will help decision makers for their next cost-efficient investment decision. The proposed framework could also be applied to other sectors in order to increase investment confidence and reveal optimum solutions. For example, the framework can be applied to the installation of floating offshore wind and wave devices, where the optimum locations can be suggested according to cost and operational aspects of each technological need.

Acknowledgements

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Appendix A

Table 6
Maximum number of turbines for each offshore site employing 10 MW turbines and 3 layout cases.

Zone	Wind farm site name	Area (km^2)	Max Number of turbines (3–5 layout, X = 3D, Y = 5D)	Max Number of turbines (5–9 layout, X = 5D, Y = 9D)	Max Number of turbines (10–18 layout, X = 10D, Y = 18D)
Moray Firth	Moray Firth Western Development Area	226	1487	492	125
Moray Firth	Moray Firth Eastern Development Area 1	295	1957	652	164
Firth of Forth	Seagreen Alpha	197	1211	404	97
Firth of Forth	Seagreen Bravo	194	1161	387	97
Dogger Bank	Creyke Beck A	515	2850	949	238
Dogger Bank	Creyke Beck B	599	3345	1119	281
Dogger Bank	Teesside A	562	3137	1047	261
Dogger Bank	Teesside B	593	3309	1079	265
Hornsea	Hornsea Project One	407	1533	510	181
Hornsea	Hornsea Project Two	483	3058	1022	204
Hornsea	Hornsea Project Three	3875	3683	1226	308
Hornsea	Hornsea Project Four	3874	4520	1502	380
East Anglia (Norfolk Bank)	East Anglia One	297	1010	340	86
East Anglia (Norfolk Bank)	East Anglia One North	206	1024	340	87
East Anglia (Norfolk Bank)	East Anglia Two	358	1242	416	105
East Anglia (Norfolk Bank)	East Anglia Three	301	3028	1014	128
East Anglia (Norfolk Bank)	Norfolk Boreas	727	3571	1226	308
East Anglia (Norfolk Bank)	Norfolk Vanguard	574	1493	497	249

Table 7
Maximum number of turbines for each offshore site employing 8 MW turbines and 3 layout cases.

Zone	Wind farm site name	Area (km^2)	Max Number of turbines (3–5 layout, X = 3D, Y = 5D)	Max Number of turbines (5–9 layout, X = 5D, Y = 9D)	Max Number of turbines (10–18 layout, X = 10D, Y = 18D)
Moray Firth	Moray Firth Western Development Area	226	1996	665	167
Moray Firth	Moray Firth Eastern Development Area 1	295	2618	876	219
Firth of Forth	Seagreen Alpha	197	1619	539	133
Firth of Forth	Seagreen Bravo	194	1566	525	131
Dogger Bank	Creyke Beck A	515	3820	1268	320
Dogger Bank	Creyke Beck B	599	4492	1491	378
Dogger Bank	Teesside A	562	4211	1401	349
Dogger Bank	Teesside B	593	4455	1483	358
Hornsea	Hornsea Project One	407	2058	683	242
Hornsea	Hornsea Project Two	483	4108	1369	276
Hornsea	Hornsea Project Three	3875	4946	1650	412
Hornsea	Hornsea Project Four	3874	6066	2024	502
East Anglia (Norfolk Bank)	East Anglia One	297	1357	452	111
East Anglia (Norfolk Bank)	East Anglia One North	206	1378	462	114
East Anglia (Norfolk Bank)	East Anglia Two	358	1680	558	140
East Anglia (Norfolk Bank)	East Anglia Three	301	4068	1355	169
East Anglia (Norfolk Bank)	Norfolk Boreas	727	4891	1655	413
East Anglia (Norfolk Bank)	Norfolk Vanguard	574	2000	669	337

Table 8
Maximum number of turbines for each offshore site employing 7 MW turbines and 3 layout cases.

Zone	Wind farm site name	Area (km^2)	Max Number of turbines (3–5 layout, X = 3D, Y = 5D)	Max Number of turbines (5–9 layout, X = 5D, Y = 9D)	Max Number of turbines (10–18 layout, X = 10D, Y = 18D)
Moray Firth	Moray Firth Western Development Area	226	2262	758	188
Moray Firth	Moray Firth Eastern Development Area 1	295	2974	988	247
Firth of Forth	Seagreen Alpha	197	1839	613	150
Firth of Forth	Seagreen Bravo	194	1775	588	151
Dogger Bank	Creyke Beck A	515	4333	1449	362
Dogger Bank	Creyke Beck B	599	5089	1693	428
Dogger Bank	Teesside A	562	4774	1591	398
Dogger Bank	Teesside B	593	5051	1691	411
Hornsea	Hornsea Project One	407	2332	777	269
Hornsea	Hornsea Project Two	483	4687	1552	315
Hornsea	Hornsea Project Three	3875	5607	1875	468
Hornsea	Hornsea Project Four	3874	6878	2294	576
East Anglia (Norfolk Bank)	East Anglia One	297	1538	1538	126
East Anglia (Norfolk Bank)	East Anglia One North	206	1562	1562	129
East Anglia (Norfolk Bank)	East Anglia Two	358	1899	633	159
East Anglia (Norfolk Bank)	East Anglia Three	301	4612	4612	197
East Anglia (Norfolk Bank)	Norfolk Boreas	727	5620	1878	462
East Anglia (Norfolk Bank)	Norfolk Vanguard	574	2269	756	376

Table 9
Maximum number of turbines for each offshore site employing 6 MW turbines and 3 layout cases.

Zone	Wind farm site name	Area (km^2)	Max Number of turbines (3–5 layout, X = 3D, Y = 5D)	Max Number of turbines (5–9 layout, X = 5D, Y = 9D)	Max Number of turbines (10–18 layout, X = 10D, Y = 18D)
Moray Firth	Moray Firth Western Development Area	226	2737	914	227
Moray Firth	Moray Firth Eastern Development Area 1	295	3596	1197	299
Firth of Forth	Seagreen Alpha	197	2229	741	182
Firth of Forth	Seagreen Bravo	194	2146	716	184
Dogger Bank	Creyke Beck A	515	5241	1746	438
Dogger Bank	Creyke Beck B	599	6157	2059	513
Dogger Bank	Teesside A	562	5777	1926	480
Dogger Bank	Teesside B	593	6118	2053	521
Hornsea	Hornsea Project One	407	2815	935	332
Hornsea	Hornsea Project Two	483	5643	1881	376
Hornsea	Hornsea Project Three	3875	6783	2257	568
Hornsea	Hornsea Project Four	3874	8326	2777	691
East Anglia (Norfolk Bank)	East Anglia One	297	1860	617	154
East Anglia (Norfolk Bank)	East Anglia One North	206	1894	627	157
East Anglia (Norfolk Bank)	East Anglia Two	358	2303	764	192
East Anglia (Norfolk Bank)	East Anglia Three	301	5579	1862	234
East Anglia (Norfolk Bank)	Norfolk Boreas	727	6799	2271	564
East Anglia (Norfolk Bank)	Norfolk Vanguard	574	2745	916	460

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Article

A Framework for the Selection of Optimum Offshore Wind Farm Locations for Deployment

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Abstract: This research develops a framework to assist wind energy developers to select the optimum deployment site of a wind farm by considering the Round 3 available zones in the UK. The framework includes optimization techniques, decision-making methods and experts' input in order to support investment decisions. Further, techno-economic evaluation, life cycle costing (LCC) and physical aspects for each location are considered along with experts' opinions to provide deeper insight into the decision-making process. A process on the criteria selection is also presented and seven conflicting criteria are being considered for implementation in the technique for the order of preference by similarity to the ideal solution (TOPSIS) method in order to suggest the optimum location that was produced by the nondominated sorting genetic algorithm (NSGAII). For the given inputs, Seagreen Alpha, near the Isle of May, was found to be the most probable solution, followed by Moray Firth Eastern Development Area 1, near Wick, which demonstrates by example the effectiveness of the newly introduced framework that is also transferable and generic. The outcomes are expected to help stakeholders and decision makers to make better informed and cost-effective decisions under uncertainty when investing in offshore wind energy in the UK.

Keywords: multi-objective optimization; nondominated sorting genetic algorithm (NSGA); multi-criteria decision making (MCDM); technique for the order of preference by similarity to the ideal solution (TOPSIS); life cycle cost

1. Introduction

The future of wind energy seems to keep growing as 18 GW are expected to be deployed by 2020 in the UK, with potential for more ambitious targets after 2020. Thus, there is a substantial need to reduce the cost of energy by identifying relevant cost reduction strategies in order to achieve these goals. The future of the UK's industry size strongly depends on these goals [1]. Significant price increases in the overall cost of turbines, operations and maintenance have a direct impact on large-scale wind projects, hence the wind energy industry is determined to lower the costs of producing energy in all phases of the wind project from predevelopment to operations. Following the UK technology roadmap, the offshore wind costs should be reduced to £100/MWh by 2020 [2]. According to [1] the costs were stabilized at £140 per MWh in 2011. The UK's Offshore Wind Programme Board (OWPB) stated that the offshore wind costs dropped below £100/MWh when 2015–2016 projects achieved a levelized cost of energy (LCOE) of £97 compared to £142 per MWh in 2010–2011, according to the Cost Reduction Monitoring Framework report in 2016 [3]. Recently, in 2017, Ørsted (formerly DONG

Energy) guaranteed a £57.5/MWh building the world's largest offshore wind farm in Hornsea 2, according to [4].

Developers and operators of offshore wind energy projects face many risks and complex decisions regarding service life cost reduction. In many cases, the manufacturers produce large volumes of parts in order to deal with the issue via economies of scale. Also, project consents can be time-consuming and difficult to obtain, however, all offshore wind farms were successfully completed regarding investment and profit [1]. Ensuring a long-term and profitable investment plan can be challenging, with both pre-consent and post-consent delays introducing considerable risks [2,5]. To this end, appropriate planning studies should be conducted at the early development stages of the project in order to minimize the investment risk. A breakdown of the key costs in an offshore wind farm can be found in [6] while studying existing projects, the location of a wind farm and the type of support structure have a great impact on the overall costs [7–9].

The aim of this paper is to develop a wind farm deployment framework, as illustrated in Figure 1, for supporting investment decisions at the initial stages of the development of Round 3 offshore wind farms in the UK by combining multi-objective optimization (MOO), life cycle cost (LCC) analysis and multicriteria decision making (MCDM). The contribution to knowledge is in developing and applying this novel and transferable framework that combines an economic analysis model by using LCC and geospatial analysis, MOO by using nondominated sorting genetic algorithm (NSGA II), survey data from real-world experts and finally MCDM by using a deterministic version and a stochastic expansion of the technique for the order of preference by similarity to the ideal solution (TOPSIS). Also, a criteria selection framework for the implementation of MCDM methods has been devised. The outcomes are expected to provide a deeper insight into the wind energy sector for future investments.

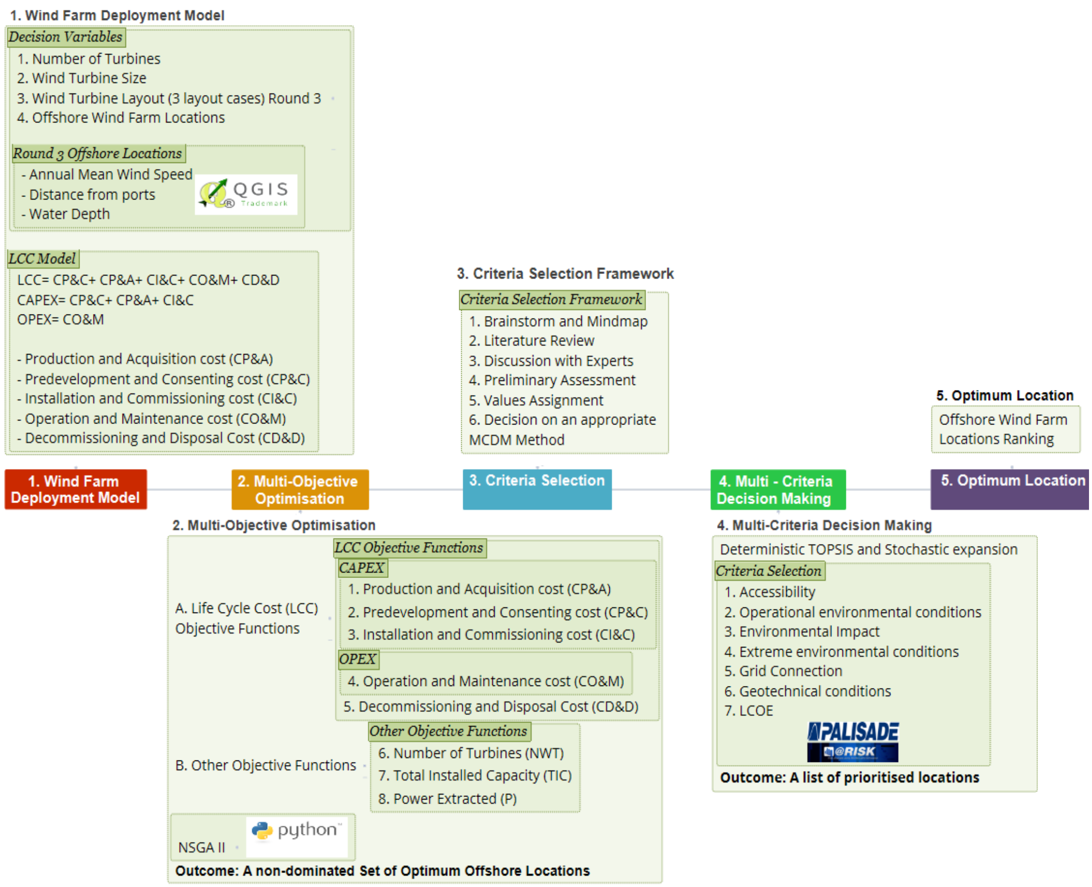

Figure 1. Main framework.

The structure of the remaining sections of this paper starts with a literature review on related studies for LCC analysis, turbine layout optimization, MCDM, and wind farm location selection in the offshore wind energy sector. Next, the development of the proposed framework is documented. The nondominated results for all zones will be analyzed and discussed followed by the prioritization process from TOPSIS. Conclusions and future work are documented at the end of the paper.

2. Literature Review

The Crown Estate has the rights of the seabed leasing up to 12 nautical miles from the UK shore and the right to exploit the seabed for renewable energy production up to 200 miles across its international waters. In recent years, the Crown Estate has run three rounds of wind farm development sites and their extensions. When the Crown Estate released the new Round 3 offshore wind site leases, they provided nine large zones of up to 32 GW power capacity [10]. The new leases encourage larger scale investments and consequently bigger wind turbines and include locations further away from the shore and in deeper waters [2,5,11–13].

Currently, all Round 3 zones have been suggested and published according to reports by the Department for Energy and Climate Change (DECC) and other stakeholders after the outcome of a strategic environmental assessment [14]. It should be noted that new offshore and onshore electricity transmission networks are needed in order to cover Round 3 connections up to 25 GW [14]. The Round 3 zones are the following; Moray Firth, Firth of Forth, Dogger Bank, Hornsea, East Anglia (Norfolk Bank), Rampion (Hastings), Navitus Bay (West Isle of Wight), Atlantic Array (Bristol Channel), and Irish Sea (Celtic Array). Every zone consists of various sites and extensions. Here, the five first zones in the North Sea are investigated in order to demonstrate the proof of the developed framework's applicability. Each location faces similar challenges such as deep waters or long distances from the shore, etc. as shown in Figure 2.

Only a few location-selection-focused studies can be found, and usually, the findings and the formulation of the problems follow a different direction that this present study. For instance [15], uses goal programming in order to obtain the optimum offshore location for a wind farm installation. The study involves Round 3 locations in the UK and discusses its flexibility to combine decision-making. The work integrates the energy production, costs and multicriteria nature of the problem while considering environmental, social, technical and economic aspects.

For instance, the following literature presents cases in renewable energy where optimization has been successfully applied by utilizing different algorithms. An approach that links a multi-objective genetic algorithm to the design of a floating wind turbine was presented in [16]. By varying nine design variables related to the structural characteristics of the support structure, multiple concepts of support structures were modelled and linked to the optimizer. In [17], the authors provide a case study for the optimization of the electricity generation mix in the UK by using hybrid MCDM and linear programming and suggest a methodology to deal with the uncertainty that is introduced in the problem by the bias in experts' opinions and other related factors. In [18], a structural optimization model for the support structures of offshore wind turbines was implemented by using a parametric Finite Element Analysis (FEA) analysis coupled with a genetic algorithm in order to minimize the mass of the structure considering multicriteria constraints.

LCC analysis evaluates costs, enabling suggestions in cost reductions throughout a project's service life. The outcome of the analysis provides pertinent information in investments and can influence decisions from the initial stages of a new project [19]. In [20], a parametric whole life cost framework for an offshore wind farm and a cost breakdown structure was presented and analyzed, where the project is divided into five different stages; the predevelopment and consenting ($C_{P\&C}$), production and acquisition ($C_{P\&A}$), installation and commissioning ($C_{I\&C}$), operation and maintenance ($C_{O\&M}$), and decommissioning and disposal ($C_{D\&D}$) stage. The advantages and disadvantages of the transition to offshore wind and an LCC model of an offshore wind development were proposed in [21]. However, the study mainly focused on a simplified model and especially the operation and maintenance stage of the LCC analysis, and it was suggested that there could be a further full-scale LCC framework in the future. In [22], a detailed failure mode identification throughout the service life of offshore wind turbines was performed and a review of the three most relevant end-of-life scenarios were presented in order to contribute to increase the return on investment and decrease the levelized cost of electricity. However, there are limited studies that integrate a high fidelity of life cycle cost (LCC) analysis into a multi-objective optimization (MOO) algorithm. LCC analysis gains more ground over the years because of the increased uncertainty of wind energy projects throughout their service life, including the cost of finance, the real cost of Operational Expenditure (OPEX) and the potential of service life extension.

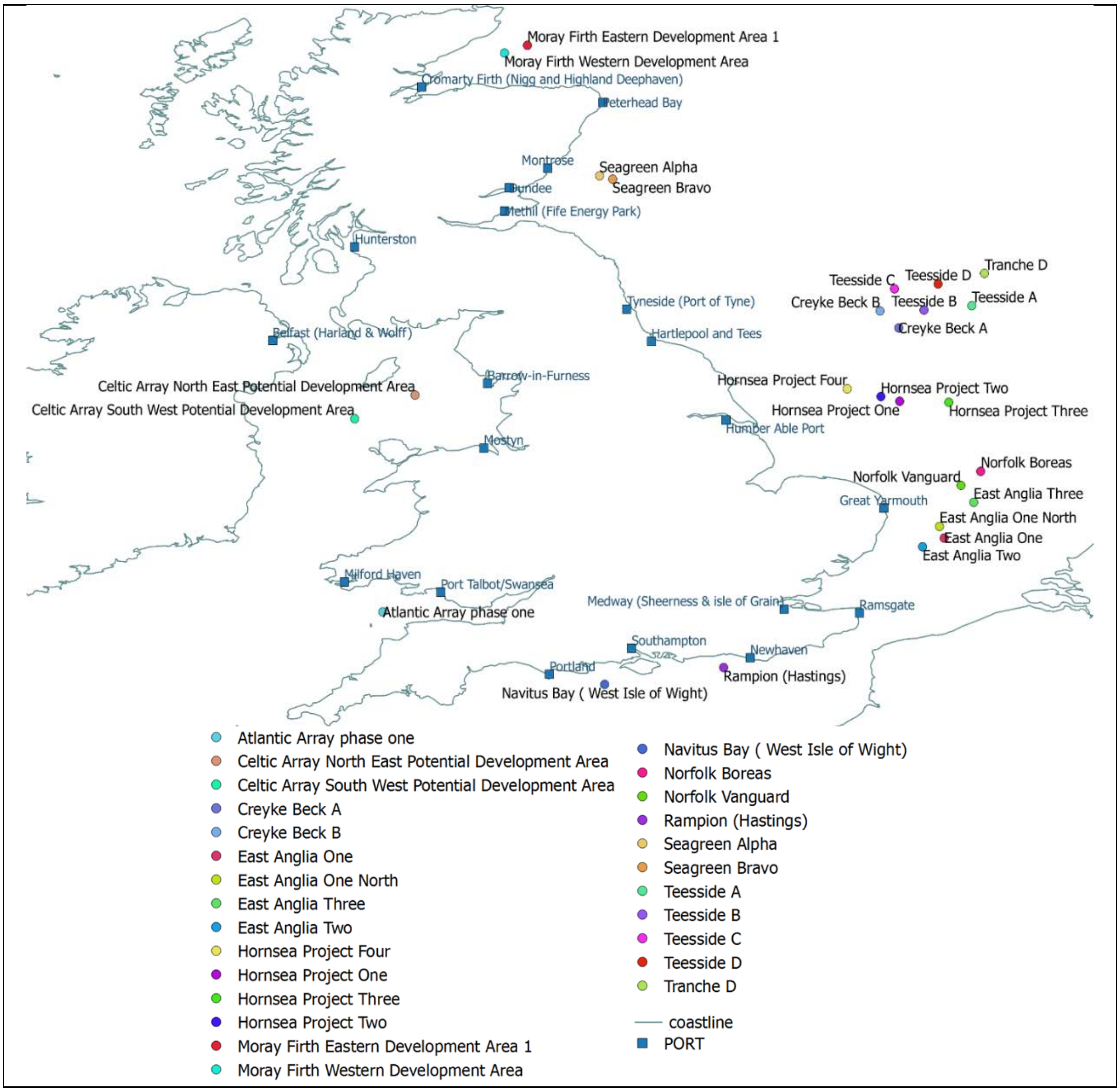

Figure 2. Round 3 offshore locations around the UK by using open source licensed geographic information system QGIS.

MCDM is beneficial for policy-making through evaluation and prioritization of available technological options because of their ability to combine both technical and non-technical alternatives as well as quantitative and qualitative attributes in the decision-making process. A number of MCDM methods are applicable to energy-related projects, however, TOPSIS was selected because of the wide applicability of the method as can be found in literature and the connection of the method to numerous energy-related studies such as [23–25]. It is common to combine stochastic and fuzzy processes in order to deal with uncertain environments. In [23], Lozano-Minguez employed a methodology on the selection of the best support structure among three design options of an offshore wind turbine, considering a set of qualitative and quantitative criteria. A similar study was reported by Kolios in [26], extending TOPSIS to consider stochasticity of inputs.

Methods and techniques to cope with a high number of criteria and high dimensionality of decision-making problems are available in the literature. The multiple criteria hierarchy process (MCHP) [27–29] has been employed in order to deal with multiple criteria in decision-making processes. MCHP is usually employed in combination with outranking MCDM methods. Further applications can be found in [30,31].

In general, classifying criteria as either qualitative or quantitative is related to their nature and fidelity of the analysis. The employed decision-making methods can be based on priority, outranking, distance or combination of the three [32]. In [23], a decision-making study was conducted in three fixed wind turbine support structure types considering both quantitative and qualitative criteria while using TOPSIS. A decision-making study on floating support structures by combining both quantitative and qualitative criteria was presented in [33].

The approach proposed here for the stochastic expansion of deterministic methods was based in [26] that has reported the expansion of different deterministic methods, under the consideration that input variables are modelled as statistical distributions (derived by fitting data collected for each value in the decision matrix and weight vector), as shown in Figure 3. By using Monte Carlo simulations, numerous iterations quantify results and identify the number of cases where the optimum solution will prevail, i.e., there is a P_i probability that option X_i will rank first.

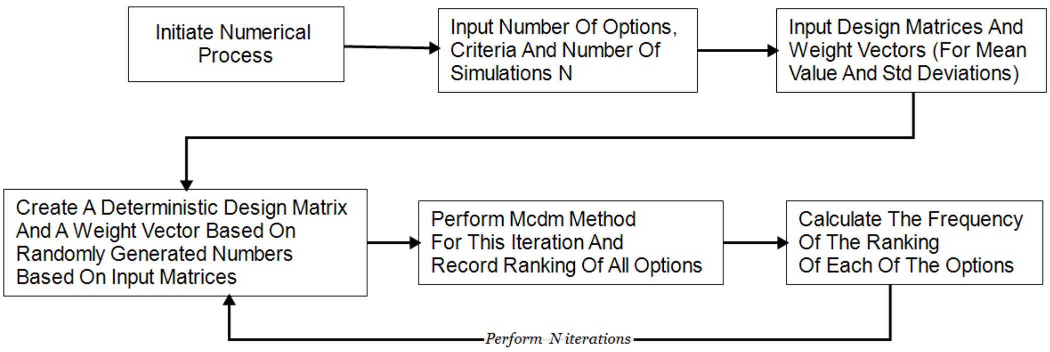

Figure 3. Stochastic expansion algorithm of deterministic Multi-Criteria Decision Making (MCDM) methods.

In [26], during deterministic TOPSIS, the weights for each criterion were considered fixed, but under stochastic modelling, statistical distributions were employed to best fit the acquired data of the experts' opinions. Perera [34] has presented a study that combines MCDM and multi-objective optimization in the designing process of hybrid energy systems (HESs), using the fuzzy TOPSIS extension along with level diagrams. In [35], MCDM under uncertainty is discussed in an application where the alternatives' weights are partially known. An extended and modified stochastic TOPSIS approach was implemented using interval estimations.

In [26], the authors extend the previous MCDM study on the decision-making of an offshore wind turbine support structure among different fixed and floating types. The decision matrix includes stochastic inputs (by using data from experts) in order to minimize the uncertainties in the study. In the same study, an iterative process has been included, and the TOPSIS method was implemented. In [36], a study suggests a methodology for classification and evaluation of 11 available offshore wind turbine support structure types while considering 13 criteria by using TOPSIS as the decision-making method.

In [24], an expansion of MCDM methods to account for stochastic input variables was conducted, where a comparative study was carried out by utilizing widely applied MCDM methods. The method was applied to a reference problem in order to select the best wind turbine support structure type for a given deployment location. Data from industry experts and six MCDM methods were considered, so as to determine the best alternative among available options, assessed against selected criteria in order to provide a level of confidence to each option.

An electricity generation systems allocation optimization model is suggested in [37] for the case of a disaster relief camp in order to minimize the total project cost and maximize the share of systems that were assessed through a decision-making process and were prioritized accordingly. Bi-objective integer linear programming and a decision-making method (VIKOR) were employed and the overall model was applied to a hypothetical map.

A study performed in [38] uses a TOPSIS model by incorporating technical, environmental and social criteria and finally combines the evaluation scores to develop a MOGLP (multi-objective grey linear programming) problem in order to assess the decision-making of power production technologies. The outcome of this work was the optimal mix of electricity generated by each option in the UK energy market. In [39], a methodology for an investment risk evaluation and optimization is suggested in order to mitigate the risks and achieve sustainability for wind energy projects in China. In this study, Monte Carlo analysis and a multi-objective programming model are used so as to increase the confidence in the planning of investment research and the sustainability of renewables in China.

In this study, NSGA II is employed because it is suitable for MOO problems with many objectives and was further analyzed in previous studies in offshore wind energy applications in [40], where a methodology was proposed to support the decision-making process at these first stages of a wind farm investment considering available Round 3 zones in the UK. Three state-of-the-art algorithms were applied and compared to a real-world case of the wind energy sector. Optimum locations were suggested for a wind farm by considering only round 3 zones around the UK. The problem comprised of techno-economic Life Cycle Cost related factors, which were modelled by using the physical aspects of each wind farm location (i.e., the wind speed, distance from the ports and water depth), the wind turbine size and the number of turbines.

3. Framework

3.1. Wind Farm Deployment Model

The wind farm deployment model implemented in this study couples the LCC analysis with a geospatial analysis as described below. The LCC analysis of a project involves all project stages described in Figure 4. In [20,41], a whole LCC formulation is provided, and this study integrates these phases into the MOO problem. Assumptions and related data in the modelling of the problem were gathered from the following references [20,41–46] based on which the present model was developed. The LCC model described in [20] is used as a guideline in this study, and along with the site characteristics and the problem's formulation, the optimization problem is formed. The type of foundation that was considered in the LCC model is the jacket structure as it constitutes a configuration that can be utilized in a range of water depths allowing for the optimization process to be automated.

The total LCC is calculated as follows:

$$LCC = C_{P\&C} + C_{P\&A} + C_{I\&C} + C_{O\&M} + C_{D\&D} \quad (1)$$

where

LCC: Life Cycle Cost
$C_{I\&C}$: Installation and Commissioning cost
$C_{P\&C}$: Predevelopment and Consenting cost
$C_{O\&M}$: Operation and Maintenance cost

$C_{P\&A}$: Production and Acquisition cost
$C_{D\&D}$: Decommissioning and Disposal Cost

$$CAPEX = C_{P\&C} + C_{P\&A} + C_{I\&C} \tag{2}$$

$$OPEX = C_{O\&M} \tag{3}$$

CAPEX: Capital expenditure
OPEX: Operational expenditure

The power extracted is calculated for each site and each wind turbine respectively as:

$$P = \frac{1}{2} A C p \rho u^3 \tag{4}$$

where
A : Turbine rotor area
ρ: Air density
C_p: Power coefficient
u : Mean annual wind speed of each specific site

The total installed capacity (TIC) of the wind farm dependents on the number of turbines and the rated power of each of them, and is calculated for every solution:

$$TIC = P_R \times NWT \tag{5}$$

where
P_R: Rated power
NWT: Number of turbines

For each offshore location, a special profile was created including the coordinates, distance from designated construction ports, annual wind speed and average site water depth, as listed in Table 1, where data was acquired from [45]. Among various data, Table 1 shows the locations that each of these zones contains.

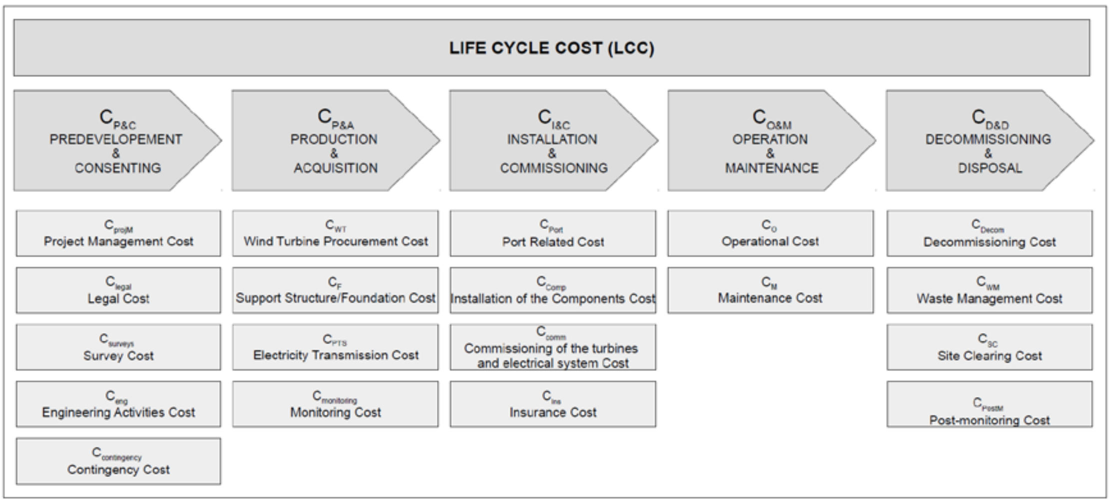

Figure 4. Life cycle cost (LCC) breakdown [20].

Table 1. Round 3 zones and sites, and specific data acquired from [45].

Site Index	Zone	Wind Farm Site Name	Centre Latitude	Centre Longitude	Port	Distance from the Port (km)	Annual Wind Speed (m/s) (at 100 m)	Average Water Depth (m)
0	Moray Firth	Moray Firth Western Development Area	58.097	−3.007	Port of Cromarty	123.691	8.82	44
1	Moray Firth	Moray Firth Eastern Development Area 1	58.188	−2.720	Port of Cromarty	157.134	9.43	44.5
2	Firth of Forth	Seagreen Alpha	56.611	−1.821	Montrose	72.598	9.92	50
3	Firth of Forth	Seagreen Bravo	56.572	−1.658	Montrose	91.193	10.09	50
4	Dogger Bank	Creyke Beck A	54.769	1.908	Hartlepool and Tess	343.275	10.01	21.5
5	Dogger Bank	Creyke Beck B	54.977	1.679	Hartlepool and Tess	319.949	10.04	26.5
6	Dogger Bank	Teesside A	55.039	2.822	Hartlepool and Tess	447.124	10.05	25.5
7	Dogger Bank	Teesside B	54.989	2.228	Hartlepool and Tess	380.788	10.04	25.5
8	Hornsea	Hornsea Project One	53.883	1.921	Grimsby	242.328	9.69	30.5
9	Hornsea	Hornsea Project Two	53.940	1.687	Grimsby	217.270	9.73	31.5
10	Hornsea	Hornsea Project Three	53.873	2.537	Grimsby	310.521	9.74	49.5
11	Hornsea	Hornsea Project Four	54.038	1.271	Grimsby	173.928	9.71	44.5
12	East Anglia (Norfolk Bank)	East Anglia One	52.234	2.478	Great Yarmouth	92.729	9.5	35.5
13	East Anglia (Norfolk Bank)	East Anglia One North	52.374	2.421	Great Yarmouth	81.104	9.73	45.5
14	East Anglia (Norfolk Bank)	East Anglia Two	52.128	2.209	Great Yarmouth	74.559	9.46	50
15	East Anglia (Norfolk Bank)	East Anglia Three	52.664	2.846	Great Yarmouth	124.969	9.56	36
16	East Anglia (Norfolk Bank)	Norfolk Boreas	53.040	2.934	Great Yarmouth	143.464	9.53	31.5
17	East Anglia (Norfolk Bank)	Norfolk Vanguard	52.868	2.688	Great Yarmouth	111.449	9.56	32

For the distances from the ports calculation an open source licensed geographic information system (GIS) called QGIS was used, which is a part of the Open Source Geospatial Foundation (OSGeo) [47]. A list of ports was acquired from [48–50]. The QGIS maps of the offshore sites were acquired from the official Crown Estate website [51] for QGIS and AutoCAD. The list contains designated, appropriate and sufficient construction ports that are suitable for the installation, manufacturing and maintenance for wind farms. New ports are to be built specifically to accommodate needs of the offshore wind industry; however, this study takes into account a selection of currently available ports around the UK. The distances were calculated assuming that the nearest port to the individual wind farm is connected in a straight line. QGIS was also employed to measure and model aspects of the LCC related to the geography and operations. The estimated metrics were integrated into the configuration settings of the whole LCC.

Three layout configurations are considered. The lower and upper limits of a theoretical array layout from [52] will be employed along with an extreme case. More specifically, in the lower limit case (layout 1), the horizontal and vertical distance between turbines is 3 and 5 times the rotor diameter, respectively. The turbine specifications used for the LCC model are listed in Table 2. In the upper limit case (layout 2), 5 and 9 times the rotor diameter were considered horizontally and vertically. In the extreme case (layout 3), the horizontal and vertical distance between turbines is 10 and 18 times the rotor diameter. All different configurations are illustrated in Figure 5. The present work focuses on the optimization of offshore wind farm locations considering the maximum wind turbine number that can fit in the selected Round 3 locations according to three different layout configuration placements. The wind farm is oriented according to the most optimal wind direction. Different layouts provide a different maximum wind turbine number that can guide the optimization process to more detailed calculations. The maximum number of wind turbines is determined by considering types of reference turbines of 6, 7, 8 and 10 MW and by following three layout cases, as listed below in Figure 5, where D is the diameter of each turbine.

Table 2. Turbine specifications.

Turbine Type Index	Rated Power (MW)	Rotor Diameter (m)	Hub Height (m)	Total Weight (t)
0	10	190	125	1580
1	8	164	123	965
2	7	154	120	955
3	6	140	100	656

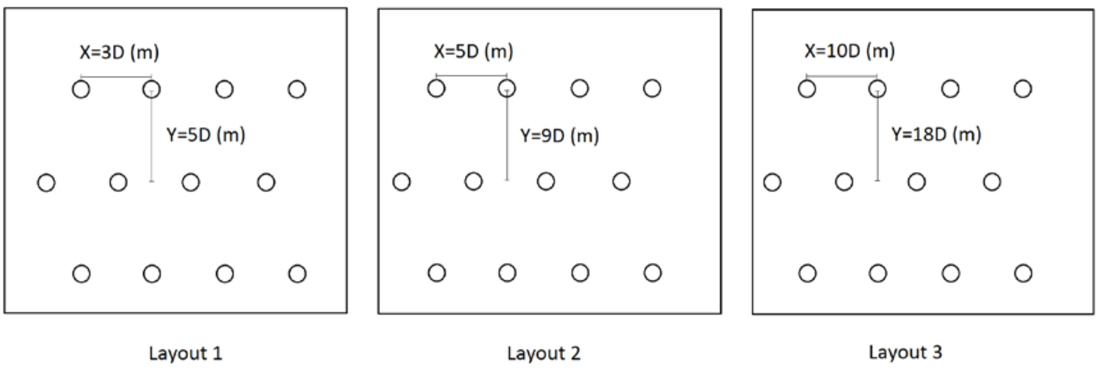

Figure 5. Demonstrating different layouts, where D corresponds to the diameter of the turbine.

For the estimation of cabling length, which is required to calculate parts of the LCC related to the spatial distribution of the wind turbines in the wind farm, the minimum spanning tree algorithm is used. The location of the turbines is treated as a vertex of a graph, and the cabling represents the edge that connects the vertices. Given a set of vertices, which are separated by each other by the different layout indices, from Figure 5, the minimum spanning tree connects all these vertices without creating any cycles, thus yielding minimum possible total edge length. This represents the minimum cabling length of the particular layout.

The way the length of the cables was calculated provides an approximation of the actual length. In the presence of relevant actual data, the calculations of both the layouts and the LCC would provide more realistic values. For instance, the cable length would be expected to be larger because of the water depth and the burial of the cables for each turbine. For each cable, both ends will have to come from the seabed to the platform, so at least twice the water depth should be added to each cable and finally allow for some contingency length for installation.

The wind rose diagrams provided the prevailing wind direction, which sets the layout orientation. The wind speeds, the wind rose graphs, and the coordinates of each location were obtained by FUGRO (Leidschendam, The Netherlands) and 4COffshore (Lowestoft Suffolk, UK) [45,53]. All wind farm sites were discovered to have dominant southwestern winds followed by western winds. For that reason, the orientation of the layouts is assumed to be southwestern (as the winds are assumed to blow predominantly from that direction). The wind rose graphs for each offshore site are determined by data acquired from [53] and the grid points they created around the UK. The nearest grid point to the offshore site is used.

An important factor to be considered is also the atmospheric stability. Although the different layouts considered in this study may be affected by the atmospheric stability states, as it impacts the layout's wake recovery pattern, it was not considered in the framework. Also, the power curves and their multiplicity in turbine type were not considered in this study because the aim is to devise and demonstrate a generic and transferable methodology. It is suggested that both elements could be further investigated in future studies to evaluate their effect in the derivation of the optimum solution.

In Figure 6, the example of Moray Firth zone (which includes Moray Firth Western Development Area and Moray Firth Eastern Development Area 1) shows the positioning of the turbines depending on the layout 1, 2 and 3 and the turbine size.

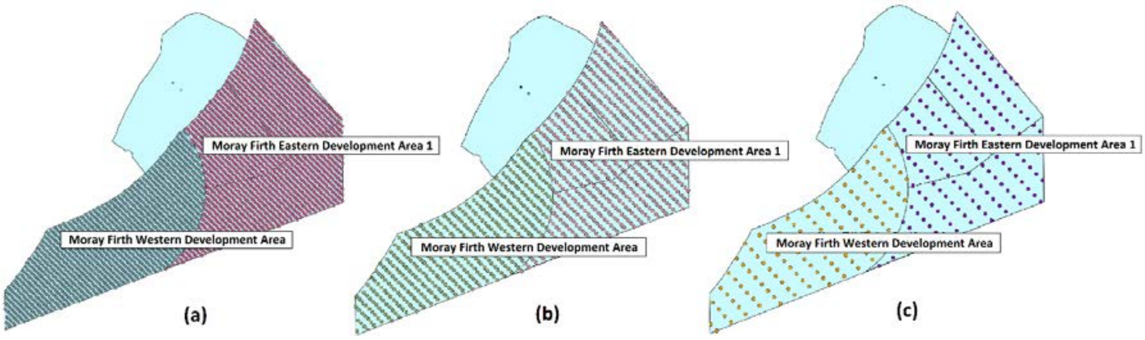

Figure 6. Moray Firth zone. A maximum number of wind turbines placed according to layout 1, layout 2 and layout 3 for the case of 10 MW turbine. In (**a**) Moray Firth, 10 MW turbines positioned in layout 1; (**b**) Moray Firth, 10 MW turbines positioned in layout 2; (**c**) Moray Firth, 10 MW turbines positioned in layout 3.

3.2. Multi-Objective Optimization

The optimization problem includes eight objectives; five LCC-related objectives, based on [20], which are the cost-related objectives to be minimized. The three additional objectives are the number of turbines (NWT), the power that is extracted (P) from each offshore site and the total installed capacity (TIC), which are to be minimized, maximized, and maximized, respectively.

More specifically, the LCC includes the predevelopment and consenting, production and acquisition, installation and commissioning, operation and maintenance and finally decommissioning and disposal costs. The power extracted is calculated by the specific mean annual wind speed of each location along with the characteristics of each wind turbine both of which are considered inputs.

The optimization problem formulates as follows:

$$\text{Minimize} \quad C_{P\&C}, C_{P\&A}, C_{I\&C}, C_{O\&M}, C_{D\&D}, \text{NWT}, (-\text{P}), (-\text{TIC}) \tag{6}$$

Subject to $0 \leq$ site index ≤ 20,
$0 \leq$ turbine type index ≤ 3
$1 \leq$ layout index ≤ 3
$50 \leq$ Number of turbines $\leq$ maximum number per site
TIC $\leq$ Maximum capacity of Round 3 sites based on the Crown Estate

Although the maximum number of turbines has been estimated by using QGIS, the maximum capacity allowed per region was also considered, as specified by the Crown Estate, as listed in Table 3. These were selected because of the possibility that the constraints might overlap in an extreme case scenario. Therefore, both constraints were added to the problem in order to secure all cases.

Table 3. Maximum capacity of Round 3 wind farms, specified by the Crown Estate [1].

Zone	Capacity (MW)
1. Moray Firth	1500
2. Firth of Forth	3465
3. Dogger Bank	9000
4. Hornsea	4000
5. East Anglia	7200
6. Rampion	665
7. Navitus Bay	1200
8. Bristol Channel	1500
9. Celtic Array	4185
TOTAL CAPACITY	32,715

The optimization part of the framework has been implemented in Python 3, employing library 'platypus' in Python [54].

3.3. Criteria Selection Process

For the MCDA, the criteria selection process follows the process illustrated in Figure 7:

1. The first step is to create a mind map of the problem and the different aspects involved. Then, via brainstorming, criteria that can potentially impact on the alternatives of the problem are listed.
2. The second step is to perform an extensive literature review on the topic. It is vital that the literature review is conducted in order to discover related studies and also confirm or reject ideas that were found in the first step. During this process, it is possible to discover gaps that will help to define the study more precisely and also discover criteria that were never considered before.
3. Step three is about discussing ideas with subject matter experts and communicating to them the aims and ideas of the project in order to obtain useful insights into the initial stages of the criteria selection. Their expertise can confirm, discard or suggest new criteria according to their opinion. Experts can also provide helpful data and confirm the value of the study.
4. In step four, the strengths and weaknesses of the work and criteria should be identified, followed by a preliminary assessment. The selected criteria should be clear and precise, and no overlaps should be present (avoiding similar terms or definitions that can potentially include other criteria). Each criterion should characterize and affect the alternatives in a different and unique way. None of the criteria should conflict with each other. The criteria should now have a detailed description. Their description and explanation should be unique to avoid confusion especially if the criteria are sent to experts in the form of a survey.

5. Step five describes how to proceed with the study. Assigning values to the criteria can be done either by calculating the values directly or by extracting them from the experts via a questionnaire. In the latter case, additional data or opinions could be considered. Via a survey, experts could either assign values or rate the criteria according to their knowledge and experience. Here, it is important to note that for a different set of criteria, different approaches can be followed. For example, in the case of criteria that need numerical values (and probably require calculations) that no expert can provide on the spot, receiving replies is challenging. The experts should provide their expertise in an easy and fast process. The definition of the criteria has to be very clear before scoring, normally at a scale of 1 to 5 or otherwise. The calculations could lead to assigned values for every criterion, but the experts could provide further insight regarding the importance of those criteria and how much they affect the alternatives. In this case, the experts provide the weights of the criteria, which is very useful in order to achieve higher credibility of the problem. In some cases, it would be very useful to include validation questions in the survey. It would also be useful to include questions in order to increase the validity of the problem, for example, to ask for further criteria that were not considered in the study. Another example would be to include a question about the perceived expertise of the experts that will answer the questionnaire. Hence, their answers will be weighted and further credible.
6. Step six is related to selecting a method for decision-making. In general, it is important to decide quite early which method of the multicriteria analysis will be used. This is important because different methods require different criteria and problem set up. In the case of hierarchy problems and pairwise comparisons, the problem has to be set up differently, and the values need to be set for every pair comparison. The important question here is how the outcomes are derived. Having a picture of the total process and aims, objectives and results early enough can help to speed up the process.

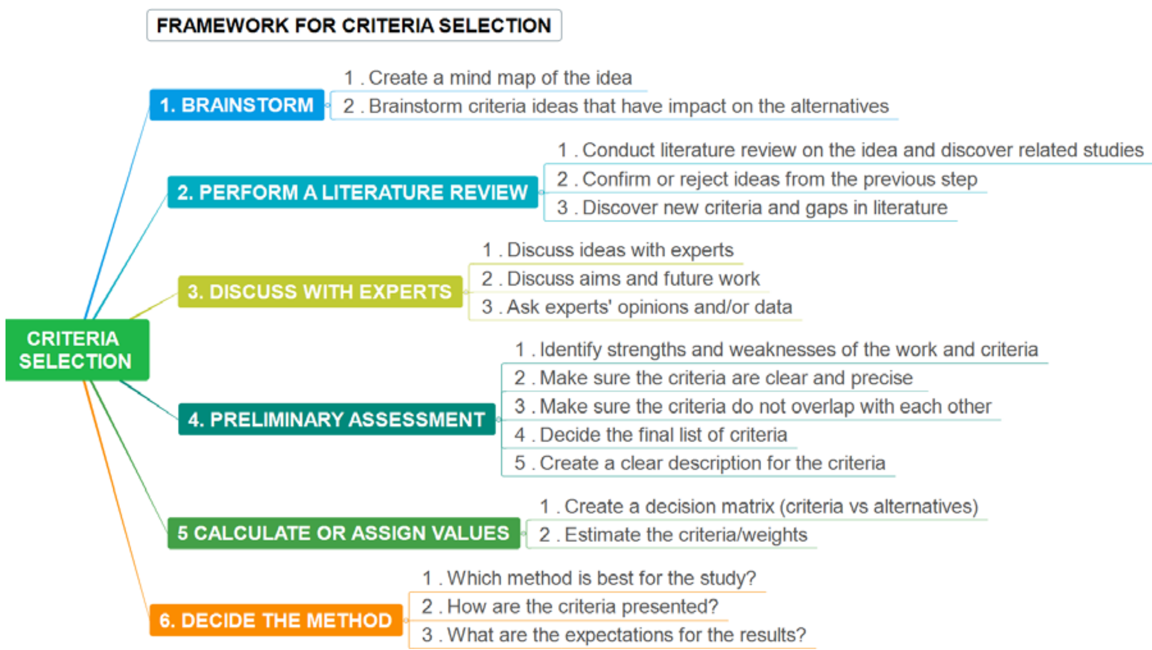

Figure 7. Criteria selection framework.

3.4. Multicriteria Decision Making

Following the process of MOO and criteria selection, two versions of the MCDM method were implemented (i.e., deterministic and stochastic TOPSIS) and were linked to the results of the previous outcomes, as shown in Figure 1. A set of qualitative and quantitative criteria is combined in order to investigate the diversity and outcomes obtained from different sets of inputs in the decision-making process. Stochastic inputs are selected and imported in TOPSIS. All data were collected from industry experts, so as to prioritize the alternatives and assess them against seven selected conflicting criteria. The outcome of the method is expected to assist stakeholders and decision makers to support decisions and deal with uncertainty, where many criteria are involved.

TOPSIS is depicted in Figure 8, initially proposed by Hwang et al. [55], and the idea behind it lies in the optimal alternative being as close in the distance as possible from an ideal solution and at the same time as far away as possible from a corresponding negative ideal solution. Both solutions are hypothetical and are derived from the method. The concept of closeness was later established and led to the actual growth of the TOPSIS theory [56,57].

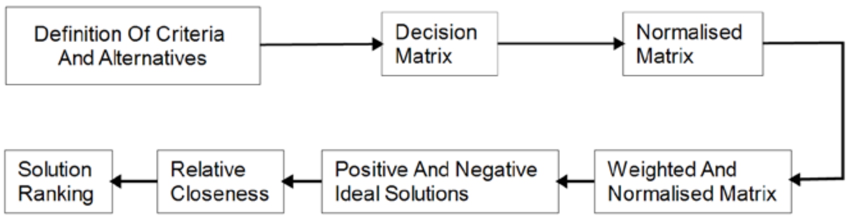

Figure 8. TOPSIS methodology.

After defining n criteria and m alternatives, the normalized decision matrix is established. The normalized value r_{ij} is calculated from the equations below, where f_{ij} is the i-th criterion value for alternative A_j ($j = 1, \ldots, m$ and $i = 1, \ldots, n$).

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{m} f_{ij}^2}} \tag{7}$$

The normalized weighted values v_{ij} in the decision matrix are calculated as follows:

$$v_{ij} = w_i r_{ij} \tag{8}$$

The positive ideal A^+ and negative ideal solution A^- are derived as shown below, where I' and I'' are related to the benefit and cost criteria (positive and negative variables).

$$A^+ = \{v_1^+, \ldots, v_n^+\} = \{(MAX_j v_{ij} | i \in I'), (MIN_j v_{ij} | i \in I'')\} \tag{9}$$

$$A^- = \{v_1^-, \ldots, v_n^-\} = \{(MIN_j v_{ij} | i \in I'), (MAX_j v_{ij} | i \in I'')\} \tag{10}$$

From the n-dimensional Euclidean distance, D_j^+ is calculated below as the separation of every alternative from the ideal solution. The separation from the negative ideal solution follows:

$$D_j^+ = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^+)^2} \tag{11}$$

$$D_j^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^-)^2} \tag{12}$$

The relative closeness to the ideal solution of each alternative is calculated from:

$$C_j = \frac{D_j^-}{\left(D_j^+ + D_j^-\right)} \tag{13}$$

After sorting the C_j values, the maximum value corresponds to the best solution to the problem.

A survey that considers all seven criteria was created and disseminated to industry experts, so as to obtain the weights for the following MCDM study. In this case, experts provided their opinions based on the importance of each criterion in the wind farm location selection process. In total, 13 experts (i.e., academics, industrial experts and university partners) with relative expertise responded and rated the criteria according to their importance. The total number of 13 experts is considered sufficient for this work because the overall number of offshore wind experts is very limited and their engagement is challenging. The input data from the 13 experts were acquired through an online survey platform where the perceived level of expertise was also provided. The assessments varied between 2 and 5 (with 1 being a non-expert and 5 being an expert) with a mean value of 3.8 and a standard deviation of 0.89.

The implementation of the stochastic version of TOPSIS was modelled through Palisade's software @Risk 7.5. Specifically, for the stochastic implementation, the Monte Carlo simulations of @Risk were combined with the survey data, providing the best distribution fit for each value to be used as inputs in the decision matrix of TOPSIS. By separately conducting a sensitivity analysis among 100, 1000, 10,000 and 100,000 iterations, 10,000 iterations for a simulation were found to deliver satisfactory results on acceptable computational effort requirements. Next, the stochastic approach is compared to the deterministic one and finally, the outcomes are presented in the next section.

All criteria and the final decision-making matrices were scaled and normalized, respectively in different phases of the process, while the seven criteria used in this study include both qualitative and quantitative inputs. Combining these two types can help decision makers to define their problems in a more reliable method. Next, both deterministic and stochastic approaches will be conducted and compared. The criteria are listed in Table 4.

Table 4. List of criteria.

Criteria	ID
1. Accessibility	C1
2. Operational environmental conditions	C2
3. Environmental Impact	C3
4. Extreme environmental conditions	C4
5. Grid Connection	C5
6. Geotechnical conditions	C6
7. LCOE	C7

The criteria were selected based on literature and a brainstorming session with academic and industrial experts. In the session, common criteria were consolidated in order to avoid double counting and finally concluded to the ones used in the study. The criteria were selected such as to have both a manageable number and to cover all aspects but at the same time not make the data collection questionnaire too onerous.

More specifically, the criteria are defined and analyzed below:

1. Accessibility: This criterion considers the accessibility of each wind farm by considering the distance from the ports and the number of nearby wind farms. The distances were acquired from the 4COffshore database [58]. The number of nearby wind farms was acquired from the interactive map of 4COffshore [45]. In order to select the number of nearby farms, only the farms that already produce energy and are located between the ports and the wind farm in question were considered. The nearby wind farms and the distance from the ports were assessed from 1 to 9 (1 being not close to any wind farms and 9 being close to many wind farms) and 9 to 1 (9 being very close to the ports and 1 being extremely far from the shore) respectively for each offshore site. The weighted values (equally weighted by 50–50) then were summed. This criterion is qualitative, and it varies from 1 to 9 (1 being not at all accessible to 9 extremely accessible).

This criterion is also considered positive in the MCDM process. Both in the deterministic and stochastic processes, the values used are the same.

2. Operational environmental conditions: This criterion considers the aerodynamic loads in the deployment location. More specifically, the wind speed (m/s) in specific points (close to each offshore sites) according to [53]. The criterion is quantitative and also positive. In the stochastic and deterministic approach, the fitted wind distributions and the mean values were used, respectively.
3. Environmental impact: This criterion considers the structures' greenhouse gas emissions during the construction and installation phase. The amount of CO_2 equivalent (CO_2e) emissions per kg of steel was estimated relative to the water depth (maximum and minimum water depth were measured in each location) and the distance from the ports. The support structure was assumed to be the jacket structure. This criterion was calculated according to an empirical formula in [23], and the water depth and distance from the ports were both considered in these calculations. Finally, an index of the square of CO_2 equivalent (CO_2e^2) was considered from the two cases as a value for each offshore site. This criterion is negative. The criterion is also quantitative, and for the stochastic approach, a triangle distribution was considered. In the deterministic approach, the mean value was used.
4. Extreme environmental conditions: This criterion considers the durability of the structure due to extreme aerodynamic environmental loads. Data were extracted from [53]. The wind distributions that represent the probabilities above the cut off wind speed (i.e., approximately 25 m/s) were considered. This criterion is quantitative and negative. For the stochastic approach, a triangle distribution was considered. In the deterministic approach, the mean values were used.
5. Grid connection: This criterion considers the possible grid connection options of a new offshore wind farm (connection costs to existing or new grid points). The inputs of this criterion consider the cost (£million) of connecting to nearby substations where other Rounds already operate, extending existing ones or building new ones. In the national grid report that was created for the Crown Estate in [14], the costs were calculated by considering more than one cases per Round 3 location. In this study, the maximum and the minimum costs were considered, and a uniform distribution was used as a stochastic input. In the deterministic approach, the mean value is used. The criterion is quantitative and represented by the above cost values, and it is considered negative.
6. Geotechnical conditions: This criterion represents the compatibility of the soil of each of the offshore locations for a jacket structure installation. Experts provided their input and rated the offshore locations according to their soil suitability from 1 to 9 (1 being very unsuitable to 9 being extremely suitable). This criterion is qualitative and positive. For the stochastic approach, a pert distribution was considered. In the deterministic approach, the mean value was used.
7. Levelized cost of electricity (LCoE): This criterion considers an estimation of the LCoE for each offshore location (2015 £/MWh). The values were calculated according to the DECC simple levelized cost of energy model in [59]. The calculations assumed an 8 MW size turbine. Jacket structure and a range of water depths (maximum and minimum water depth measured in each site) per offshore site. The criterion is quantitative and negative. In the stochastic approach, the triangle distribution was used and in the deterministic, the mean value.

This study considered the criteria that have greater impact than others in the final decision-making process by assigning weights derived from the insights of experts.

It should be noted that some aspects were excluded for this analysis as they do not appear to affect the location selection process or they already included in the existing selected criteria and other steps of the framework. Fisheries and aquaculture is a criterion that considers the positive effects of the aquaculture and the fisheries around the wind farms. The criterion could be assessed according to similar fisheries and aquacultures that seem to benefit from nearby wind farms. This information is hard to obtain systematically or does not meet the unique characteristics of the wind farm locations. Regarding the environmental extensions, such as birds and fish, these were not considered in the environmental impact criterion. The Department for Energy and Climate Change conducted a strategic environmental assessment on the offshore sites for over 60m of water depth around the UK and the Crown Estate identified possible suitable areas for offshore wind farm deployments aligned with government policy and released the 3 Rounds [11,13]. Further, service life extension will not be considered because of the nature of the problem. In order to consider life extension, a sample of individual turbines is monitored, tested and investigated. There is no evidence whether there is a link of life extension possibility to the offshore location. Finally, marine growth or artificial reefs will not be included in the study because it does not reveal the uniqueness of the offshore sites. Marine growth exists in all offshore structures.

4. Results and Discussion

The data obtained from the experts were analysed and used in MCDM both deterministically and stochastically. The results from all locations (from all five zones) are provided and illustrated in Figure 9 as cost breakdown analysis. All 7 solutions shown and discussed were obtained from the execution of the NSGA II, and they are equally optimal solutions, according to the Pareto equality. The problem considered all 18 sites from the five selected Round 3 zones and the optimum results minimize CAPEX, OPEX and $C_{D\&D}$, as shown in Figure 9. At the same time, the remaining objectives are also optimized. All layouts were found to deliver optimal solutions, where layout 3 was found only once with few turbines.

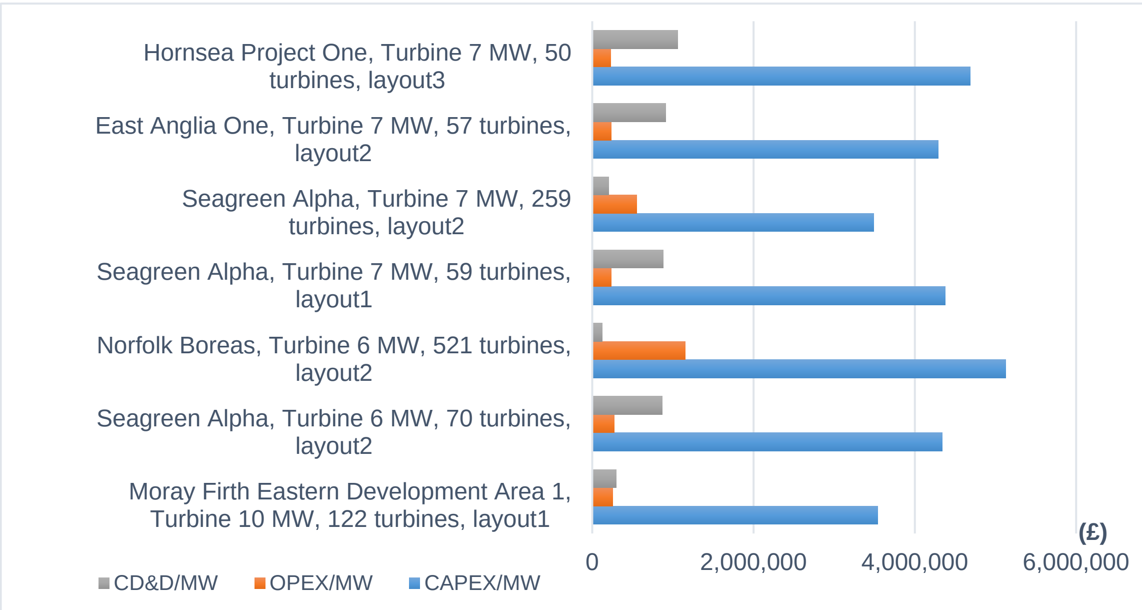

Figure 9. Cost breakdown per MW For all Pareto Front solutions for layout cases 1, 2 and 3.

All optimal solutions are listed in Table 5. The solution that includes Hornsea Project One and layout 3 delivered the lowest costs of the optimal solutions. Although that was expected as it was found that only 50 turbines were selected by the optimizer, the same solution is the second most expensive per MW as shown in Figure 9. Moray Firth Eastern Development Area 1 could deliver the lowest cost per MW. The three solutions of the Seagreen Alpha included both layouts 1 and 2. The fact that Seagreen Alpha was selected three times shows the flexibility of multiple options for a suitable budget assignment that the framework can deliver to the developers. The $C_{D\&D}$ presents low fluctuations for all solutions. In the range between £2 and £2.3 billion of the total cost, four solutions were discovered, for the areas of Seagreen Alpha (twice), East Anglia One and Hornsea Project One. Figure 10 illustrates the % frequency of the occurrences of the optimal solutions. Five locations were selected from the 18 in total. Seagreen Alpha was selected three times more than the rest of the optimum solutions.

Table 5. Numerical results for all zones.

Offshore Wind Farm Site	Layout Selected	Turbine Size (MW)	NWT	OPEX (£)	CD&D [£]	CAPEX [£]	Total Cost [£]
Moray Firth Eastern Development Area 1	layout 1	10	122	307,322,672	365,371,991	4,316,454,016	4,989,148,680
Seagreen Alpha	layout 2	6	70	115,563,086	365,329,300	1,821,862,415	2,302,754,802
Norfolk Boreas	layout 2	6	521	3,612,087,515	383,807,107	16,034,493,829	20,030,388,452
Seagreen Alpha	layout 1	7	59	97,590,070	363,801,519	1,806,818,815	2,268,210,405
Seagreen Alpha	layout 2	7	259	996,944,713	373,550,029	6,323,114,490	7,693,609,234
East Anglia One	layout 2	7	57	93,654,614	364,474,208	1,712,388,330	2,170,517,154
Hornsea Project One	layout 3	7	50	81,096,384	371,523,572	1,640,942,787	2,093,562,744

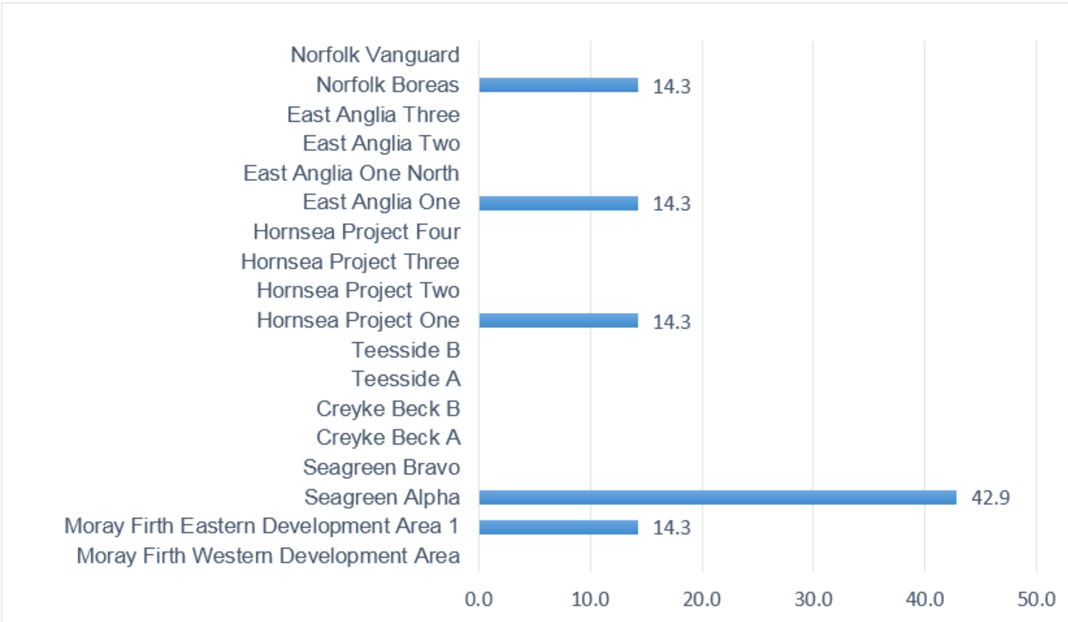

Figure 10. Percent of frequency of occurrences of optimal locations. Five sites were revealed by the optimizer.

The output of MOO is used as an input to the MCDM process. The output of TOPSIS is a prioritization of the alternatives (i.e., the five offshore sites). Two variations of TOPSIS (i.e., deterministic and stochastic) are employed. By combining those two methods, MOO and MCDM, the best location is identified, and the decision maker's confidence increases. These five locations were selected to take part in the MCDM process in order to be further discussed and to obtain a ranking of the locations using the stochastic expansion of TOPSIS. Following the process of TOPSIS, the considered alternatives are listed in Table 6, which are all considered to be unoccupied and available for a new wind farm installation for the purposes of the problem.

Table 7 shows the final decision matrix with the mean values for every alternative versus criterion. The criteria and alternatives' IDs were used for clarity and simplification. All qualitative inputs were scaled from 1 to 9, as mentioned before. Table 8 shows the frequency of the experts' preference per criterion and the normalized mean values of the weights extracted from them.

Table 6. List of alternatives.

Alternatives/Zones	Wind Farm Site Name	ID
Moray Firth	Moray Firth Eastern Development Area 1	A1
Firth of Forth	Seagreen Alpha	A2
Hornsea	Hornsea Project One	A3
East Anglia (Norfolk Bank)	East Anglia One	A4
East Anglia (Norfolk Bank)	Norfolk Boreas	A5

Table 7. Decision matrix.

Alternatives/Criteria	C1	C2	C3	C4	C5	C6	C7
A1	4.5	11.5	61,979,649,702	25.8	226	5.6	118.7
A2	4.5	10.4	31,984,700,386	25.8	157.5	6.4	129.2
A3	7	10.0	65,153,119,337	26.0	5939	6.4	114.2
A4	6	9.8	29,122,509,239	25.8	1859	6.7	114.5
A5	4.5	10.0	39,619,870,326	25.8	1859	6.7	114.2

Table 8. Frequency of experts' preference per criterion.

Rate (1–5)	Criteria						
	C1	C2	C3	C4	C5	C6	C7
1 Not at all important	0	0	0	0	0	0	0
2. Slightly important	1	1	5	1	1	0	1
3. Moderately important	5	1	3	6	2	5	1
4. Very important	4	7	2	2	6	7	4
5. Extremely important	3	4	3	4	4	1	7
Normalized mean weights	0.138	0.153	0.121	0.138	0.150	0.138	0.161

Specifically for the calculation of C6 against alternatives in Table 7, input from three experts was considered. Although the number of experts replying to the seven criteria was mentioned before (i.e., 13), a different number of experts (i.e., 3) was involved in the estimation of the geotechnical condition criterion in order to form the distribution from their answers. The reason that the number of experts was not the same in the two procedures is that different expertise was required in both cases. The geotechnical conditions can be better perceived by geotechnical engineers, and the total number of experts is very specific and more difficult to engage with. Based on experts' answers, the normalized mean weights of the criteria are estimated by the frequency of experts' preferences per criterion in Table 8.

The results of both variations of TOPSIS are listed in Table 9. By implementation, the stochastic variation reveals more quantitative information about the alternatives and assigns the probability that an option will rank first, as shown in Figure 11. According to stochastic TOPSIS, the alternative that involves Seagreen Alpha was the most probable solution, followed by Moray Firth Eastern Development Area 1. Also, the former is three times more probable to be selected compared to the latter. The probability of other options to be selected is significantly lower, and Hornsea Project One is unlikely to be selected.

Table 9. Results of deterministic and stochastic Technique for the Order of Preference by Similarity to the Ideal Solution (TOPSIS).

Alternatives	Deterministic TOPSIS		Stochastic TOPSIS	
	Score	Rank	Score	Rank
A1	0.733	2	21.88%	2
A2	0.816	1	64.44%	1
A3	0.181	5	0.00%	5
A4	0.712	3	10.22%	3
A5	0.660	4	3.50%	4

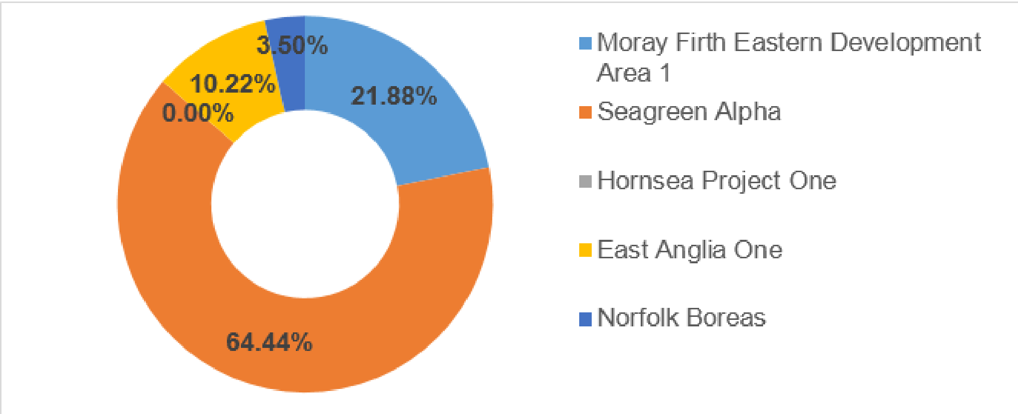

Figure 11. Probability chart of the stochastic TOPSIS.

In the survey, the experts were asked to make recommendations or leave comments about the criteria in order to include their insight in future studies or the limitations section. As expected, most experts made some recommendations that are worth considering in the next steps. Some experts responded according to their understanding of the work that is carried out and the work that was done before this study. Some of them pointed out factors that were already included in the study in the modelling of the work or already included in the criteria given to them, for example, the grid availability and the power prices.

The importance of the operational environmental conditions was pointed out and how critical they think it is as it drives the wind farm's maximum output and capacity factor. It was also stated that the wind speed should be taken into account separately in the study. The geotechnical conditions and the soil's impact on the design (both substructure and transmission system) were also pointed out. One expert made clear this should not be overlooked. The geotechnical conditions were studied separately and finally incorporated into this study as explained above.

At the end of the survey, the experts were asked to include any other criteria that can affect the location selection. One suggestion was to include the consenting process as it can be affected by environmental reasons such as the protection of biodiversity. This problem was seen in a wind farm due to Sabellaria reefs in the past. The ease and time of consent were also raised by another expert. It was suggested that specific stakeholders should be asked to participate such as the Ministry of Defence, air traffic, shipping, fishing, etc.

The government support mechanism came up in the comments a few times. It was also mentioned that the government regulations for each location need to be checked, because in many cases it might be a better decision to open the market in other continents. Also, the project financing and other contracts for difference (CfD) opportunities were mentioned. On top of that, the access to human resources was pointed out to show the impact of different locations.

Also, it was mentioned that if floating support structures were considered in the study, then the water depth and availability of relatively large and deep shipyards would be very important constraints. In this case, floating structures were not considered, but they could be included in the future.

The results of the study could also impact the criteria and the way these locations are selected by the Crown Estate providing more informed and cost-efficient options for future developers. Considerable actions are mandated on top of the development plans for minimizing investment, developing the supply chain, securing consents, ensuring economic grid investment and connection, and accessing finance [2,5].

5. Conclusions

The coupling of MOO with MCDM and expert surveys was demonstrated in this paper, as a method to increase the confidence of wind energy developers at the early stages of the investment. A set of locations from Round 3 and types of turbines were considered in the LCC analysis. By employing NSGAII and two variations of TOPSIS, optimum solutions were revealed and ranked based on experts' preferences. In the current problem formulation, among the optimum solutions, Seagreen Alpha was the best option, and Hornsea Project One was the least probable to be selected. From the surveys, additional criteria and stakeholders were recommended by the participants, which will be considered in the future.

The proposed methodology could also be applied to other sectors in order to increase investment confidence and provide optimum solutions. For example, the installation of floating offshore wind and wave devices could benefit from the framework where the optimum locations can be suggested concerning cost and operational aspects of each technological need. The foundation in this study is considered to be the jacket structure because the LCC is formulated accordingly. More LCC parametric analyses can be investigated in the future for different types of structures.

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A Comparative Study of Multiple-Criteria Decision-Making Methods under Stochastic Inputs

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Abstract: This paper presents an application and extension of multiple-criteria decision-making (MCDM) methods to account for stochastic input variables. More in particular, a comparative study is carried out among well-known and widely-applied methods in MCDM, when applied to the reference problem of the selection of wind turbine support structures for a given deployment location. Along with data from industrial experts, six deterministic MCDM methods are studied, so as to determine the best alternative among the available options, assessed against selected criteria with a view toward assigning confidence levels to each option. Following an overview of the literature around MCDM problems, the best practice implementation of each method is presented aiming to assist stakeholders and decision-makers to support decisions in real-world applications, where many and often conflicting criteria are present within uncertain environments. The outcomes of this research highlight that more sophisticated methods, such as technique for the order of preference by similarity to the ideal solution (TOPSIS) and Preference Ranking Organization method for enrichment evaluation (PROMETHEE), better predict the optimum design alternative.

Keywords: multi-criteria decision methods; wind turbine; support structures; weighted sum method (WSM); weighted product method (WPM); technique for the order of preference by similarity to the ideal solution (TOPSIS); analytical hierarchy process (AHP); preference ranking organization method for enrichment evaluation (PROMETHEE); elimination et choix traduisant la realité (ELECTRE); stochastic inputs

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1. Introduction

Multiple-criteria decision-making (MCDM) is a procedure that combines the performance of decision alternatives across several, contradicting, qualitative and/or quantitative criteria and results in a compromise solution [1]. Relevant methods are frequently applicable, implicitly or explicitly, in numerous real-life problems and can be encountered in industrial activities where sets of decision alternatives are evaluated against conflicting criteria [2]. MCDM methods are widely used in problems within the renewable energy (RE) industry. Indicatively, methods employed include the weighted sum and weighted product methods (WSM/WPM), the analytical hierarchy process (AHP), the technique for the order of preference by similarity to the ideal solution (TOPSIS), elimination et choix traduisant la realité (ELECTRE) and the preference ranking organization method for enrichment evaluation (PROMETHEE), among others. These methods have been successfully applied in a wide range of applications related to energy and sustainability problems [3,4]. Reference to the generic methodology behind MCDM can be found in [3,5], where one can find the most popular approaches to the most widely-applied multi-criteria methods in order to evaluate alternative solutions for real-world applications. MCDM was introduced by Saaty [6–8] and was initially developed to evaluate priorities. MCDM is very useful for policy making, new technologies and energy sources' evaluation, being capable of incorporating both technical and non-technical attributes, i.e., economic, influencing factors [9], in the decision-making process.

Successful selection of the most appropriate multi-criteria methodology should consider a range of different perspectives in order to comprehend all sides of the problem and, when necessary, consider inter-connections among the criteria. MCDM methods need to structure the decision procedure, to demonstrate the trade-off among the criteria, to assist decision-makers to reflect upon, articulate and apply worthy judgments related to satisfactory trade-offs, resulting in suggestions when considering alternatives, to estimate risk and uncertainty more consistently and reasonably, to simplify negotiation and to keep a record of how decisions are made [10]. Real-world applications are often considered as MCDM problems; however, complications can be encountered when, for example, outlining the nature of the problem before defining the necessary alternatives, quantifying data and, finally, finding the optimum solution. Even in the seemingly simpler cases of qualitative attributes, the quality of data can be a significant source of statistical uncertainty. Further, the alternatives are derived from a wide range of choices, which are aimed at being prioritised and finally ranked or arranged in a hierarchical manner. An important issue that should be carefully considered is the fact that different attributes/criteria can cause conflicts due to their degree of completeness, redundancy, mutuality and independence, which can further complicate the decision-making process [5].

This paper aims to provide a comparative study of widely-applied MCDM methods in a real-world application and to introduce a methodology for their extension to account for stochastic inputs. An overview of selected multi-criteria methods is presented, together with a detailed analysis of the process of each method, for the easy implementation and discussion of their generic advantages and disadvantages. A case study of the selection of the optimum configuration of a support structure for a wind farm in a given location is then presented, where the criteria and alternatives of the problem are defined. Next, the data obtained through expert elicitation are presented together with the results from the implementation of each of the methods, deterministically and stochastically. A review of the results is carried out to highlight the differences and discrepancies in order to draw useful conclusions.

2. Literature Review

2.1. Review of Multiple-Criteria Decision-Making (MCDM) Methods

A focused study of MCDM over the last 12 years illustrated the effectiveness of applying these methods in the areas of sustainable and renewable energy applications [11]. The development of MCDM methods has been widely reported in the literature throughout the years, for example by Peng et al. [12], where different methods and their extensions, among others, were employed to solve a problem. Kolios et al. [13] have performed a Political, Economic, Social, Technological, Legal and Environmental (PESTLE) study, employing two different MCDM approaches for multi-criteria risk prioritisation. Kabak and Dağdeviren [9] have used a hybrid MCDM method when studying the energy sector and prioritising the alternative renewable energy sources (RESs) in developing countries. Shafiee and Kolios [14] have applied an MCDM method in order to minimise the operational risks of wind energy assets, while Govindan et al. [15] conducted research on hybrid MCDM methods, including AHP for green supplier selection using a range of conflicting environmental criteria. Localised renewable energy planning has been studied for the island of Thassos in Greece by Mourmouris [16], who implemented an MCDM methodology, defining several criteria for the exploitation of RESs, the local optimum energy mix and electricity production. MCDM methods have also been applied in various engineering problems due to their clarity and robustness after years of study [17,18].

For the purpose of this paper, several methods have been reviewed, and eventually, the following ones have been selected, as they are the most widely applied in multi-criteria analysis problems for energy applications: WSM, WPM, TOPSIS, AHP, ELECTRE and PROMETHEE. In the next paragraphs, a brief review is given with indicative applications of each of them in the literature.

Despite the disadvantages of WSM and WPM, i.e., sensitivity to units' ranges and exaggeration of specific scores, there are numerous applications in the literature that employ either of them primarily due to their straightforward implementation. Pilavachi et al. [19] have used an MCDM method according to a statistical estimation of weighted factors, while technical, social and economic features have also been considered. The method has been employed on the problem of risk identification and assessment within the tidal energy sector, as can be seen in [13,20], also introducing a comparison between the TOPSIS and WSM methods and showing results with good agreement.

Among many methods, TOPSIS is used extensively in different areas of research. Lozano-Minguez et al. [18] employed this deterministic methodology on the selection of the most desirable support structure of an offshore wind turbine, among three design options, under the consideration of a combination of multiple qualitative and quantitative criteria. The same concept was extended by Kolios et al. [17], where an extended version of TOPSIS is introduced, which takes into consideration the stochasticity of inputs, which is a common issue towards the successful implementation of MCDMs. With the same aim, Martin et al. [21] presented a methodology to evaluate a number of floating support structure configurations, for offshore wind turbines deployed in deep waters. Doukas et al. [22] used TOPSIS on energy policy objectives for sustainable development and renewable energy preferences, while Datta et al. [23] identified the best islanding detection method for a solar photovoltaic system by using TOPSIS along with other MCDM methods. Saelee et al. [24] employed TOPSIS as the best tool for the selection of the best among three biomass types of boiler. Finally, TOPSIS has been applied to a wide range of applications, as described in [25], where it was suggested to further investigate how to calculate the distance among positive and negative solutions.

Considering relevant applications implementing the AHP method, Kahraman and Kaya [10] implemented a fuzzy MCDM method, based on the AHP method, so as to find the optimum amongst energy policies in Turkey. Cobuloglu and Büyüktahtakın [26] developed a new AHP-based methodology applicable to problems where uncertain data were available, and the criteria weights are identified from the MCDM case. Other applications of AHP in renewable energy-related problems can be found in [27,28], which deal with the evaluation of solar water heating systems and assessment of the local viability of renewable energy sources. AHP and the analytical network process (ANP) have been presented in [29], by using a commercial software package, so as to demonstrate the diversity of applications to which it could be employed.

Applications can certainly be found in the literature, as the use of ELECTRE is widespread. Indicatively in [30], the goal was to select the optimum site location to install an offshore wind farm among four different choices/alternatives through an innovative method based on many MCDM methods, including ELECTRE. In [31], the ELECTRE method was applied to the optimisation of decentralised energy systems. A comprehensive review of the applications of ELECTRE can be found in [32], which supports the argument that it is still an active field of research.

Outranking methods in general, such as PROMETHEE, after several applications have demonstrated their suitability in energy-related problems. PROMETHEE has been used in a wide range of renewable-related applications, such as in [33], where the authors developed and tested a decision support system using the PROMETHEE II method in RES exploitation, and [34] implemented both PROMETHEE and AHP methods in order to choose the most appropriate desalination system in RES plants. In [35], the PROMETHEE method was applied in order to choose the best among four alternative energy exploitation projects in an MCDM problem. More applications and a comprehensive literature review can be found in [36–38], where different renewable energy scenarios were explored for energy planning.

Continuing from the above, multi-objective optimisation (MOO) is another important MCDM method and is one of the most commonly-encountered types of optimisation problems. If there are a number of different and conflicting objectives, then the problem will fall into the category of MOO. Naturally, as a process, MOO reveals a number of non-dominated solutions [39]. A significant renewable energy-related problem is described, modelled and solved in [40], where the optimum design of switching converters was searched, in order to be integrated into related renewable technologies. The conflicting objectives were efficiency and reliability, where the optimum solution is obtained from solutions in the Pareto front. In a study on photovoltaic systems and electro-thermal methods, MOO was suggested and applied to two conflicting objectives: the maximisation of the efficiency of the solutions from Europe and their cost minimisation [41]. A lot-sizing mixed integer linear optimisation model was proposed in order to find the optimum ethanol production from several biomass sources, so as to minimise the cost and the environmentally-related issues in [42]. The trade-offs between two types of crop, i.e., food and biofuel crops, was optimised using multi-objective mixed integer programming. A model was proposed and the optimum solution obtained according to economic advantages and environmental impacts in [43]. More studies of MOO can be found in [40,44,45]. The methodology suggested by the authors in the present paper can be further applied to MOO under uncertain inputs.

2.2. Review of the Stochastic Expansion of Deterministic MCDM

A study that focused on earlier applications of MCDM methods demonstrated that developing fuzzy MCDM methods is the upcoming trend [46]. Many instances of the applications of fuzzy MCDM methods can be found in [47,48], where it was highlighted that most of the applications had selected to implement variants based on AHP. In [49], a novel fuzzy multi-actor MCDM method was used in an application of hydrogen technology, where 15 criteria were used for the sustainability assessment. In [17], during deterministic TOPSIS, the weights for each criterion were considered fixed, but under stochastic modelling, statistical distributions were employed to best fit the acquired data of the experts' opinions. In [50,51], fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and AHP methods were applied using nine evaluation criteria for the assessment of renewable energy technologies in Turkey. The performance of several types of wind turbines was assessed in a case study in Taiwan, where the fuzzy ANP method was implemented [52]. The fuzzy ANP method was also implemented in [53], so as to mitigate the risks related to offshore wind farms, and finally, a comparison between these outcomes with the ANP and AHP methods was provided. Perera [54] has presented a study that combines MCDM and MOO in the designing process of Hybrid Energy Systems (HESs), using the fuzzy TOPSIS extension along with level diagrams. In [55], MCDM under uncertainty is discussed in an application where the alternatives' weights are partially known. An extended and modified stochastic TOPSIS approach was implemented using interval estimations. In [56], a new stochastic-fuzzy MCDM method, called Fuzzy Stochastic Ordered Weighted Averaging (FSOWA), is presented so as to rank the alternatives and acquire the optimum alternative. The Monte Carlo method is applied to a decision-making, multi-stakeholder and hydro-environmental management case study in order to solve the uncertainty problem in [57]. A fuzzy MCDM method was also applied among energy technology alternatives so as to treat uncertainty. The AHP method under fuzziness is implemented while evaluating scores from experts [10].

3. Methodology

3.1. An Overview of Selected MCDM Methods

3.1.1. Weighted Sum Method (WSM) and Weighted Product Method (WPM)

The WSM is the simplest available method, applicable to single-dimensional problems, due to the fact that it follows an intuitive process. In the background of this method, the additive utility hypothesis is applied, which implies that the overall value of every alternative is equivalent to the products' total sum. In problems with the same units' ranges across criteria, WSM is easily applicable; however, when the units' ranges vary, for example when qualitative and quantitative attributes are employed, the problem becomes difficult to handle, as the aforementioned hypothesis is violated, and hence, normalisation schemes should be employed. It is common practice to use WSM along with other methods, for instance AHP, because of the method's plain nature.

For the case of n criteria and m alternatives, the optimum solution to the problem is obtained by the following equation:

$$A^*_{WSM} = max\sum_{i}^{m} a_{ij}w_j \tag{1}$$

where $i = 1, \ldots, m$, A^*_{WSM} represents the weighted sum score, a_{ij} is the score of the i-th alternative with respect to the j-th criterion and w_j is the weight of the j-th criterion.

An alternative to the WSM is the WPM. WPM is closely related to the WSM with the main difference being a product instead of a sum in the method. Each alternative is compared to the rest through a multiplication of ratios that are related to every criterion. Finally, WPM is considered suitable for both single and multi-dimensional cases.

This method compares alternatives A_k and A_l in the equation below. The optimum solution in a pairwise comparison is the one that is at least equal to the rest of the alternatives, and more specifically, the best solution is A_k when $\mathrm{R}\left(\frac{A_k}{A_l}\right) > 1$ (when considering a maximisation problem).

$$\mathrm{R}\left(\frac{A_k}{A_l}\right) = \prod_{j=1}^{n}\left(\frac{a_{kj}}{a_{lj}}\right)^{w_j} \tag{2}$$

where, as previously, a_{ij} is the score of the i-th alternative with respect to the j-th criterion and w_j is the weight of the j-th criterion.

3.1.2. TOPSIS

TOPSIS, depicted in Figure 1, was initially proposed by Hwang et al. [58], and the idea behind it lies in the optimal alternative being as close in distance as possible from an ideal solution and at the same time as far away as possible from a corresponding negative ideal solution. Both solutions are hypothetical and are derived within the method. The concept of closeness was later established and led to the actual growth of the TOPSIS theory [59,60].

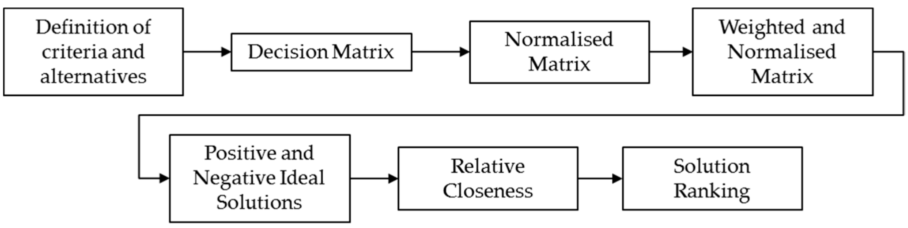

Figure 1. TOPSIS methodology.

After defining n criteria and m alternatives, the normalised decision matrix is established. The normalised value r_{ij} is calculated from Equation (3), where f_{ij} is the i-th criterion value for alternative A_j ($j = 1, \ldots, m$ and $i = 1, \ldots, n$).

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{m} f_{ij}^2}} \tag{3}$$

The normalised weighted values v_{ij} in the decision matrix are calculated as follows:

$$v_{ij} = w_i r_{ij} \tag{4}$$

The positive ideal A$^+$ and negative ideal solution A$^-$ are derived as shown below, where I' and I'' are related to the benefit and cost criteria (positive and negative variables).

$$A^+ = \{v_1^+, \ldots, v_n^+\} = \{(MAX_j v_{ij} | i \in I'), (MIN_j v_{ij} | i \in I'')\} \tag{5}$$

$$A^- = \{v_1^-, \ldots, v_n^-\} = \{(MIN_j v_{ij} | i \in I'), (MAX_j v_{ij} | i \in I'')\} \tag{6}$$

From the n-dimensional Euclidean distance, D_j^+ is calculated in (7) as the separation of every alternative from the ideal solution. The separation from the negative ideal solution follows in (8).

$$D_j^+ = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^+)^2} \tag{7}$$

$$D_j^- = \sqrt{\sum_{i=1}^{n} (v_{ij} - v_i^-)^2} \tag{8}$$

The relative closeness to the ideal solution of each alternative is calculated from:

$$C_j = \frac{D_j^-}{\left(D_j^+ + D_j^-\right)} \tag{9}$$

After sorting the C_j values, the maximum value corresponds to the best solution to the problem.

3.1.3. AHP

AHP was developed by Saaty [7], in 1980, and it is extensively applied in problems involving multiple, often conflicting, criteria [34]. The aim of AHP is to define the optimum alternative and to categorise the others considering the criteria that describe them. In order to apply the original AHP method, four steps should be followed, as shown in Figure 2.

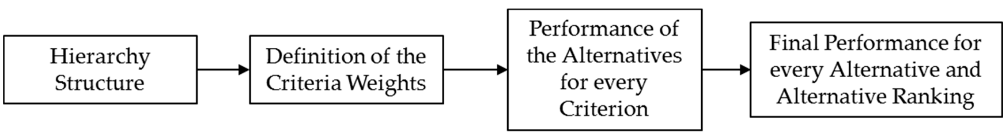

Figure 2. AHP methodology.

The first phase involves the structuring of the decision problem into a hierarchical structure. The aim is at the top of the hierarchy; the next level includes the criteria affecting the decision; and finally, the alternatives are placed at the bottom of the hierarchy. In the second phase, the weights for each criterion should be obtained. A pairwise comparison matrix (A), or judgmental matrix, should be compiled. The entry in row i and column j of A (a_{ij}) represents how much more important criterion i is than j with respect to the alternative. Saaty [7] suggested, for the quantification of qualitative data, a scale of relative importance, i.e., the values used for any given pair vary from 1 (where i and j have equal importance) to 9 (where i is absolutely more important than j). If criterion i. has one of the previous non-zero numbers assigned to it when compared to j, then j has the reciprocal value when compared to i. W_i reflects the importance of the i-th criterion and is estimated as the average of the entries in row i of the A matrix normalised. Equations (10) and (11) are used to check the consistency of the pairwise comparisons.

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{i^{th} \ entry \ in \ AW^T}{i^{th} \ entry \ in \ W^T} \tag{10}$$

where λ_{max} is the maximum Eigen value, A is the pairwise comparison matrix and W is the weight vector.

The Consistency Index (CI) is defined as:

$$CI = \frac{(\lambda_{max}) - n}{n - 1} \tag{11}$$

where λ_{max} is the maximum Eigen value from the previous equation.

The CI is then compared to the Random Index (RI) for the appropriate value of n (Table 1).

Table 1. Random Index (RI) for different values of n [3].

n	2	3	4	5	6	7	8	9	10
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

If $CI/RI > 0.10$, serious inconsistencies may exist, while if $CI/RI < 0.10$, the degree of consistency is considered satisfactory.

The third step refers to finding the score of each alternative for each criterion. A pairwise comparison matrix for each aim must be constructed. In the end, the best alternative (in the maximisation case) is the one that has the greatest value in the following expression:

$$AHP_i = \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \times w_j \tag{12}$$

where AHP_i is the score of the i-th alternative, m is the number of alternatives, n is the number of the criteria, a_{ij} represents the actual value of the i-th alternative in terms of the j-th criterion and w_j is the weight of importance of the j-th criterion.

The AHP is particularly relevant when qualitative criteria, such as environmental or political impacts, are considered. It is widely employed for energy planning problems because of its plainness and its ability to check consistency. Furthermore, throughout this method, the hierarchy is revealed after the breakdown of the problem, which enables understanding and defining the process itself. It is also suitable for dealing with technological characteristics and future aspects that are not well known [3,34]. It should be noted that AHP cannot directly consider potential associations amongst many components, as it performs poorly when different levels are independent, which implies that the method is unsuccessful in representing the complicated connections among the components. A few extensions of the AHP method have been proposed that are able to deal with these problems [61], such as the ANP method [14].

3.1.4. Elimination Et Choix Traduisant la Realité (ELECTRE)

The ELECTRE method was conceived of by Bernard Roy [62]. ELECTRE is not just a method, but a different decision support philosophy. Until recently, it has been successfully applied in many diverse fields. ELECTRE appears in the following variations: ELECTRE I, II, III, IV, IS and TRI [12]. Each extension is based on the same background, but they operate in different ways [63]. Through a selection procedure, when employing ELECTRE I and IS, a single option or group of options is selected and assigned to a kernel of preferred alternatives. A ranking of all options considered in pairs is achieved by employing ELECTRE II, III and IV, which serve as classification procedures. Finally, all options to predefined categories are assigned by ELECTRE TRI [4,64]. The method is characterised by thresholds and the outranking notion. ELECTRE presents the indifference threshold idea, and the preferences are defined again [63]. The decision-makers are the ones to define the indifference threshold. Theoretically, there is a good reason to insert a middle area in between the indifference and the strict preference. Such a hesitation zone is regarded as a weak preference [63].

ELECTRE generates a whole system of binary outranking relations among the alternatives. Since the system may be incomplete, the preferred alternative occasionally cannot be identified. A core of leading alternatives is produced. According to this method, there is a better view of the alternatives when the least favourable choices are removed, which is particularly suitable when there are only a few criteria and many alternatives in the case [5].

As mentioned earlier, there are many variations of ELECTRE. In this study, ELECTRE I is selected, as described in [4,65], and as based on the scope and relevant literature, seems the most appropriate variation. In general two new matrices have to be created: the concordance matrix and dis-concordance matrix, as shown below:

$$C\,(hSk) = \frac{\sum_{j\in l'} w_j}{\sum_{j\in l} w_j} \tag{13}$$

where l denotes the whole set of criteria and l' corresponds to the set of criteria that belong to the concordant coalition, by following ELECTRE's outranking framework.

$$D\,(hSk) = \underset{\left\{j\,:\,r_{hj} < r_{kj}\right\}}{max} \left\{r_{kj} - r_{hj}\right\} / d_{max} \tag{14}$$

where r_{hj} represents the performance of the i-th alternative against the j-th criterion and d_{max} denotes the maximal difference between the performance of alternatives.

3.1.5. Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)

PROMETHEE is an MCDM method that was developed in 1985 [66]. Six different extensions based on the ranking were developed and used by decision-makers. First, PROMETHEE I uses partial ranking; PROMETHEE II uses complete ranking; PROMETHEE III ranks based on intervals; PROMETHEE IV is the continuous instance of the previous; PROMETHEE V includes integer linear programming and net flows; and PROMETHEE VI represents the human brain. PROMETHEE ranks the alternatives using the outranking procedure.

PROMETHEE is applied in five steps as shown in Figure 3. First, the decision-maker's preference between two actions is presented by a preference function independently. Second, the proposed set alternatives are compared between each other with respect to the preference function, and third, the comparisons' results and the criterion's value of each alternative are illustrated in a matrix. At the fourth step, PROMETHEE I's approach is used so as to sort out the partial ranking, and finally, the fifth action contains the PROMETHEE II process in order to finish the alternative rankings [3].

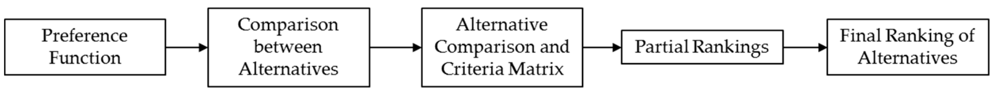

Figure 3. PROMETHEE methodology.

The formulae used in this implementation of PROMETHEE I are listed below, as described in [3,67]. An important feature of PROMETHEE I is that the sum of the scores equals zero, which informs the reader how far an alternative is from the average performance of the whole set. The decision-makers may select different types of criteria, which are associated with different graphical representations of the preference function. The Type I (usual) and Type IV (level from) preference functions are the best options for qualitative criteria, while the Type III (V-shaped) and Type V (linear) preference functions are the best options for quantitative criteria [68]. The choice between them (Type I or IV; and Type III or V) will depend on whether the decision-maker wants to introduce an indifference threshold or not.

The Type II (U-shaped) and Type VI (Gaussian) preference functions are used less often. The preference functions of both Types I and V are defined below, since in the case study to follow, qualitative criteria are included.

The preference function for Type I is:

$$p(x) = \begin{cases} 0, for \ \forall \ x \leqslant 0 \\ 1. for \ \forall \ x > 0 \end{cases} \tag{15}$$

where x denotes the numerical difference in the evaluation of two alternatives for a certain criterion.

The preference function for Type V is:

$$p(x) = \begin{cases} 0, & for \ x \leqslant s \\ \frac{x-s}{r}, & for \ s \leqslant x \leqslant s+r \\ 1, & for \ x \geqslant s+r \end{cases} \tag{16}$$

where s and $(s+r)$ denote the indifference and preference for each evaluation x. The multi-criteria preference degree is calculated from:

$$\pi(a,b) = \sum_{h=1}^{K} w_h \, p(a,b) \tag{17}$$

where w represents the weight of each criterion.

Outgoing flow is represented as:

$$\Phi^+(\alpha) = \sum_{x \in K} \pi(a,x) \tag{18}$$

Incoming flow is defined as:

$$\Phi^-(\alpha) = \sum_{x \in K} \pi(x,a) \tag{19}$$

Net flow is derived from:

$$\Phi(\alpha) = \Phi^+(\alpha) - \Phi^-(\alpha) \tag{20}$$

3.2. Stochastic Expansion of Deterministic MCDM

In a real-life scenario, there are always unknown facts, which are often practically impossible to identify. For this reason, vague simplifications are often necessary in order to represent a realistic condition. The earlier researchers and practitioners used to address uncertainty by assigning numerical values to each factor and logically combining them together [69], i.e., through employing most likely values or corresponding quantiles. The term "deterministic" is related to a certain entity. Deterministic models are used to describe one out of many possible results in a reference problem. On the other hand, "stochastic" comes from the Greek "to aim" and refers to a "random" outcome. A number of potential outcomes, which are characterised by their probabilities or likelihood, is best represented through stochastic modelling. Consequently, stochastic processes denote the set of random variables that are related to a varying factor. Such processes consist of a state space, which represents the potential values, where the random variables may be related to each other [57].

Real-life problems and human judgment are, in most cases, unclear and vague and cannot be represented as fixed values. For that reason, the fuzzy set logic is often implemented in MCDM problems. Fuzzy logic allows capturing the concept of the fuzziness of a system as measurable values. Fuzzy logic and probabilities show a different view and expression for uncertainty. The former theory implements the concept of fuzzy set membership, whereas the latter implements the concept of subjective probability [70]. A wider review of the fuzzy modelling and renewable energy systems is provided in [70].

A stochastic method can be more informative than a deterministic method because the former accounts for the uncertainty due to the varying behavioural characteristics of the target system. Deterministic methods are mainly used to describe simple, natural phenomena on the basis of physical laws and are not fit-for-purpose for large and complicated applications. Consequently, real-world behaviour is better reflected by employing methods relevant to stochastic simulations. The latter can include the uncertainty of real-world applications, where system modelling is not trivial. Stochastic methods can increase the confidence of the decision-maker in the final results and analysis and can be more appropriate for cases where the heterogeneity of important factors is critical as the uncertainty of the considered system increases. In general, it is not feasible to obtain an analytical expression for stochastic problems, which would require more computational time and resources to deliver a satisfactory solution [57].

The Monte Carlo simulation method is a particularly useful approach in stochastic modelling, as it can mitigate the problems of deterministic analysis. Such an expansion of deterministic methods is developed in this paper. Principally, the Monte Carlo simulation method is an approach to represent the random nature of stochastic processes. The most fundamental part of such a method is the generation of random numbers as input sets, which are drawn randomly. Algorithms that implement the Monte Carlo simulation method consist of a sequence of finite states, a mapping function for the finite states, the probability distribution of finite states, the output space and a mapping function between the finite states and the output space [71].

The approach proposed in this paper for the stochastic expansion of deterministic methods, follows the approach proposed in [17], expanded for different methods, and is based on the fact that input variables are considered stochastically as statistical distributions that are derived by best fitting of the data collected for each value in the decision matrix and weight vector. Stochastic input data will allow Monte Carlo simulations to perform numerous iterations of analysis in order to quantify results and identify the number of cases where the optimum solution will prevail, i.e., there is a P_i probability that option X_i will rank first. Figure 4. Stochastic expansion algorithm of deterministic MCDM methods illustrates the sequence of steps followed.

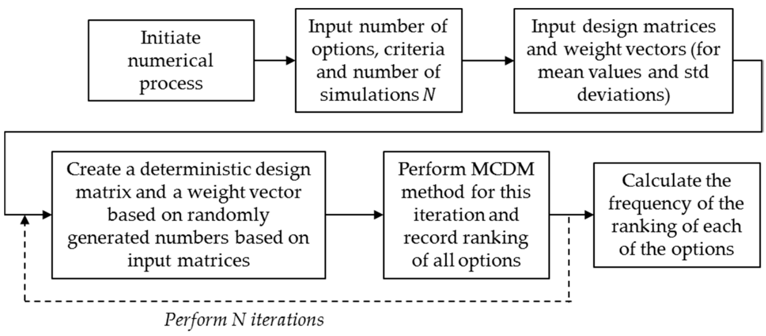

Figure 4. Stochastic expansion algorithm of deterministic MCDM methods.

4. Case Study

Among most of the operating offshore wind turbines installed in the Round 1 and 2 regions in the U.K., monopile foundations have been constructed in water depths of no more than 35 m [72] while the average water depth in an offshore wind farm in Europe was 27 m and distance from shore 43 km, as recorded by 2016 [73,74]. Due to risk and cost limitations related to fabrication, transportation and installation, these foundation options are not considered viable solutions in depths that exceed 30–35 m [72], although extensive research is currently taking place to push this boundary further. Moving further away from the shore, towards deeper waters, can lead to higher electricity production primarily due to the higher wind shear, more available space and lower social impact; however, deep water installations demand considerably higher volumes of materials and installation effort, resulting in higher costs.

The advantage of fixed structures is that the designs have already been deployed in many wind farms for years and similar concepts have been deployed for decades in the oil and gas industry. However, fixed structures are not compatible in deeper waters because the designs became impractical, more complicated and unsuitable for mass production. For sites that exceed the limit of 60–70 m, the bottom-fixed foundations encounter both technical and economic restrictions, and it is expected that the floating wind turbine support structure concepts will become more applicable solutions [75,76]. Currently, several floating concepts are being developed and tested in order to qualify for scaling and further production. Floating structures still have high costs, face issues with the footprint of the moorings, limitations for the minimum water depth in which to operate and finally design constraints regarding the complications of volume construction.

In this case study, data were collected considering both fixed and floating structures from structured questionnaires from 20 experts in the wind energy field, with at least seven years' experience in the design and implementation of RE projects. The data received were statistically processed accordingly in a preliminary study of the authors, as presented extensively in [17]. This present study aims to highlight the suitability of different MCDM methods for this problem with a view toward illustrating how well each method performs following a qualitative validation of the outcomes.

Decision Criteria and Alternatives

For this analysis, 10 design alternatives for offshore support structures are chosen, each evaluated based on 10 different criteria, listed in Tables 2 and 3 (where TLP stands for Tensioned Leg Platform). These were selected so as to extend previous work and for comparison purposes [18,21,75,77,78]. The 10 selected criteria have been qualified through a comprehensive list of 36 criteria for practicality purposes, based on semi-structured experts' interviews and have been evaluated using qualitative variables.

- The compliance/maximum displacement of the rotor is considered to be a negative variable, and it represents the maximum displacement likely to be expected at the hub of the rotor that is affected by the support structure. It is treated in a different way for the floating and fixed structures; however, it does affect the rotor similarly for both structures.
- Dynamic performance is a positive variable, and it defines qualitatively the performance of a support structure in combination with the environmental effects and the operating loads. It is treated in a different way for the floating and fixed structures; the former has to combine the coupled effect of waves and turbine loads.
- Design redundancy is a positive variable, and it defines the capability to redistribute the load when a local failure is encountered.
- The cost of maintenance is a negative variable, and it reflects the qualitative assessment of the possible maintenance costs when, for example, any necessary equipment is involved or weather issues occur.
- The cost of installation is a negative variable, and it represents the qualitative assessment of the possible installation costs along with procedures, such as piling, etc.
- Environmental impact is a negative variable regarding the installation, operation and decommissioning impact of the foundation. Impacts on the natural environment can be considered as noise, visual, shadowing effects, disruption of the fish population's routes, etc.
- Carbon footprint is a negative variable that takes into account the CO_2 emissions that were produced during all of the procedures needed for the support structure, such as the fabrication and installation processes.
- Certification is a positive variable and reflects the confidence level against a range of engineering uncertainties. This covers a number of cases from existing installations related to the current application, to different applications or no applications at all.

- The likely cost is a negative variable. It represents the relative qualitative assessment of each of the concept's costs, which, to some extent, could be quantified through the Net Present Value (NPV).
- Depth compatibility is a positive variable and represents the confidence levels when deploying a concept, which considers current installations for any applications with respect to a reference depth.

A Likert scale has been employed in the questionnaires in order to provide uniform input data. The experts were asked to identify their level of agreement or disagreement using a number from within the 1–9 scores, as the Likert scale suggests. The scale usually states nine as the most critical response. The same 1–9 scales was used to rank the different alternatives that correspond to the design criteria. According to the positive or negative nature of the criteria, nine and one are the optima, respectively. Although usually in practice, the Likert scale is defined through a 1–5 scale, due to the fact that statistical processing has followed the collection of the data, a broader range of values was deemed more appropriate.

Table 2. List of criteria.

ID	Decision Criterion
A	Compliance/Max Displacement of Rotor
B	Dynamic Performance
C	Design Redundancy
D	Cost of Maintenance
E	Cost of Installation
F	Environmental Impact
G	Carbon Footprint
H	Certification
I	Likely Cost
J	Depth Compatibility

Table 3. List of alternatives.

ID	Decision Alternative
A1	Jacket
A2	Tripod
A3	Monopile
A4	Suction Bucket
A5	Jack-up
A6	Spar
A7	Barge
A8	TLP
A9	Semi-Submersible
A10	Tri-floater

In order to define the problem, a relatively large-scale wind turbine (such as 5.5 MW) was considered to be installed in a 40-m water depth, and 10 design configurations were proposed for the support structure against the 10 selected criteria. The depth is considered to be a key parameter of the problem, as it is expected that it will influence the final outcome based on the experts' responses. The designs included five fixed and five floating support options.

All design alternatives have both advantages and disadvantages, and that is the reason behind the proposed criteria and how their aggregation can qualify as the best performance. Several more support structures can be found in the literature, including some concepts that combine different types' features in a single design. These types usually have some advantages, overcoming some of the problems, and are suitable for a wide range of water depths. These hybrid structures are outside the scope of this paper, but could be investigated further in the future; however, the approach suggested in this paper is applicable for their assessment.

In Table 4, the mean evaluation values of the processed questionnaires are presented.

5. Results and Discussion

5.1. Deterministic Results

The results of the deterministic application of the MCDM methods are presented in this section. In the context of this application, certain criteria had to be maximised, and others had to be minimised. Here, only maximisation is considered, and any criteria for minimisation are multiplied by −1, where relevant. Most of the methods provide absolute scores, which are used for ordering the solutions at the end. Since maximisation is considered, the score should be as high as possible. When a method generates a pairwise solution, the solution that outperforms most of the other alternatives is considered to be the optimum.

As can be seen from Figure 5, in most cases, the methods derive close optimum solutions. Table 5 summarises the WSM, WPM, TOPSIS, AHP, PROMETHEE I and ELECTRE I results and ranking.

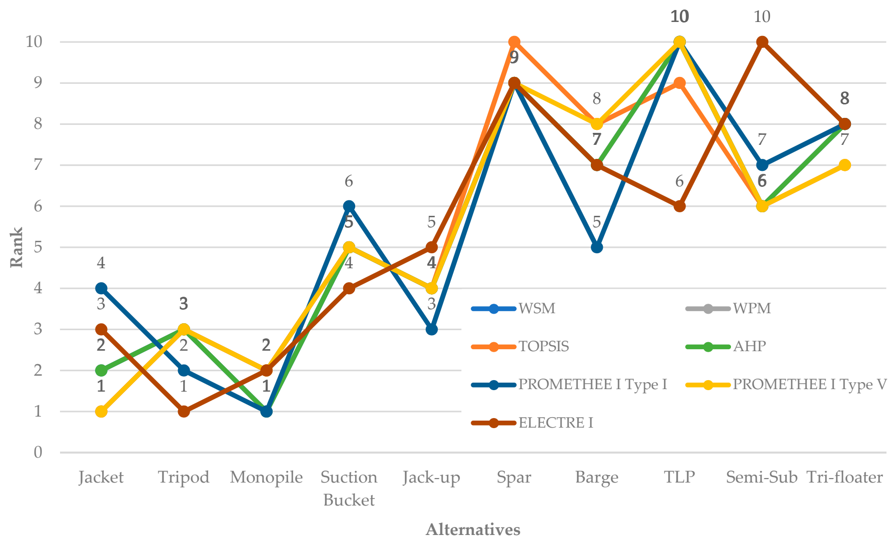

Figure 5. Ranks comparison for the WSM, WPM, TOPSIS, AHP, PROMETHEE I and ELECTRE I methods.

In more detail:

- WSM: This has been the simplest method applied, and the result for the optimal solution is Alternative A3, the monopile design, followed by A1 (jacket) as the second option.
- WPM: WPM generates a matrix with pairwise comparison performance, as shown in Table 6. Hence, in this case, A1 (jacket) is superior to all of the other alternatives, because the ratio is higher than one in all cases. Following this, the monopile stands as the second best option.
- TOPSIS: According to this method, again, the jacket (A1) design achieves the highest score followed by the monopile concept.
- AHP: This method ranks the monopile (A3) design highest, followed by the jacket. The final ranking seems to be closer to the rest of the methods, and this can be explained due to the similarity of this method to the WSM.
- PROMETHEE I: Two different types of criteria were employed for the PROMETHEE I method. First, the Type I preference function was applied, and the monopile (A3) was found to be the best alternative in this case. Second, the results from the Type V preference function indicate that the jacket design achieves the highest score (A1).
- ELECTRE I: As a result, this method generates two matrices, which cumulatively qualify the tripod (A2) as the best option followed by the monopile and jacket.

Table 4. Mean evaluation values (design matrix) and normalised mean values of the weights.

Alternatives/Criteria	Compliance/ Max Displacement of Rotor	Dynamic Performance	Design Redundancy	Cost of Maintenance	Cost of Installation	Environmental Impact	Carbon Footprint	Certification	Likely Cost	Depth Compatibility
Jacket	1.6	7.7	7.8	5.9	6.6	7.4	6.6	7.7	5.7	7.7
Tripod	2	7.2	6.3	5.8	6.2	6.9	6.2	7.2	5.3	7
Monopile	2.7	6.5	5.7	4.7	5.9	6.5	5.2	7.8	4.4	6.1
Suction Bucket	3.3	6.1	5	5	5.3	6.5	5.1	5.9	4.5	5.3
Jack-up	3.2	6.6	6.1	5.4	4.6	5	5.9	6.8	7	6.4
Spar	5.8	5.9	5.1	4.8	4.8	3.6	5.3	5.4	6.5	3.9
Barge	6.6	4.6	5.3	4.6	3.8	3.4	5.3	5.2	5.9	5.6
TLP	4.2	6.6	4.4	5.7	5.6	5.2	6	5.5	7.3	5
Semi-Submersible	5.6	5.8	5.3	4.6	4.2	3.7	5.9	5.6	6.7	5.9
Tri-floater	5.5	5.7	4.9	5	3.9	3.5	5.7	4.3	6.4	5.7
Normalised weight values	0.11	0.09	0.09	0.13	0.12	0.08	0.07	0.09	0.13	0.10

Table 5. WSM, TOPSIS, AHP, PROMETHEE I and ELECTRE I results and rank.

Alternatives	WSM		WPM	TOPSIS		AHP		PROMETHEE I Type I		PROMETHEE I Type V		ELECTRE I
	Score	Rank	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Rank
A1	−0.68968	2	1	0.6278	1	−0.0191	2	0.0956	4	0.225556	1	3
A2	−0.84274	3	3	0.6222	3	−0.0218	3	0.1071	2	0.11	3	1
A3	−0.67306	1	2	0.6237	2	−0.019	1	0.3758	1	0.153333	2	2
A4	−1.0571	5	5	0.5423	5	−0.0258	5	0.0336	6	0.046667	5	4
A5	−0.93839	4	4	0.5899	4	−0.0233	4	0.1023	3	0.088889	4	5
A6	−1.485	9	9	0.3662	10	−0.0344	9	−0.2051	9	−0.17889	9	9
A7	−1.27484	7	7	0.4108	8	−0.0309	7	0.059	5	−0.10111	8	7
A8	−1.6779	10	10	0.3815	9	−0.0372	10	−0.4568	10	−0.18111	10	6
A9	−1.21339	6	6	0.4347	6	−0.0293	6	0.0123	7	−0.08	6	10
A10	−1.33065	8	8	0.429	7	−0.0312	8	−0.1238	8	−0.08333	7	8

Table 6. WPM pairwise comparison matrix.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
A1	1	1.0361	1.0188	1.0975	1.0750	1.1993	1.1391	1.2405	1.2405	1.1311
A2	0.9651	1	0.9833	1.0592	1.0375	1.1575	1.0994	1.1972	1.0916	1.1168
A3	0.9814	1.0169	1	1.0772	1.0551	1.1771	1.1180	1.2176	1.1101	1.1358
A4	0.9110	0.9440	0.9282	1	0.9794	1.0927	1.0378	1.1302	1.0305	1.0543
A5	0.9301	0.9638	0.9477	1.0209	1	1.1156	1.0596	1.1539	1.0521	1.0764
A6	0.8337	0.8639	0.8495	0.9151	0.8963	1	0.9498	1.0343	0.9431	0.9648
A7	0.8778	0.9095	0.8944	0.9635	0.9437	1.0528	1	1.0890	0.9929	1.0158
A8	0.8060	0.8352	0.8212	0.8847	0.8665	0.9667	0.9182	1	0.9117	0.9328
A9	0.8840	0.9160	0.9007	0.9703	0.9504	1.0603	1.0070	1.0967	1	1.0230
A10	0.8641	0.8953	0.8804	0.9484	0.9289	1.0363	0.9843	1.0720	0.9774	1

Jacket qualifies as the best alternative for WPM, TOPSIS and PROMETHEE I Type V, while monopile is the best alternative for WSM, AHP and PROMETHEE I Type I. From experience, it would be expected that these two concepts would score higher, as their implementation would introduce lower risk, as they are the most widely-used concepts to date [74]. Although the applicability boundaries of monopiles are pushed to account for deeper waters in order to take advantage of their ease in fabrication and installation, the threshold of 35 m would still face challenges to be achieved due to practical, technical difficulties [79–81]. Hence, the jacket would be expected to be the prevailing concept for this problem.

It is not surprising that WSM, AHP and PROMETHEE I Type I methods consider the monopile as the best alternative, since they are the least sophisticated methods among those evaluated. The maintenance and likely costs, which have a negative nature, are the criteria that obtained the highest values for the vector weight, and for both of them, the monopile has a much lower score than the jacket; hence, it can be concluded that the effect of these extreme scores has been underestimated by using these less sophisticated methods. Results obtained from the deterministic application of the different methods employed in this paper can be supported by the findings of other studies for similar problems comparing different MCDM methods, i.e., [82–84].

5.2. Stochastic Results

For all deterministic MCDM methods, stochastic expansion through Monte Carlo simulations was performed through appropriately-developed stochastic algorithms, following the process presented in Section 3. Input variables were modelled through truncated normal distributions. Each Monte Carlo iteration produced random inputs for each of the stochastic variables, which were fed into an iterative generation of deterministic decision matrices. The output from each case was recorded, and the best solution for each iteration was stored, so as to aggregate how frequently each alternative outperformed the others. Due to the relatively high probabilities of failure to be captured, the rule of thumb of two orders of magnitude more simulations than the expected measured probability was followed (resolution of 1%), consisting of 100,000 iterations for each simulation. A convergence study highlighted that this resolution of analysis was sufficient for this problem. Figure 6 presents the probability of an alternative to score first, while Table 7 lists the results for 100,000 iterations with the probability of each design alternative scoring in each rank.

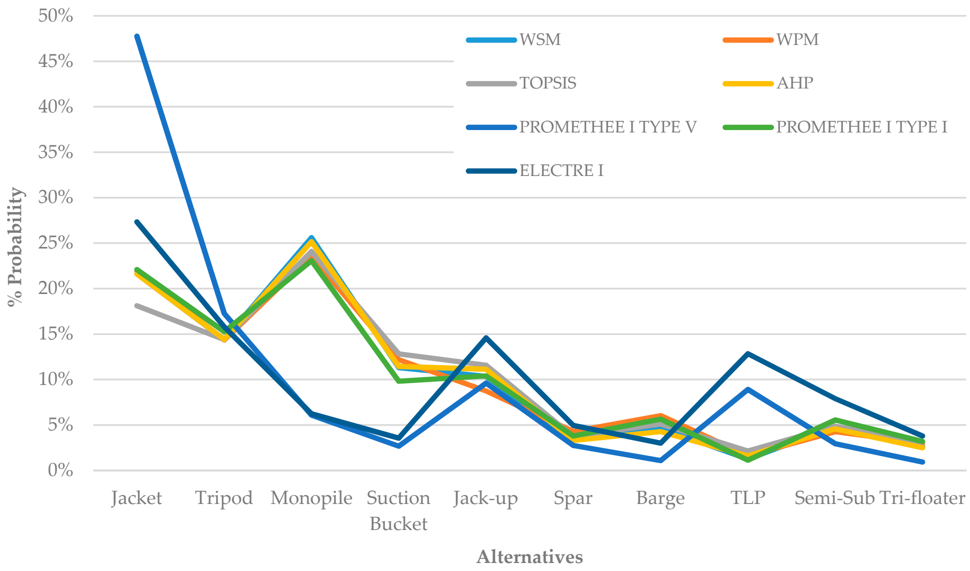

Figure 6. Comparative stochastic MCDM results: probability of an alternative to score first.

From the results of the stochastic analysis, it can be observed that Alternatives A1, A2 and A3 (jacket, tripod and monopile) consistently perform better than the rest with probabilities of ranking first between 49.4% (ELECTRE I) and 71.1% (PROMETHEE I TYPE V). Comparing fixed with floating options, the former rank higher with probabilities between 67.5% (ELECTRE I) and 83.7% (AHP). It should be noted that the PROMETHEE I TYPE V exaggerates in the prediction of the optimum alternative and presents some relative inconsistency with respect to the others, while ELECTRE I also seems to be mis-ranking the least optimum options; hence, these methods seem to be less suitable for the reference application.

Table 7. Stochastic WSM, TOPSIS, AHP, PROMETHEE I and ELECTRE I results.

Alternatives	WSM	WPM	TOPSIS	AHP	PROMETHEE TYPE V	PROMETHEE I TYPE I	ELECTRE I
A1	21.64%	21.94%	18.12%	21.62%	47.75%	22.09%	27.33%
A2	14.39%	14.34%	14.40%	14.40%	17.26%	15.27%	15.80%
A3	25.62%	23.59%	24.09%	25.16%	6.07%	23.07%	6.24%
A4	11.30%	12.19%	12.84%	11.43%	2.67%	9.81%	3.55%
A5	10.35%	8.73%	11.58%	11.13%	9.62%	10.41%	14.59%
A6	3.37%	4.29%	3.73%	3.31%	2.75%	3.80%	4.96%
A7	4.65%	6.04%	5.11%	4.28%	1.09%	5.65%	3.01%
A8	1.24%	1.64%	2.14%	1.60%	8.92%	1.13%	12.84%
A9	4.83%	4.27%	4.88%	4.57%	2.94%	5.56%	7.90%
A10	2.60%	2.97%	3.11%	2.50%	0.93%	3.20%	3.79%

The results above are countersigned by current practice as fixed support structures, and particularly, monopiles and jackets have reached far higher Technology Readiness Level (TRL) than floating concepts, which are still to achieve full commercialisation due to the various risks associated with their wider implementation (i.e., design for volume production, cost of moorings, dynamic performance, etc.). It should also be observed that the definition of the problem, referring to a 40-m depth deployment, consists of a determining factor of this conclusion, as it is expected that for the case of a deeper installation (i.e., 70 m), fixed concepts would have scored much lower in the criteria of cost of maintenance, cost of installation, certification, likely cost and depth compatibility.

Based on the results obtained, two separate studies were also evaluated, considering separately the fixed and floating concepts. The outcomes have shown again that the three fixed concepts (jacket, monopole and tripod) have significantly higher scores than the suction bucket and jack-up, while for the floating concepts, spar, barge and TLP outperform the tri-floater and semi-sub. These findings illustrate that the stochastic approach proposed in this paper is able to evaluate the relative risks encountered with the selection of each of the chosen options.

6. Conclusions

The application of MCDM methods in engineering problems and particularly those related to renewable energy applications, can provide useful insight for decision-makers towards more qualified decisions. The present study demonstrated the application of six MCDM methods that are frequently used on numerous renewable energy applications, namely WSM, WPM, TOPSIS, AHP, PROMETHEE I and ELECTRE I, and their extension to consider stochastic inputs and assign confidence levels in the resulting outputs.

For the reference case study, 10 significant technical and non-technical criteria were employed to assess the optimal solution among 10 different alternatives of support structures for offshore wind turbines. After applying the MCDM methods on the case deterministically, it can be concluded that most methods agree on identifying the set with the highest score, with the most sophisticated methods, i.e., TOPSIS and PROMETHEE, more accurately predicting the jacket type configuration as the prevailing one, followed by the monopile. The expansion of the methods to account for uncertain inputs has shown similar results, qualifying the fixed concepts and, in particular, the jacket, tripod and monopile, as the prevailing options. A reasonable agreement can be observed among the methods, with the exceptions of PROMETHEE I TYPE V and ELECTRE I, which seem less suitable for this purpose, as they misjudge the ranking of the less optimal options. It should be noted here that a conclusion cannot be generalised, i.e., that one method outperforms the rest, as accuracy in prediction depends on the nature of the problem, as well as the data collection and processing in a way that best fits each individual method and application.

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```
'''
Code to create a layout for turbines given horizontal and vertical distances

@author: Vera Mytilinou - Cranfield University 2018
'''
import numpy as np
import math
import matplotlib.pyplot as plt

from CablingEstimator import calculate_length_of_minimum_spanning_tree


class CablingLayoutGenerator():


    def __init__(self, total_number_of_turbines, turbineDiameter, layoutSelector):
        '''
        total_number_of_turbines integer

        turbineDiameter in meters

        layout 1 X=3D (m)     layout 1 Y=5D (m)
        layout 2 X=5D (m)     layout 2 Y=9D (m)
        layout 3 X=10D (m)     layout 3 Y=18D (m)
        '''
        numberOfTurbinesVertically = 1
        numberOfTurbinesHorizontally = 1

        self.__total_number_of_turbines = total_number_of_turbines
        self.__numberOfTurbinesVertically = numberOfTurbinesVertically
        self.__numberOfTurbinesHorizontally = numberOfTurbinesHorizontally
        self.__turbineDiameter = turbineDiameter
        self.__layoutSelector = layoutSelector

        self.__layout = {1:{"X":3, "Y":5},
                         2:{"X":5, "Y":9},
                         3:{"X":10, "Y":18}
                         }

        self.__edge_length_of_the_square_area = self.estimate_the_nearest_square(self.
        __total_number_of_turbines)

        self.__horizontal_offset = self.__layout[self.__layoutSelector]["X"] * self.
        __turbineDiameter
        self.__vertical_offset = self.__layout[self.__layoutSelector]["Y"] * self.
        __turbineDiameter

#         print "self.__horizontal_offset -> ", self.__horizontal_offset
#         print "self.__vertical_offset -> ", self.__vertical_offset

    def calculate_the_length_of_cables_for_windfarm_of(self):
        """
         Calculate the overall length of cabling of a wind farm given the following input

         layout 1 X=3D (m)     layout 1 Y=5D (m)
         layout 2 X=5D (m)     layout 2 Y=9D (m)
         layout 3 X=10D (m)     layout 3 Y=18D (m)

         :param total_number_of_turbines: (integer)
         :param turbineDiameter: (meters)
         :param layoutSelector: (integer)

         :return: length in [km]
         """
        output = 1000000000

        if (self.__total_number_of_turbines < 2000):
```

```
            coordinates_of_the_windFarm = self.generateCoordinatesForWindFarm()
            output = calculate_length_of_minimum_spanning_tree(coordinates_of_the_windFarm) /
             1000.0

        return output

    def estimate_the_nearest_square(self, value):
        return math.ceil( math.sqrt(value))

    def calculateXcoordinate(self, index):
        return (int(index) / int(self.__edge_length_of_the_square_area)) * self.
        __horizontal_offset + (int(index)%2)* (self.__horizontal_offset / 2)


    def calculateYcoordinate(self, index):
        return (int(index) % int(self.__edge_length_of_the_square_area)) * self.
        __vertical_offset


    def generateCoordinatesForWindFarm(self):
        '''
        returns a numpy array, where each element is a pair of coordinates
        '''
        self.__coordinates_map =   np.zeros((self.__total_number_of_turbines, 2))

        current_point = [0,0]
        for turbine_index in range(self.__total_number_of_turbines):

            current_point[0] = self.calculateXcoordinate(turbine_index)
            current_point[1] = self.calculateYcoordinate(turbine_index)

            self.__coordinates_map [turbine_index] = current_point

#             print turbine_index, '-->', current_point


        return self.__coordinates_map


    def showTurbines(self):
        Xcoor = self.__coordinates_map[:,0]
        Ycoor = self.__coordinates_map[:,1]

#         self.__coordinates_map
        plt.plot(Xcoor, Ycoor, 'ro')

        plt.show()



def test_run_a_single_case():
    C1 = CablingLayoutGenerator(50, 90, 2)

    coordinates_of_the_windFarm = C1.generateCoordinatesForWindFarm()

    calculate_length_of_minimum_spanning_tree(coordinates_of_the_windFarm)

def calculate_the_length_of_cables_for_windfarm_of(total_number_of_turbines, turbineDiameter,
 layoutSelector):
    """
    Calculate the overall length of cabling of a wind farm given the following input

    layout 1 X=3D (m)     layout 1 Y=5D (m)
    layout 2 X=5D (m)     layout 2 Y=9D (m)
    layout 3 X=10D (m)     layout 3 Y=18D (m)

    :param total_number_of_turbines: (integer)
```

```
    :param turbineDiameter: (meters)
    :param layoutSelector: (integer)

    :return: length in [km]
    """


    C1 = CablingLayoutGenerator(total_number_of_turbines, turbineDiameter, layoutSelector)
    coordinates_of_the_windFarm = C1.generateCoordinatesForWindFarm()
    return calculate_length_of_minimum_spanning_tree(coordinates_of_the_windFarm) / 1000.0


def test_run_multiple_cases():
    for t in [50, 60, 100, 200, 500]:
        for d in [90, 110, 120]:
            for layout in [1,2,3]:
                print str(t), str(d), str(layout),
                calculate_the_length_of_cables_for_windfarm_of(t, d, layout)



if __name__ == "__main__":
    test_run_multiple_cases()
```

```
'''
Capacity Constraint for a layout by providing the maximum number of turbines

@author: Vera Mytilinou - Cranfield University 2018
'''
import numpy as np
from lxml.html.builder import AREA
import json


'''
first area, turbine type, layout -> max number of turbines

'''

class capacity_constraint:

    __invalid_number_of_turbines = -1
    __capacity_constraint = {
             'area1': {
                       'turbine_7MW' : {
                                        'layout1': 100,
                                        'layout2': 200
                                        },

                        'turbine_8MW' : {
                                        'layout1': 90,
                                        'layout2': 170
                                        }

                       },
            'area1888': {
                       'turbine_7MW' : {
                                        'layout1': 100,
                                        'layout2': 200
                                        },

                        'turbine_8MW' : {
                                        'layout1': 90,
                                        'layout2': 170
                                        }

                       }
    }

    def __init__(self, custom_capacity_constraint = None):
        if custom_capacity_constraint!= None and isinstance(custom_capacity_constraint, (str,
         unicode)):
            with open(custom_capacity_constraint) as external_file:
                data = json.load(external_file)

            self.__capacity_constraint = data[
            "capacity_per_area_per_type_of_turbine_and_per_layout"]

            self.__installed_capacity_constraint = data["location_porfolio"]

    def validate_constraint(self, area=None, turbine_type = None, layout = None):
        '''
        Returns true if the constraint is ok
        '''
        result = False

        if area in self.__capacity_constraint:
            if turbine_type in self.__capacity_constraint[area] :
                if layout in self.__capacity_constraint[area][turbine_type] :
                    result = True
```

```
        return result


    def query_the_maximum_number_of_turbines(self, area=None, turbine_type = None, layout =
    None):

        result = self.__invalid_number_of_turbines
        if self.validate_constraint(area, turbine_type, layout):
            result = self.__capacity_constraint[area][turbine_type][layout]

        return result


    def query_the_maximum_installed_capacity(self, area=None):
        """
        :param area: area to deploy a wind farm, from round 3
        :return: maximum_installed_capacity in W
        """
        return self.__installed_capacity_constraint[area]["max_capacity[GW]"]*1000000.0


def read_file(filename=None):

    c1 = capacity_constraint()
    pass



if __name__ == "__main__" :
    read_file()
    print "finished!"
```

```python
'''
Link results on database to sensitivity analysis

@author: Vera Mytilinou - Cranfield University 2018
'''

import sqlite3
import numpy as np
import os

class dataBroker():
    '''
    class to map data from database to python data

    e.g. can be used with sensitivity analysis modules etc.
    '''


    def __init__(self, database_path_for_SQLite):
        self.__database_path_for_SQLite = os.path.join('paper4results',
        database_path_for_SQLite)


    def getColumnAsAnArrayFromTable(self, column_name, table_name):
        conn = sqlite3.connect(self.__database_path_for_SQLite)
        cursor1 = conn.cursor()



        sql_fetch_query = """SELECT `%s` FROM %s where validity == 1 limit 10000""" % (
        column_name, table_name)

        cursor1.execute(sql_fetch_query )

        data_from_query = cursor1.fetchall()
        size_of_data = len(data_from_query)


        output_data = np.zeros([size_of_data])

        for i in range(size_of_data):
            output_data[i] = data_from_query[i][0]

        output_data = np.array(output_data)

        cursor1.close()
        conn.close()

        return output_data
```

```
'''
Reformat data from json to csv

@author: Vera Mytilinou - Cranfield University 2018
'''
import logging
from itertools import chain
import json
import csv
from io import StringIO
import sys
from six import string_types



def remove_empty_lines(in_fnam, filename_prefix = 'cleaned', delimiter=','):
    out_fnam = filename_prefix+"_"+in_fnam
    input = open(in_fnam, 'rb')
    output = open(out_fnam, 'wb')
    writer = csv.writer(output, delimiter=delimiter)
    for row in csv.reader(input):
        if row:
            writer.writerow(row)
    input.close()
    output.close()


def json_to_csv(input_file_path, output_file_path):
    with open(input_file_path) as input_file:
        json = input_file.read()
    dicts = json_to_dicts(json)
    with open(output_file_path, "w") as output_file:
        dicts_to_csv(dicts, output_file)

    remove_empty_lines(output_file_path)
    remove_empty_lines(output_file_path, filename_prefix='xdat', delimiter=' ')

def json_to_dicts(json_str):
    try:
      objects = json.loads(json_str)
    except json.decoder.JSONDecodeError:
      objects = [json.loads(l) for l in json_str.split('\n') if l.strip()]

    return [dict(to_keyvalue_pairs(obj)) for obj in objects]

def to_keyvalue_pairs(source, ancestors=[], key_delimeter='_'):
    def is_sequence(arg):
        return (not isinstance(arg, string_types)) and (hasattr(arg, "__getitem__") or
        hasattr(arg, "__iter__"))

    def is_dict(arg):
        return isinstance(arg, dict)

    if is_dict(source):
        result = [to_keyvalue_pairs(source[key], ancestors + [key]) for key in source.keys()]
        return list(chain.from_iterable(result))
    elif is_sequence(source):
        result = [to_keyvalue_pairs(item, ancestors + [str(index)]) for (index, item) in
        enumerate(source)]
        return list(chain.from_iterable(result))
    else:
        return [(key_delimeter.join(ancestors), source)]

def dicts_to_csv(source, output_file):
    def build_row(dict_obj, keys):
        return [dict_obj.get(k, "") for k in keys]
```

```
    keys = sorted(set(chain.from_iterable([o.keys() for o in source])))
    rows = [build_row(d, keys) for d in source]

    cw = csv.writer(output_file)
    cw.writerow(keys)
    for row in rows:
        cw.writerow([c if isinstance(c, string_types) else c for c in row])

def write_csv(headers, rows, file):
    cw = csv.writer(file)
    cw.writerow(headers)
    for row in rows:
        cw.writerow([c.encode('utf-8') if isinstance(c, str) or isinstance(c, unicode) else c
         for c in row])
```

```
{
  "LifeCycleCost": {
    "cost_of_predevelopment_and_consenting": {
      "type_of_cost": "CAPEX"
    },
    "cost_of_production_and_acquisition": {
      "type_of_cost": "CAPEX"
    },
    "cost_of_installation_and_commissioning": {
      "type_of_cost": "CAPEX"
    },
    "cost_of_operation_and_maintenance": {
      "type_of_cost": "OPEX"
    },
    "cost_of_decommissioning_and_disposal": {
      "type_of_cost": "OPEX"
    }
  },
  "optimisation": {
    "decision_variables": {},
    "objectives": {},
    "constraints": {}
  },
  "MCDM": {},
  "location_porfolio": {
    "Moray_Firth_Western_Development_Area": {
      "average_water_depth[m]": 44,
      "average_wind_speed[m/s]": 8.82,
      "distance_to_shore[km]": 26,
      "area[km2]": 226,
      "max_capacity[GW]": 1.5,
      "Distance_from_the_port_[km]": 123.691,
      "average_length_of_array_cable[km]": 100
    },
    "Moray_Firth_Eastern_Development_Area_1": {
      "average_water_depth[m]": 44.5,
      "average_wind_speed[m/s]": 9.43,
      "distance_to_shore[km]": 30.8,
      "area[km2]": 295,
      "max_capacity[GW]": 1.5,
      "Distance_from_the_port_[km]": 157.134,
      "average_length_of_array_cable[km]":112

    },
    "Seagreen_Alpha": {
      "average_water_depth[m]": 50,
      "average_wind_speed[m/s]": 9.92,
      "distance_to_shore[km]": 36.8,
      "area[km2]": 197,
      "max_capacity[GW]": 3.465,
      "Distance_from_the_port_[km]": 72.598,
      "average_length_of_array_cable[km]":530
    },
    "Seagreen_Bravo": {
      "average_water_depth[m]": 50,
      "average_wind_speed[m/s]": 10.09,
      "distance_to_shore[km]": 47.3,
      "area[km2]": 194,
      "max_capacity[GW]": 3.465,
      "Distance_from_the_port_[km]": 91.193,
      "average_length_of_array_cable[km]": 207.6
    },
    "Creyke_Beck_A": {
      "average_water_depth[m]": 21.5,
      "average_wind_speed[m/s]": 10.01,
```

```
      "distance_to_shore[km]": 148.2,
      "area[km2]": 515,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 343.275,
      "average_length_of_array_cable[km]": 91.62
    },
    "Creyke_Beck_B": {
      "average_water_depth[m]": 26.5,
      "average_wind_speed[m/s]": 10.04,
      "distance_to_shore[km]": 149,
      "area[km2]": 599,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 319.949,
      "average_length_of_array_cable[km]":47.13
    },
    "Teesside_A": {
      "average_water_depth[m]": 25.5,
      "average_wind_speed[m/s]": 10.05,
      "distance_to_shore[km]": 214,
      "area[km2]": 562,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 447.124,
      "average_length_of_array_cable[km]": 154.6
    },
    "Teesside_B": {
      "average_water_depth[m]": 25.5,
      "average_wind_speed[m/s]": 10.04,
      "distance_to_shore[km]": 178.3,
      "area[km2]": 593,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 380.788,
      "average_length_of_array_cable[km]":142
    },
    "Teesside_C": {
      "average_water_depth[m]": 32,
      "average_wind_speed[m/s]": 10.05,
      "distance_to_shore[km]": 176.6,
      "area[km2]": 4,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 344.587,
      "average_length_of_array_cable[km]": 142.2
    },
    "Teesside_D": {
      "average_water_depth[m]": 35,
      "average_wind_speed[m/s]": 10.05,
      "distance_to_shore[km]": 207.8,
      "area[km2]": 4,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 405.248,
      "average_length_of_array_cable[km]": 142.2
    },
    "Tranche_D_": {
      "average_water_depth[m]": 37.5,
      "average_wind_speed[m/s]": 10.06,
      "distance_to_shore[km]": 245.5,
      "area[km2]": 5044,
      "max_capacity[GW]": 9,
      "Distance_from_the_port_[km]": 471.284,
      "average_length_of_array_cable[km]": 142.2
    },
    "Hornsea_Project_One": {
      "average_water_depth[m]": 30.5,
      "average_wind_speed[m/s]": 9.69,
      "distance_to_shore[km]": 114.5,
      "area[km2]": 407,
```

```
      "max_capacity[GW]": 4,
      "Distance_from_the_port_[km]": 242.328,
      "average_length_of_array_cable[km]": 426
    },
    "Hornsea_Project_Two": {
      "average_water_depth[m]": 31.5,
      "average_wind_speed[m/s]": 9.73,
      "distance_to_shore[km]": 107.7,
      "area[km2]": 483,
      "max_capacity[GW]": 4,
      "Distance_from_the_port_[km]": 217.27,
      "average_length_of_array_cable[km]": 51.16
    },
    "Hornsea_Project_Three": {
      "average_water_depth[m]": 49.5,
      "average_wind_speed[m/s]": 9.74,
      "distance_to_shore[km]": 132.9,
      "area[km2]": 3875,
      "max_capacity[GW]": 4,
      "Distance_from_the_port_[km]": 310.521,
      "average_length_of_array_cable[km]": 24.32
    },
    "Hornsea_Project_Four": {
      "average_water_depth[m]": 44.5,
      "average_wind_speed[m/s]": 9.71,
      "distance_to_shore[km]": 87.2,
      "area[km2]": 3874,
      "max_capacity[GW]": 4,
      "Distance_from_the_port_[km]": 173.928,
      "average_length_of_array_cable[km]": 24.32
    },
    "East_Anglia_One": {
      "average_water_depth[m]": 35.5,
      "average_wind_speed[m/s]": 9.5,
      "distance_to_shore[km]": 53.8,
      "area[km2]": 297,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 92.729,
      "average_length_of_array_cable[km]":170
    },
    "East_Anglia_One_North": {
      "average_water_depth[m]": 45.5,
      "average_wind_speed[m/s]": 9.73,
      "distance_to_shore[km]": 46.6,
      "area[km2]": 206,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 81.104,
      "average_length_of_array_cable[km]": 170
    },
    "East_Anglia_Two": {
      "average_water_depth[m]": 50,
      "average_wind_speed[m/s]": 9.46,
      "distance_to_shore[km]": 40.2,
      "area[km2]": 358,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 74.559,
      "average_length_of_array_cable[km]":353.96
    },
    "East_Anglia_Three": {
      "average_water_depth[m]": 36,
      "average_wind_speed[m/s]": 9.56,
      "distance_to_shore[km]": 74.6,
      "area[km2]": 301,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 124.969,
```

```
      "average_length_of_array_cable[km]": 63.42
    },
    "Norfolk_Boreas": {
      "average_water_depth[m]": 31.5,
      "average_wind_speed[m/s]": 9.53,
      "distance_to_shore[km]": 90.4,
      "area[km2]": 727,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 143.464,
      "average_length_of_array_cable[km]": 324
    },
    "Norfolk_Vanguard": {
      "average_water_depth[m]": 32,
      "average_wind_speed[m/s]": 9.56,
      "distance_to_shore[km]": 68.6,
      "area[km2]": 574,
      "max_capacity[GW]": 7.2,
      "Distance_from_the_port_[km]": 111.449,
      "average_length_of_array_cable[km]": 324
    },
    "Rampion_(Hastings)": {
      "average_water_depth[m]": 29,
      "average_wind_speed[m/s]": 6.43,
      "distance_to_shore[km]": 17.2,
      "area[km2]": 79,
      "max_capacity[GW]": 0.7,
      "Distance_from_the_port_[km]": 39.382
    },
    "Navitus_Bay_(_West_Isle_of_Wight)": {
      "average_water_depth[m]": 42.5,
      "average_wind_speed[m/s]": 9.32,
      "distance_to_shore[km]": 21,
      "area[km2]": 153,
      "max_capacity[GW]": 0.9,
      "Distance_from_the_port_[km]": 77.578
    },
    "Atlantic_Array_phase_one": {
      "average_water_depth[m]": 40,
      "average_wind_speed[m/s]": 9.89,
      "distance_to_shore[km]": 26.4,
      "area[km2]": 201,
      "max_capacity[GW]": 1.5,
      "Distance_from_the_port_[km]": 85.069
    },
    "Celtic_Array_North_East_Potential_Development_Area": {
      "average_water_depth[m]": 36,
      "average_wind_speed[m/s]": 9.86,
      "distance_to_shore[km]": 57.7,
      "area[km2]": 358,
      "max_capacity[GW]": 4.2,
      "Distance_from_the_port_[km]": 101.749
    },
    "Celtic_Array_South_West_Potential_Development_Area": {
      "average_water_depth[m]": 50.5,
      "average_wind_speed[m/s]": 10.15,
      "distance_to_shore[km]": 37.6,
      "area[km2]": 267,
      "max_capacity[GW]": 4.2,
      "Distance_from_the_port_[km]": 154.763
    },
    "Rhiannon_Wind_Farm": {
      "average_water_depth[m]": 51,
      "average_wind_speed[m/s]": 9.95,
      "distance_to_shore[km]": 29.7,
      "area[km2]": 497,
```

```
      "max_capacity[GW]": 4.2,
      "Distance_from_the_port_[km]": 115.542
    }
  },
  "turbine_speficiations": {
    "T10": {
      "nominal_power_rate[MW]": 10,
      "radius": 95,
      "hubHeight": 125,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 1580
    },
    "T8": {
      "nominal_power_rate[MW]": 8,
      "radius": 82,
      "hubHeight": 118,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 965
    },
    "T7": {
      "nominal_power_rate[MW]": 7,
      "radius": 85.5,
      "hubHeight": 110,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 955
    },
    "T6": {
      "nominal_power_rate[MW]": 6,
      "radius": 76,
      "hubHeight": 124,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 656
    },
    "T5": {
      "nominal_power_rate[MW]": 5,
      "radius": 63,
      "hubHeight": 90,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 707.5
    },
    "T3.6": {
      "nominal_power_rate[MW]": 3.6,
      "radius": 53.5,
      "hubHeight": 107,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 476
    },
```

```
    "T3": {
      "nominal_power_rate[MW]": 3,
      "radius": 45,
      "hubHeight": 80,
      "powerCoefficient": 0.4,
      "sweptArea": 10000,
      "object": null,
      "areaForInstalation": 1000000,
      "total_weight[tonnes]": 362.6
    }
  },
  "capacity_per_area_per_type_of_turbine_and_per_layout": {
    "Creyke_Beck_A": {
      "T6": {
        "layout1": 5241,
        "layout2": 1746,
        "layout3": 438
      },
      "T7": {
        "layout1": 4333,
        "layout2": 1449,
         "layout3": 362
      },
      "T8": {
        "layout1": 3820,
        "layout2": 1268,
        "layout3": 320
      },
      "T10": {
        "layout1": 2850,
        "layout2": 949,
         "layout3": 238
      }
    },
    "Creyke_Beck_B": {
      "T6": {
        "layout1": 6157,
        "layout2": 2059,
         "layout3": 513
      },
      "T7": {
        "layout1": 5089,
        "layout2": 1693,
         "layout3": 428
      },
      "T8": {
        "layout1": 4492,
        "layout2": 1491,
         "layout3": 378
      },
      "T10": {
        "layout1": 3345,
        "layout2": 1119,
         "layout3": 281
      }
    },
    "East_Anglia_One": {
      "T6": {
        "layout1": 1860,
        "layout2": 617,
         "layout3": 154
      },
      "T7": {
        "layout1": 1538,
        "layout2": 1538,
```

```
        "layout3": 126
      },
      "T8": {
        "layout1": 1357,
        "layout2": 452,
        "layout3": 111
      },
      "T10": {
        "layout1": 1010,
        "layout2": 340,
        "layout3": 86
      }
    },
    "East_Anglia_One_North": {
      "T6": {
        "layout1": 1894,
        "layout2": 627,
        "layout3": 157
      },
      "T7": {
        "layout1": 1562,
        "layout2": 1562,
        "layout3": 129
      },
      "T8": {
        "layout1": 1378,
        "layout2": 462,
        "layout3": 114
      },
      "T10": {
        "layout1": 1024,
        "layout2": 340,
        "layout3": 87
      }
    },
    "East_Anglia_Three": {
      "T6": {
        "layout1": 5579,
        "layout2": 1862,
        "layout3": 234
      },
      "T7": {
        "layout1": 4612,
        "layout2": 4612,
        "layout3": 197
      },
      "T8": {
        "layout1": 4068,
        "layout2": 1355,
        "layout3": 169
      },
      "T10": {
        "layout1": 3028,
        "layout2": 1014,
        "layout3": 128
      }
    },
    "East_Anglia_Two": {
      "T6": {
        "layout1": 2303,
        "layout2": 764,
        "layout3": 192
      },
      "T7": {
        "layout1": 1899,
```

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      "layout2": 633,
      "layout3": 159
    },
    "T8": {
      "layout1": 1680,
      "layout2": 558,
      "layout3": 140
    },
    "T10": {
      "layout1": 1242,
      "layout2": 416,
      "layout3": 105
    }
  },
  "Hornsea_Project_Four": {
    "T6": {
      "layout1": 8326,
      "layout2": 2777,
      "layout3": 691
    },
    "T7": {
      "layout1": 6878,
      "layout2": 2294,
      "layout3": 576
    },
    "T8": {
      "layout1": 6066,
      "layout2": 2024,
      "layout3": 502
    },
    "T10": {
      "layout1": 4520,
      "layout2": 1502,
      "layout3": 380
    }
  },
  "Hornsea_Project_One": {
    "T6": {
      "layout1": 2815,
      "layout2": 935,
      "layout3": 332
    },
    "T7": {
      "layout1": 2332,
      "layout2": 777,
      "layout3": 269
    },
    "T8": {
      "layout1": 2058,
      "layout2": 683,
      "layout3": 242
    },
    "T10": {
      "layout1": 1533,
      "layout2": 510,
      "layout3": 181
    }
  },
  "Hornsea_Project_Three": {
    "T6": {
      "layout1": 6783,
      "layout2": 2257,
      "layout3": 568
    },
    "T7": {
```

```
        "layout1": 5607,
        "layout2": 1875,
         "layout3": 468
      },
      "T8": {
        "layout1": 4946,
        "layout2": 1650,
         "layout3": 412
      },
      "T10": {
        "layout1": 3683,
        "layout2": 1226,
         "layout3": 308
      }
    },
    "Hornsea_Project_Two": {
      "T6": {
        "layout1": 5643,
        "layout2": 1881,
         "layout3": 376
      },
      "T7": {
        "layout1": 4687,
        "layout2": 1552,
         "layout3": 315
      },
      "T8": {
        "layout1": 4108,
        "layout2": 1369,
         "layout3": 276
      },
      "T10": {
        "layout1": 3058,
        "layout2": 1022,
         "layout3": 204
      }
    },
    "Moray_Firth_Eastern_Development_Area_1": {
      "T6": {
        "layout1": 3596,
        "layout2": 1197,
         "layout3": 299
      },
      "T7": {
        "layout1": 2974,
        "layout2": 988,
         "layout3": 247
      },
      "T8": {
        "layout1": 2618,
        "layout2": 876,
         "layout3": 219
      },
      "T10": {
        "layout1": 1957,
        "layout2": 652,
         "layout3": 164
      }
    },
    "Moray_Firth_Western_Development_Area": {
      "T6": {
        "layout1": 2737,
        "layout2": 914,
         "layout3": 227
      },
```

```
      "T7": {
        "layout1": 2262,
        "layout2": 758,
         "layout3": 188
      },
      "T8": {
        "layout1": 1996,
        "layout2": 665,
         "layout3": 167
      },
      "T10": {
        "layout1": 1487,
        "layout2": 492,
         "layout3": 125
      }
    },
    "Norfolk_Boreas": {
      "T6": {
        "layout1": 6799,
        "layout2": 2271,
         "layout3": 564
      },
      "T7": {
        "layout1": 5620,
        "layout2": 1878,
         "layout3": 462
      },
      "T8": {
        "layout1": 4891,
        "layout2": 1655,
         "layout3": 413
      },
      "T10": {
        "layout1": 3571,
        "layout2": 1226,
         "layout3": 308
      }
    },
    "Norfolk_Vanguard": {
      "T6": {
        "layout1": 2745,
        "layout2": 916,
         "layout3": 460
      },
      "T7": {
        "layout1": 2269,
        "layout2": 756,
         "layout3": 376
      },
      "T8": {
        "layout1": 2000,
        "layout2": 669,
         "layout3": 337
      },
      "T10": {
        "layout1": 1493,
        "layout2": 497,
         "layout3": 249
      }
    },
    "Seagreen_Alpha": {
      "T6": {
        "layout1": 2229,
        "layout2": 741,
         "layout3": 182
```

```
      },
      "T7": {
        "layout1": 1839,
        "layout2": 613,
         "layout3": 150
      },
      "T8": {
        "layout1": 1619,
        "layout2": 539,
         "layout3": 133
      },
      "T10": {
        "layout1": 1211,
        "layout2": 404,
         "layout3": 97
      }
    },
    "Seagreen_Bravo": {
      "T6": {
        "layout1": 2146,
        "layout2": 716,
         "layout3": 184
      },
      "T7": {
        "layout1": 1775,
        "layout2": 588,
         "layout3": 151
      },
      "T8": {
        "layout1": 1566,
        "layout2": 525,
         "layout3": 131
      },
      "T10": {
        "layout1": 1161,
        "layout2": 387,
         "layout3": 97
      }
    },
    "Teesside_A": {
      "T6": {
        "layout1": 5777,
        "layout2": 1926,
         "layout3": 480
      },
      "T7": {
        "layout1": 4774,
        "layout2": 1591,
         "layout3": 398
      },
      "T8": {
        "layout1": 4211,
        "layout2": 1401,
         "layout3": 349
      },
      "T10": {
        "layout1": 3137,
        "layout2": 1047,
         "layout3": 261
      }
    },
    "Teesside_B": {
      "T6": {
        "layout1": 6118,
        "layout2": 2053,
```

```
          "layout3": 521
        },
        "T7": {
          "layout1": 5051,
          "layout2": 1691,
           "layout3": 411
        },
        "T8": {
          "layout1": 4455,
          "layout2": 1483,
           "layout3": 358
        },
        "T10": {
          "layout1": 3309,
          "layout2": 1079,
           "layout3": 265
        }
      }
    }
  }
```

```
'''
Multi-Objective Optimisation

@author: Vera Mytilinou - Cranfield University 2018
'''
from platypus.core import Problem
from platypus.types import Real, Integer
from platypus.algorithms import NSGAII, NSGAIII, SPEA2

from sitesPortfolio import sitesPortfolio
import turbinePortfolio
from scenarioEvaluator import scenarioEvaluator
from solution_evaluator_by_using_LCC import solution_evaluator_by_using_LCC
from utilities import convert_all_variables_to_integers

from paretoFilter import paretoFilter, filterHistoryOf
from time import gmtime, strftime
import json
import json2csv

from utilities import create_timestamped_name
import sqlite3

from SolutionDecoderForPlatypus import convertBooleanToDecimal

turbines_helper = turbinePortfolio.turbinePortfolio()
sites_helper = sitesPortfolio()


def format_output_to_a_line(optimisation_solution):
    individual_variables_in_booleanList = optimisation_solution.variables[:]

    individual_variables = [0] * len(individual_variables_in_booleanList)

    individual_variables[0] = convertBooleanToDecimal(individual_variables_in_booleanList[0],
     0)
    individual_variables[1] = convertBooleanToDecimal(individual_variables_in_booleanList[1],
     0)
    individual_variables[2] = convertBooleanToDecimal(individual_variables_in_booleanList[2],
     50)
    individual_variables[3] = convertBooleanToDecimal(individual_variables_in_booleanList[3],
     1)

    individual_objectives = optimisation_solution.objectives[:]
    return " ".join(map(str, individual_variables + individual_objectives)) + "\n"


def decode_all_variables(all_variables):


    list_of_variables_with_converted_values = convert_all_variables_to_integers(all_variables)

    deciphered_list = 4 * [""]


    deciphered_list[0] = str(list_of_variables_with_converted_values[0])

    deciphered_list[1] = turbines_helper.getNameOfTurbineWithIndex(
    list_of_variables_with_converted_values[1])

    deciphered_list[2] = str(list_of_variables_with_converted_values[2])

    deciphered_list[3] = 'layout' + str(list_of_variables_with_converted_values[3])
```

```
    return " ".join(deciphered_list)



class FullAssemblyOfOptimisation():
    __log_file = ""
    __pareto_front_log = ""
    __database_filename = ""
    __counter = 0

    def WindFarmLifeCycleModel(self, variables):

        internal_penalty_value = 1e20

        temporary_scenario_evaluator1 = scenarioEvaluator(self.temporary_turbine_portfolio1,
                                                          self.temporary_sites_portfolio1)

        siteIndex = variables[0]
        turbineIndex = variables[1]
        number_of_turbines = variables[2]
        layout = 'layout' + str(variables[3])

        turbine = self.temporary_turbine_portfolio1.getTurbineWithIndex(turbineIndex)
        site = self.temporary_sites_portfolio1.getSiteWithIndex(siteIndex)
        case_name = "case_" + str(siteIndex) + "_" + str(turbineIndex) + "_" + str(
        number_of_turbines) + "_" + layout

        temporary_solution1 = solution_evaluator_by_using_LCC(case_name, site, turbine,
                                                              number_of_turbines=
                                                              number_of_turbines,
                                                              number_of_variables=len(
                                                              variables),
                                                              number_of_objectives=self.
                                                              number_of_objectives,
                                                              layout=layout)
        temporary_solution1.log_solution()
        temp_solution = temporary_solution1.get_solution()

        if temporary_solution1.check_against_capacity_constraints():
            temporary_solution1.set_validity(1)

            obj1 = temporary_solution1.get_P_and_A()
            obj2 = temporary_solution1.get_I_and_C()
            obj3 = temporary_solution1.get_number_of_turbines_for_minimisation()
            obj4 = temporary_solution1.get_negative_of_installed_capacity_for_minimisation()
            obj5 = temporary_solution1.get_P_and_C()
            obj6 = temporary_solution1.get_O_and_M()
            obj7 = temporary_solution1.get_negative_of_total_power_extracted_for_minimisation
            ()
            obj8 = temporary_solution1.get_D_and_D()


        else:
            temporary_solution1.set_validity(0)

            obj1 = internal_penalty_value
            obj2 = internal_penalty_value
            obj3 = internal_penalty_value
            obj4 = internal_penalty_value
            obj5 = internal_penalty_value
            obj6 = internal_penalty_value
            obj7 = internal_penalty_value
            obj8 = internal_penalty_value

        self.__all_solutions_evaluated.append(temp_solution)
```

```
        formated_solution_for_database = temporary_solution1.
        export_solution_in_tuple_format_for_database_insertion()

        self.__add_evaluated_case_into_the_history(formated_solution_for_database)

        self.__counter += 1
        print "counter:", self.__counter

        return obj1, obj2, obj3, obj4, obj5, obj6, obj7, obj8

    def reset_log_file(self):
        with open('evaluation_history.log', 'w') as logfile:
            pass

    def __initiate_database(self):
        self.__database_filename = create_timestamped_name('database_for_paper4_all_sites',
        '.db')
        self.connection_to_database = sqlite3.connect(self.__database_filename)
        self.cursor_to_database = self.connection_to_database.cursor()

        self.cursor_to_database.execute(
            '''CREATE TABLE history_of_all_solutions_evaluated_by_LCC (case_name text,
            validity integer, years_of_operation integer, number_of_turbines integer,
            turbine_name text, site_name text,
            "production_hours_of_a_single_turbine_throughout_its_lifetime" integer,
            "load_factor" real, "foundation_weight[tonnes]" real, "sum_of_all_losses" real,
            "CAPEX[M]" real, "OPEX[M]" real, "cost_of_predevelopment_and_consenting" real,
            "cost_of_production_and_acquisition" real,
            "cost_of_installation_and_commissioning" real,
            "cost_of_operation_and_maintenance" real, "cost_of_decommissioning_and_disposal"
            real, "installed_capacity[MW]" real, "nominal_installed_capacity[MW]" real,
            "power_extracted[MW]" real, "total_power_extracted[MW]" real, "layout" text)''')
        self.cursor_to_database.execute(
            '''CREATE TABLE optimum_solutions (siteName text, turbineName text,
            numberOfTurbines integer, layout text, "P&A" real, "I&C" real,
            "number_of_turbines" integer, "-installed_capacity" real, "P&C" real, "O&M"
            real, "-total_power_extracted" real, "D&D" real)''')
        self.connection_to_database.commit()

    def __add_evaluated_case_into_the_history(self, solution):


        case_name = solution[0]
        validity = solution[1]
        years_of_operation = solution[2]
        number_of_turbines = solution[3]
        turbine_name = solution[4]
        site_name = solution[5]
        production_hours_of_a_single_turbine_throughout_its_lifetime = solution[6]
        load_factor = solution[7]
        foundation_weight = solution[8]
        sum_of_all_losses = solution[9]
        CAPEX = solution[10]
        OPEX = solution[11]
        cost_of_predevelopment_and_consenting = solution[12]
        cost_of_production_and_acquisition = solution[13]
        cost_of_installation_and_commissioning = solution[14]
        cost_of_operation_and_maintenance = solution[15]
        cost_of_decommissioning_and_disposal = solution[16]
        installed_capacity = solution[17]
        nominal_installed_capacity = solution[18]
        power_extracted = solution[19]
        total_power_extracted = solution[20]
        layout = solution[21]

        sql_command = "INSERT INTO history_of_all_solutions_evaluated_by_LCC VALUES ( '" +
        case_name + "'," + str(
```

```
            validity) + "," + str(years_of_operation) + "," + str(
            number_of_turbines) + ",'" + turbine_name + "','" + site_name + "'," + str(
            production_hours_of_a_single_turbine_throughout_its_lifetime) + "," + str(
            load_factor) + "," + str(
            foundation_weight) + "," + str(sum_of_all_losses) + "," + str(CAPEX) + "," + str(
            OPEX) + "," + str(
            cost_of_predevelopment_and_consenting) + "," + str(
            cost_of_production_and_acquisition) + "," + str(
            cost_of_installation_and_commissioning) + "," + str(
            cost_of_operation_and_maintenance) + "," + str(
            cost_of_decommissioning_and_disposal) + "," + str(installed_capacity) + "," + str(
            nominal_installed_capacity) + "," + str(power_extracted) + "," + str(
            total_power_extracted) + ",'" + layout + "')"
        self.cursor_to_database.execute(sql_command)

        self.connection_to_database.commit()

    def __add_optimum_solution_into_the_repository_of_optimum_solutions(self, platypus_result
    ):

        solution = platypus_result.variables[:] + platypus_result.objectives[:]

        print 'solution', solution

        siteName = solution[0]
        turbineName = solution[1]
        numberOfTurbines = solution[2]
        layout = solution[3]
        PandA = solution[4]
        IandC = solution[5]
        number_of_turbines = solution[6]
        negative_installed_capacity = solution[7]
        PandC = solution[8]
        OandM = solution[9]
        negative_total_power_extracted = solution[10]
        DandD = solution[11]

        sql_command = "INSERT INTO optimum_solutions VALUES ( '" + siteName + "', '" +
        turbineName + "'," + str(
            numberOfTurbines) + ", '" + layout + "', " + str(PandA) + ", " + str(IandC) + ","
             + str(
            number_of_turbines) + "," + str(negative_installed_capacity) + "," + str(PandC) +
             "," + str(
            OandM) + "," + str(negative_total_power_extracted) + "," + str(DandD) + ")"
        self.cursor_to_database.execute(sql_command)

        self.connection_to_database.commit()

    def __select_all_sites_for_paper4(self):
        return sitesPortfolio(sites_to_remove=["Teesside_C", "Teesside_D", "Tranche_D_",
        "Rampion_(Hastings)",
                                               "Navitus_Bay_(_West_Isle_of_Wight)",
                                               "Atlantic_Array_phase_one",

                                               "Celtic_Array_North_East_Potential_Development_
                                               Area",

                                               "Celtic_Array_South_West_Potential_Development_
                                               Area",
                                               "Rhiannon_Wind_Farm", ])

    def __select_Moray_Firth_sites_for_paper4(self):
        standard_sites_to_remove = ["Teesside_C", "Teesside_D", "Tranche_D_",
        "Rampion_(Hastings)",
                                    "Navitus_Bay_(_West_Isle_of_Wight)",
                                    "Atlantic_Array_phase_one",
                                    "Celtic_Array_North_East_Potential_Development_Area",
```

```
                                "Celtic_Array_South_West_Potential_Development_Area",
                                "Rhiannon_Wind_Farm"]

        extra_sites_to_remove = [
            'Seagreen_Alpha',
            'Seagreen_Bravo',
            'Creyke_Beck_A',
            'Creyke_Beck_B',
            'Teesside_A',
            'Teesside_B',
            'Hornsea_Project_One',
            'Hornsea_Project_Two',
            'Hornsea_Project_Three',
            'Hornsea_Project_Four',
            'East_Anglia_One',
            'East_Anglia_One_North',
            'East_Anglia_Two',
            'East_Anglia_Three',
            'Norfolk_Boreas',
            'Norfolk_Vanguard'
        ]

        return sitesPortfolio(sites_to_remove = standard_sites_to_remove +
        extra_sites_to_remove)

    def __select_Firth_of_Forth_sites_for_paper4(self):
        standard_sites_to_remove = ["Teesside_C", "Teesside_D", "Tranche_D_",
        "Rampion_(Hastings)",
                                "Navitus_Bay_(_West_Isle_of_Wight)",
                                "Atlantic_Array_phase_one",
                                "Celtic_Array_North_East_Potential_Development_Area",
                                "Celtic_Array_South_West_Potential_Development_Area",
                                "Rhiannon_Wind_Farm"]

        extra_sites_to_remove = [
            'Moray_Firth_Western_Development_Area',
            'Moray_Firth_Eastern_Development_Area_1',
            'Creyke_Beck_A',
            'Creyke_Beck_B',
            'Teesside_A',
            'Teesside_B',
            'Hornsea_Project_One',
            'Hornsea_Project_Two',
            'Hornsea_Project_Three',
            'Hornsea_Project_Four',
            'East_Anglia_One',
            'East_Anglia_One_North',
            'East_Anglia_Two',
            'East_Anglia_Three',
            'Norfolk_Boreas',
            'Norfolk_Vanguard'
        ]

        return sitesPortfolio(sites_to_remove=standard_sites_to_remove +
        extra_sites_to_remove)

    def __select_Dogger_Bank_sites_for_paper4(self):
        standard_sites_to_remove = ["Teesside_C", "Teesside_D", "Tranche_D_",
        "Rampion_(Hastings)",
                                "Navitus_Bay_(_West_Isle_of_Wight)",
                                "Atlantic_Array_phase_one",
                                "Celtic_Array_North_East_Potential_Development_Area",
                                "Celtic_Array_South_West_Potential_Development_Area",
                                "Rhiannon_Wind_Farm"]

        extra_sites_to_remove = [
            'Moray_Firth_Western_Development_Area',
```

```
            'Moray_Firth_Eastern_Development_Area_1',
            'Seagreen_Alpha',
            'Seagreen_Bravo',
            'Hornsea_Project_One',
            'Hornsea_Project_Two',
            'Hornsea_Project_Three',
            'Hornsea_Project_Four',
            'East_Anglia_One',
            'East_Anglia_One_North',
            'East_Anglia_Two',
            'East_Anglia_Three',
            'Norfolk_Boreas',
            'Norfolk_Vanguard'
        ]

        return sitesPortfolio(sites_to_remove=standard_sites_to_remove +
        extra_sites_to_remove)

    def __select_Hornsea_sites_for_paper4(self):
        standard_sites_to_remove = ["Teesside_C", "Teesside_D", "Tranche_D_",
        "Rampion_(Hastings)",
                                    "Navitus_Bay_(_West_Isle_of_Wight)",
                                    "Atlantic_Array_phase_one",
                                    "Celtic_Array_North_East_Potential_Development_Area",
                                    "Celtic_Array_South_West_Potential_Development_Area",
                                    "Rhiannon_Wind_Farm"]

        extra_sites_to_remove = [
            'Moray_Firth_Western_Development_Area',
            'Moray_Firth_Eastern_Development_Area_1',
            'Seagreen_Alpha',
            'Seagreen_Bravo',
            'Creyke_Beck_A',
            'Creyke_Beck_B',
            'Teesside_A',
            'Teesside_B',
            'East_Anglia_One',
            'East_Anglia_One_North',
            'East_Anglia_Two',
            'East_Anglia_Three',
            'Norfolk_Boreas',
            'Norfolk_Vanguard'
        ]

        return sitesPortfolio(sites_to_remove=standard_sites_to_remove +
        extra_sites_to_remove)

    def __select_East_Anglia_sites_for_paper4(self):
            standard_sites_to_remove = ["Teesside_C", "Teesside_D", "Tranche_D_",
            "Rampion_(Hastings)",
                                        "Navitus_Bay_(_West_Isle_of_Wight)",
                                        "Atlantic_Array_phase_one",
                                        "Celtic_Array_North_East_Potential_Development_Area",
                                        "Celtic_Array_South_West_Potential_Development_Area",
                                        "Rhiannon_Wind_Farm"]

            extra_sites_to_remove = [
                'Moray_Firth_Western_Development_Area',
                'Moray_Firth_Eastern_Development_Area_1',
                'Seagreen_Alpha',
                'Seagreen_Bravo',
                'Creyke_Beck_A',
                'Creyke_Beck_B',
                'Teesside_A',
                'Teesside_B',
                'Hornsea_Project_One',
                'Hornsea_Project_Two',
```

```
                'Hornsea_Project_Three',
                'Hornsea_Project_Four'
            ]

            return sitesPortfolio(sites_to_remove=standard_sites_to_remove +
            extra_sites_to_remove)


    def __init__(self):
        self.__initiate_database()

        self.temporary_turbine_portfolio1 = turbinePortfolio.turbinePortfolio(
            turbines_to_remove=["turbine1", "turbine2", "turbine134", 'T5', 'T3'])
        self.temporary_sites_portfolio1 = self.__select_all_sites_for_paper4()

        self.reset_log_file()
        self.number_of_variables = 4
        self.number_of_objectives = 8
        self.problem = Problem(self.number_of_variables, self.number_of_objectives)
        total_number_of_areas = self.temporary_sites_portfolio1.getNumberOfSitesInThePorfolio
        ()
        total_number_of_types_of_turbines = 4
        max_number_of_turbines_allows = 8326  # for all the zones: 8326

        self.problem.types[0] = Integer(0, total_number_of_areas - 1)  # site index
        self.problem.types[1] = Integer(0, total_number_of_types_of_turbines - 1)  # turbine
        type index
        self.problem.types[2] = Integer(50, max_number_of_turbines_allows - 1)  #
        number_of_turbines
        self.problem.types[3] = Integer(1, 3)  # layout type



        self.problem.function = self.WindFarmLifeCycleModel

        self.optimisation_header = ['#siteName', 'turbineName', 'numberOfTurbines', 'layout',
         "P&A", "I&C",
                                    "number_of_turbines", "-installed_capacity", "P&C", "O&M"
                                    , "-total_power_extracted",
                                    "D&D"]

        self.__all_solutions_evaluated = []

    def export_all_solutions_to_json(self):
        export_filename = create_timestamped_name('all_solutions_for_paper4_', '.json')

        with open(export_filename, 'w') as fp:
            json.dump(self.__all_solutions_evaluated, fp, sort_keys=True, indent=4)

        json2csv.json_to_csv(export_filename, export_filename + ".csv")
        print 'All solutions in json format were saved at ' + str(export_filename)

    def __perform_final_database_operations(self):
        self.connection_to_database.commit()
        self.connection_to_database.close()

    def __finalise(self):
        print 'optimisation finished!'
        with open(self.__pareto_front_log, 'w') as outfile:

            outfile.write(" ".join(map(str, self.optimisation_header)) + "\n")
            for solution in self.algorithm.result:

                line = format_output_to_a_line(solution)
                outfile.write(line)

        filterHistoryOf('evaluation_history.log', self.__pareto_front_log +
```

```
        "_PF_with_solutions.txt",
                        self.number_of_variables, self.number_of_objectives, headers=self.
                        optimisation_header,
                        default_separator_when_reading_from_file=" ")
        self.export_all_solutions_to_json()

        self.__perform_final_database_operations()

    def optimiseWithNSGAIII(self):
        self.__pareto_front_log = "NSGAIII_PF.txt"
        self.algorithm = NSGAIII(self.problem, 12)
        self.algorithm.run(1000)

        self.__finalise()

    def optimiseWithNSGAII(self):
        self.__pareto_front_log = "NSGAII_PF.txt"
        self.algorithm = NSGAII(self.problem)
        self.algorithm.run(1000)

        self.__finalise()

    def optimiseWithSPEA2(self):
        self.__pareto_front_log = "SPEA2_PF.txt"
        self.algorithm = SPEA2(self.problem)
        self.algorithm.run(10000)

        self.__finalise()

    def run_a_single_case(self, v1=1, v2=1, v3=100, layout=1, d1=50, d2=50):
        variables = [v1, v2, v3, layout, d1, d2]

        evaluation_output = self.WindFarmLifeCycleModel(variables)
        print evaluation_output


def optimisationTrial4():
    a1 = FullAssemblyOfOptimisation()
    #     a1.optimiseWithNSGAIII()
    a1.optimiseWithNSGAII()
#     a1.optimiseWithSPEA2()

if __name__ == "__main__":
    optimisationTrial4()

    print 'optimisation successfully finished'
```

```python
'''
Filter all explored points by using pareto optimality

@author: Vera Mytilinou - Cranfield University 2018
'''
import math
from sets import Set
import csv

class paretoFilter(object):

    solutionsMatrix = None
    paretoFront = None
    numberOfVariables = None
    numberOfObjectives = None

    def __init__(self, solutionsMatrix, numberOfVariables, numberOfObjectives,
    default_separator_when_reading_from_file = ","):
        '''
            solutionsMatrix of the form
            [variable1, variable2, variable3, .... variableN, objective1, objective 2]
        '''
        self.solutionsMatrix = solutionsMatrix
        self.numberOfVariables = numberOfVariables
        self.numberOfObjectives = numberOfObjectives
        if default_separator_when_reading_from_file != ",":
            self.__default_separator_when_reading_from_file=
            default_separator_when_reading_from_file


    @staticmethod
    def objectivesVectorAdominatesObjectivesVectorB(objectivesVectorA, objectivesVectorB):
        '''
            objectivesVectorA should be a list.
            domination assumes minimisation
        '''
        nGreater = 0
        nLess = 0
        numberOfObjectives = len(objectivesVectorA)

        for i in range(numberOfObjectives):
            if objectivesVectorA[i] > objectivesVectorB[i]   :
                nGreater += 1

            if objectivesVectorA[i] < objectivesVectorB[i]  :
                nLess += 1

        if nGreater > 0 and nLess==0 :
            return -1
        else:
            if nLess > 0 and nGreater==0 :
                return 1
            else:
                return 0

    @staticmethod
    def isDifferentDecisionVector(decisionPointA, decisionPointB):
        samePoint = False
        for i in range(len(decisionPointA)):
            if isinstance(decisionPointA[i], basestring ) :
                if decisionPointA[i] is not decisionPointB[i]:
                    samePoint = True
            else:
                if math.fabs(decisionPointA[i] - decisionPointB[i]) > 1e-4:
                    samePoint = True
        return  samePoint
```

```
    def getVariablesVector(self, solution):
        return  solution[0:self.numberOfVariables]

    def getObjectivesVector(self, solution):
        return solution[self.numberOfVariables:self.numberOfVariables+self.numberOfObjectives]

    def removeDominatedPoints(self):
        container = self.solutionsMatrix

        blackListedItemsToRemove = Set([ ])
        for solution_A in container:
            for solution_B in container:
                decisionPointA= self.getVariablesVector(solution_A)
                decisionPointB= self.getVariablesVector(solution_B)
                if self.isDifferentDecisionVector(decisionPointA, decisionPointB):
                    objectivesA = self.getObjectivesVector(solution_A)
                    objectivesB = self.getObjectivesVector(solution_B)
                    if self.objectivesVectorAdominatesObjectivesVectorB(objectivesA,
                    objectivesB) == 1:
                        blackListedItemsToRemove.add( tuple(solution_B) )

        for item in blackListedItemsToRemove:
            itemInListFormat = list(item)


            if itemInListFormat in container:
                container.remove(itemInListFormat)

        self.paretoFront = container

    def printParetoFront(self):
        print 'Pareto Front:', self.paretoFront



    def saveParetoFrontToAFile(self, filename,headers=None):
        with open(filename, "wb") as outFile:
            outFile = csv.writer(outFile, delimiter=' ')

            if headers is not None:
                outFile.writerow(headers)

            for items in self.paretoFront:

                outFile.writerow(items)

        print 'Pareto Front saved on file: ' + filename



    def getParetoFront(self):
        return self.paretoFront

    def readDataFromFile(self, filenameWithData):
        with open(filenameWithData,'r') as readFile:
            next(readFile)
            array = []
            for line in readFile:
                print 'line', line
                split_line = line.split(self.__default_separator_when_reading_from_file)
                parsed_line = []
                for variable_index in range(self.numberOfVariables):

                    parsed_line.append(split_line[variable_index])
```

```
                for objective_index in range(self.numberOfVariables, self.numberOfVariables+
                self.numberOfObjectives):
                    parsed_line.append(float(split_line[objective_index]))

                array.append(parsed_line)

            self.solutionsMatrix = array
            print "So far, the following has been read:"
            print self.solutionsMatrix


def simpleExample():
    testMatrix = []
    testMatrix.append( [ 1, 2, 3, 2, 1] )
    testMatrix.append( [ 1, 5, 9, 1, 2] )
    testMatrix.append( [ 2, 5, 7, 3, 3] )
    testMatrix.append( [ 2, 8, 3, 4, 4] )

    pf1 = paretoFilter(testMatrix, 3, 2)

    pf1.removeDominatedPoints()
    pf1.printParetoFront()
    print 'all finished'

def simpleExampleReadingFromExternalFile():
    testMatrix = []
    pf1 = paretoFilter(testMatrix, 4, 2)
    pf1.readDataFromFile("report9.txt")

    pf1.removeDominatedPoints()
    pf1.printParetoFront()
    pf1.saveParetoFrontToAFile("report9_PF.txt")
    print 'all finished'

def simpleExampleReadingFromFile(input_filename, variables =4, objectives = 8):
    testMatrix = []
    pf1 = paretoFilter(testMatrix, variables, objectives)
    pf1.readDataFromFile(input_filename)

    pf1.removeDominatedPoints()

    pf1.saveParetoFrontToAFile(input_filename+"_PF.txt", headers=["site_name", "turbine_name"
    ,"layout", "number_of_turbines", "P&C", "P&A", "I&C", "O&M", "D&D",
    "-installed_capacity_MW", "-total_power_extrracted_MW"])
    print 'finished filtering file '+input_filename

def simpleExampleToFilterParetoFromHistoricLog():
    testMatrix = []
    pf1 = paretoFilter(testMatrix, 3, 6)
    pf1.readDataFromFile('evaluation_history.log')

    pf1.removeDominatedPoints()
    pf1.printParetoFront()
    pf1.saveParetoFrontToAFile("test_PF.txt")
    print 'all finished for', 'evaluation_history.log'

def insert_pareto_front_to_a_database(dabase_filename, headers):

    pass

def filterHistoryOf(history_filename, export_filename, number_of_variables,
number_of_objectives, headers, default_separator_when_reading_from_file=None):
    testMatrix = []
    if default_separator_when_reading_from_file is None:
        pf1 = paretoFilter(testMatrix, number_of_variables, number_of_objectives)
    else:
        pf1 = paretoFilter(testMatrix, number_of_variables, number_of_objectives,
```

```
        default_separator_when_reading_from_file)

    pf1.readDataFromFile(history_filename)

    pf1.removeDominatedPoints()
    pf1.printParetoFront()
    pf1.saveParetoFrontToAFile(export_filename, headers)
    print 'new Pareto was created based on', history_filename

if __name__ == "__main__":
#    simpleExampleReadingFromExternalFile()
#    simpleExampleToFilterParetoFromHistoricLog()

    simpleExampleReadingFromFile('t3.csv', variables= 3, objectives=8)
```

```
'''
Evaluate an individual scenario of an offshore wind farm by using LCC

@author: Vera Mytilinou - Cranfield University 2018
'''
import windTurbine
import turbinePortfolio
import random
from sitesPortfolio import sitesPortfolio
import math
from paretoFilter import paretoFilter
from sensitivityAnalysis import *
import json

class scenarioEvaluator(object):


    __name = None

    example_windTurbine = windTurbine.windTurbine()
    turbinePortfolio = None
    sitesPortfolio = None
    scenario_counter = 0

    simplifiedMatrixForOptimisation = []

    numberOfVariables = 3
    numberOfObjectives = 3
    headersForOptimisation = ["water_depth",
                              "wind_speed",
                              "number_of_turbines",
                              "predevelopment_and_consenting[M]",
                              "production_and_acquisition[M]",
                            "operation_and_maintenance[M]"
                              ]



    scenarioTemplate =  {
                            "turbineName":"",
                            "siteName":"",
                            "years_of_operation":1000,
                            "production_hours":100000,
                            "number_of_days":22222,
                            "load_factor":1,
                            "constant_FiT":0,
                            "wind_speed":0,
                            "income[M]":0,
                            "transmission_costs":999999,
                            "water_depth":999999,
                            "cost_of_foundation[M]":999999,
                            "power_rate[W]":999999,
                            "CAPEX[M]": 100000 ,
                            "number_of_turbines": 999999,
                            "installed_capacity[M]": 999999,

                            "predevelopment_and_consenting[M]": 999999, # (P&C)
                            "production_and_acquisition[M]": 999999, #(P&A)
                            "installation_and_commissioning[M]": 999999, #(I&C)
                            "operation_and_maintenance[M]": 999999, #(O&M)
                            "decommissioning_and_disposal[M]": 999999,  #(D&D)
                            "LCOE[M]": 999999

                            }


    report_of_calculated_scenarios = {
```

```
                                     }


    def addToCalculatedScenarios(self, completeScenario):
        self.scenario_counter += 1
        newScenarioName = "scenario_"+str(self.scenario_counter)

        self.report_of_calculated_scenarios.update({newScenarioName: completeScenario})



    def __init__(self, turbinePortfolio, sitesPortfolio, name=None):
        '''
        Constructor
        '''
        self.scenario_counter = 0
        self.turbinePortfolio = turbinePortfolio
        self.sitesPortfolio = sitesPortfolio
        if name is not None:
            self.__name = str(name)



    @staticmethod
    def calculateTurbinePower(windTurbine=example_windTurbine, windSpeed=10 , rho=1.23):
        return 0.5 * windTurbine.get_swept_area() * rho * (windSpeed ** 3) * windTurbine.
        get_power_coefficient()


    @staticmethod
    def calculateIncomeOverAPediod(turbinePower , numberOfDays=10 , FiT=13.6):
        '''
        FiT : Feed-in-Tarrif in pence per kW per hr
        '''
        return turbinePower * FiT * (numberOfDays * 24) / 10.


    def calculateIncomeOfASingleTurbineOverAPediodWithSpecificWindSpeed(self, turbine=
    "turbine1", numberOfDays=10 , FiT=13.6, windSpeed=10):
        power = self.turbinePortfolio.calculateTheTurbinePerformanceOfTurbineAtWindSpeed(
        turbine, windSpeed)

        return  power * FiT * (numberOfDays * 24) / 10.


    def calculateTransmissionCost(self, turbine="turbine1", numberOfDays=10 ,  windSpeed=10
    ):
        '''
        from table 5 from
        http://www.climatexchange.org.uk/files/4014/3325/2377/Main_Report_-_Life_Cycle_Costs_a
        nd_Carbon_Emissions_of_Offshore_Wind_Power.pdf
        '''
        average_transmission_costs = 7.5
        power = self.turbinePortfolio.calculateTheTurbinePerformanceOfTurbineAtWindSpeed(
        turbine, windSpeed)
        return  power * (numberOfDays * 24) * average_transmission_costs / 1000


    def calculateCostOfFoundation(self, turbine, water_depth, hub_height, rotor_diameter,
    windSpeed):
        part1 = 1 + 0.02 * ( water_depth - 8)
        part2 = 1 + 0.8 * 1e-6 * (hub_height * 0.25* rotor_diameter - 1e5)
        power_rate = self.turbinePortfolio.calculateTheTurbinePerformanceOfTurbineAtWindSpeed
        (turbine, windSpeed)
        cost_of_foundation = 339200 * power_rate * part1 * part2
```

```
        return cost_of_foundation


    def reportToFile(self, nameOfFile):
        with open(nameOfFile, 'w') as outFile:
            header = "No of Turbines" + "\t"
            header += "Turbine size" + "\t"
            header += "Offshore locations" + "\t"
            header += "Water depths" + "\t"
            header += "duration [days]" + "\t"
            header += "duration [hours]" + "\t"
            header += "FiTs [p/kWh]" + "\t"
            header += "FiTs [pounds/kWh]"

            outFile.write(header + "\n")


    def calculateCostOfEngineering(self):
        Cbase = 862500
        Cengliner = 529.33 * self.currentScenario["installed_capacity[M]"]
        Cengvalid = 57500
        return Cbase + Cengliner * ( self.currentScenario["installed_capacity[M]"]*1000000 -
        108) + Cengvalid


    def calculateCostOfSurveys(self):

        cost_of_environmental_survey = 8938 * self.currentScenario["installed_capacity[M]"]
        cost_of_met_ocean_survey = 4360000
        cost_of_coastal_processes_survey = 500 * self.currentScenario["installed_capacity[M]"]
        cost_of_sea_bed_survey = 19620 * self.currentScenario["installed_capacity[M]"]
        return (cost_of_environmental_survey + cost_of_met_ocean_survey +
        cost_of_coastal_processes_survey) * self.currentScenario["installed_capacity[M]"]*
        1000000 + cost_of_sea_bed_survey


    def calculatePredevelopmentAndConsenting(self):
        CprojM = 0.03 * self.currentScenario["CAPEX[M]"] * 1000000
        self.currentScenario['CprojM'] = CprojM
        Clegal = 0.0013 * self.currentScenario["CAPEX[M]"] * 1000000
        self.currentScenario['Clegal'] = Clegal
        Csurveys = self.calculateCostOfSurveys()
        self.currentScenario['Csurveys'] = Csurveys
        Ceng = self.calculateCostOfEngineering()
        self.currentScenario['Ceng'] = Ceng
        Ccontingency = 0.1 * self.currentScenario["CAPEX[M]"] * 1000000
        self.currentScenario['Ccontingency'] = Ccontingency

        cost_of_predevelopment_and_consenting = CprojM + Clegal + Csurveys + Ceng +
        Ccontingency
        return cost_of_predevelopment_and_consenting / 1000000


    def calculateInstalledCapacity(self):
        return self.currentScenario["power_rate[W]"] * self.currentScenario[
        "number_of_turbines"] / 1000000


    def calculateCostOfWTTransport(self):

        Vhr = 100000
        N_WT = self.currentScenario["number_of_turbines"]
        N_WT_per_trip = 2
        distance_manufacturing_WT = 1000.
        vessel_speed = 23

        return Vhr * (N_WT/N_WT_per_trip) * 2 * (distance_manufacturing_WT/vessel_speed)
```

```
    def calculateCostOfWindTurbine(self):

        C_of_WTsubassemblies = 3000000 * math.log(self.currentScenario["power_rate[W]"]) -
        662400
        C_of_transport = self.calculateCostOfWTTransport()
        return C_of_WTsubassemblies * self.currentScenario["number_of_turbines"] +
        C_of_transport


    def calculate_cost_of_cables(self):

        return 7490 * self.currentScenario["installed_capacity[M]"] * self.currentScenario[
        "number_of_turbines"]

    def calculate_cost_of_offsub(self):
        if self.currentScenario["installed_capacity[M]"]*1000000 < 100000000:
            return 0
        else :
            return 107900 * self.currentScenario["installed_capacity[M]"]*1000000 + 583300



    def calculateCostOfPowerTransmissionSystem(self):
        cost_of_cables = self.calculate_cost_of_cables()
        cost_of_offsub = self.calculate_cost_of_offsub()
        cost_of_onsub = cost_of_offsub * 0.5
        return cost_of_cables + cost_of_offsub + cost_of_onsub


    def calculateCostOfMonitoring(self):

        cost_of_scada = 10300 * self.currentScenario["installed_capacity[M]"]
        cost_of_CMS = 14420 * self.currentScenario["installed_capacity[M]"]
        return (cost_of_scada + cost_of_CMS) * self.currentScenario["number_of_turbines"]


    def calculateCostOfProcurementAndAcquisition(self):
        cost_of_wind_turbine = self.calculateCostOfWindTurbine()
        self.currentScenario['cost_of_wind_turbine'] = cost_of_wind_turbine
        cost_of_foundation = self.currentScenario["cost_of_foundation[M]"] * 1000000
        self.currentScenario['cost_of_foundation'] = cost_of_foundation
        cost_of_power_transmission_system = self.calculateCostOfPowerTransmissionSystem()
        self.currentScenario['cost_of_power_transmission_system'] =
        cost_of_power_transmission_system
        cost_of_monitoring = self.calculateCostOfMonitoring()
        self.currentScenario['cost_of_monitoring'] = cost_of_monitoring
        return (cost_of_wind_turbine + cost_of_foundation + cost_of_power_transmission_system
         + cost_of_monitoring) / 1000000


    def calculateCostOfInstallationAndCommissioning(self):
        self.currentScenario['C_I&C_port'] = 1
        self.currentScenario['C_I&C_comp'] = 1
        self.currentScenario['C_comm'] = 1
        self.currentScenario['C_I&C_ins'] = 1
        return self.currentScenario['C_I&C_port'] + self.currentScenario['C_I&C_comp'] + self
        .currentScenario['C_comm'] + self.currentScenario['C_I&C_ins']

    def calculateElectricityProduced(self):
        '''
        Electricity Produced in [WM]
        '''
        downtime_hours = 60 * self.currentScenario["number_of_turbines"] + 27567 * self.
        currentScenario["years_of_operation"]
        availability = (self.currentScenario["production_hours"] - downtime_hours ) / self.
        currentScenario["production_hours"]
```

```
        return self.currentScenario["number_of_turbines"] * self.currentScenario[
        "power_rate[W]"] * self.currentScenario["load_factor"] * availability * ( 1 - 0.141/
        100) / 1000000


    def calculateCostOfOperation(self):
        electricity_produced = self.calculateElectricityProduced()
        lease = 0.02
        electricity_price = 50
        cost_of_lease = lease * electricity_produced * electricity_price
        cost_of_insurance_rate_OandM = 14560
        cost_of_operation_insurance = cost_of_insurance_rate_OandM * self.currentScenario[
        "installed_capacity[M]"]
        cost_of_transmission_unit_charge = 71790 * self.currentScenario[
        "installed_capacity[M]"]
        cost_of_transmission_charges = cost_of_transmission_unit_charge * self.
        currentScenario["installed_capacity[M]"] * 1000000
        return cost_of_lease + cost_of_operation_insurance + cost_of_transmission_charges


    def calculateFixedMaintenanceCost(self):

        cost_of_port_rent_for_OandM = 561000 * self.currentScenario["years_of_operation"]
        cost_of_fixed_vessel_per_year = 2 * 1591200
        cost_of_onshore_labour_OandM = 66300 * self.currentScenario["years_of_operation"]

        cost_of_of_monitoring_CMS_and_SCADA_and_activities_coordination = 12240  * self.
        currentScenario["number_of_turbines"]

        return cost_of_port_rent_for_OandM + cost_of_fixed_vessel_per_year +
        cost_of_onshore_labour_OandM * self.currentScenario["number_of_turbines"]


    def calculateMaintenanceCostBasedOnMaintenanceActivities(self):
        '''
            i represents the nature of the maintenance, scheduled (i=1) or corrective (i=2)
            j represents the component maintained
        '''
        lamdas = [4.5, 3, 0.05]
        f = [ [1, 0.2, 0.2] , [lamdas[0], lamdas[1], lamdas[2]] ]

        C_consumables = [ [13916.5, 652.089, 215704] , [3386, 3548, 18676] ]
        C_men = [ [180, 120, 120 ], [200, 200, 200] ]
        N_men = [ [3, 3, 3] , [3, 3, 3]]
        d = [[], []]

        P_d = 0.9 / 100.0

        Ct = [ [2, 360, 400], [2, 360, 400]]

        C_transport = 2

        C_labour = [ [0, 0, 0] , [0, 0, 0]]
        for i in [0,1]:
            for j in [0,1,2]:
                C_labour[i][j] = N_men[i][j] * C_men[i][j] * ()

        cost_of_preventive_maintenance = 0
        cost_of_scheduled_maintenance = 0
        cost_of_abnormal_system_behaviour = 0
        return cost_of_abnormal_system_behaviour


    def calculateCostOfMaintenance(self):
        cost_of_fixed_maintenance = self.calculateFixedMaintenanceCost()
        cost_based_on_maintenance_activities = self.
```

```
        calculateMaintenanceCostBasedOnMaintenanceActivities()
        return cost_of_fixed_maintenance + cost_based_on_maintenance_activities


    def calculateCostOfOperationAndMaintenance(self):
        return self.calculateCostOfOperation() + self.calculateCostOfMaintenance()


    def calculateCAPEX(self):
        '''
        CAPEX[M]

        '''
        pound_over_dollar = 1.33
        return ( 5384 * pound_over_dollar  / 1000 ) * self.currentScenario[
        "installed_capacity[M]"]


    def convertDataForSimplifiedMatrix(self):
        simplifiedMatrix = []
        print self.simplifiedMatrixForOptimisation


        list_of_all_scenarios = self.report_of_calculated_scenarios.values()
        print "VALUES:", list_of_all_scenarios

        print "random1:", self.simplifiedMatrixForOptimisation[1]
        print "random4:", self.simplifiedMatrixForOptimisation[4]
        print "random14:", self.simplifiedMatrixForOptimisation[14]
        for values in list_of_all_scenarios:

            line = []
            for items in self.headersForOptimisation:
               line.append(values[items])

            simplifiedMatrix.append(line)

        print "within simplified matrix:", simplifiedMatrix
        return simplifiedMatrix


    def __generate_line_for_CAPEX_reporting(self, cost_of_category, cost_element_name,
    total_cost_of_the_element, separation_character = '\t'):

        line = str(cost_element_name)
        line += separation_character
        line += str(total_cost_of_the_element)
        line += separation_character
        line += str(total_cost_of_the_element/self.currentScenario["installed_capacity[M]"])
        line += separation_character
        line += str(total_cost_of_the_element*100.0/cost_of_category)
        line += separation_character
        line += str(total_cost_of_the_element*100.0/self.__CAPEX)
        self.__CAPEX_report.write(line+'\n')

    def exportPareFront(self):


        simplifiedSolutionsMatrix = self.simplifiedMatrixForOptimisation
        self.exportSimplifiedMatrixWithAllSolutions(simplifiedSolutionsMatrix)
        paretoFrontFilter = paretoFilter(simplifiedSolutionsMatrix, self.numberOfVariables,
        self.numberOfObjectives)
        paretoFrontFilter.removeDominatedPoints()
        paretoFront = paretoFrontFilter.getParetoFront()
        with open('ParetoFront.txt','w') as paretoFrontFile:
            fileHeader = ""
            for item in self.headersForOptimisation:
```

```
                fileHeader += item+" "
            paretoFrontFile.write(fileHeader+"\n")
            for line in paretoFront:
                paretoFrontFile.write(" ".join(map(str,line))+"\n")


    def __report_predevelopment_and_consenting_for_CAPEX(self):
        self.__CAPEX_report.write('P&C'+'\n')
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'CprojM', self.currentScenario['CprojM'] )

        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'Clegal', self.currentScenario['Clegal'] )

        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'Csurveys', self.currentScenario['Csurveys'] )

        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'Ceng', self.currentScenario['Ceng'] )

        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'Ccontingency', self.currentScenario[
        'Ccontingency'] )
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "predevelopment_and_consenting[M]"], 'C_P&C', self.currentScenario[
        "predevelopment_and_consenting[M]"] )

    def __report_PA_for_CAPEX(self):
        self.__CAPEX_report.write('P&A'+'\n')
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "production_and_acquisition[M]"], 'CWT',  self.currentScenario['cost_of_wind_turbine'
        ])
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "production_and_acquisition[M]"], 'CSS',  self.currentScenario['cost_of_foundation'])
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "production_and_acquisition[M]"], 'CPTS',  self.currentScenario[
        'cost_of_power_transmission_system'])
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "production_and_acquisition[M]"], 'Cmonitoring',  self.currentScenario[
        'cost_of_monitoring'])
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "production_and_acquisition[M]"], 'C_P&A', self.currentScenario[
        "production_and_acquisition[M]"] )



    def __report_IC_for_CAPEX(self):
        self.__CAPEX_report.write('I&C'+'\n')
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "installation_and_commissioning[M]"], 'C_I&C_port', self.currentScenario["C_I&C_port"
        ] )
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "installation_and_commissioning[M]"], 'C_I&C_comp', self.currentScenario["C_I&C_comp"
        ] )
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "installation_and_commissioning[M]"], 'C_comm', self.currentScenario["C_comm"] )
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "installation_and_commissioning[M]"], 'C_I&C_ins', self.currentScenario["C_I&C_ins"]
        )
        self.__generate_line_for_CAPEX_reporting(self.currentScenario[
        "installation_and_commissioning[M]"], 'C_I&C', self.currentScenario[
        "installation_and_commissioning[M]"] )



    def __export_CAPEX_report(self):
        separation_character  = '\t'
```

```
        self.__CAPEX_report_header = ['Cost_element','Total_Cost(x1000_GBP)',
                                      'Cost_per_MW_installed(GBP/MW)',
                                      '%Phase_Contribution',
                                      '%CAPEX_Contribution']

        self.__CAPEX = self.currentScenario["predevelopment_and_consenting[M]"] + \
                self.currentScenario["production_and_acquisition[M]"] + \
                self.currentScenario["installation_and_commissioning[M]"]

        with open(self.__name+'_CAPEX_report.txt', 'w') as self.__CAPEX_report:
            self.__CAPEX_report.write( separation_character.join(self.__CAPEX_report_header)+
            '\n')
            self.__report_predevelopment_and_consenting_for_CAPEX()
            self.__report_PA_for_CAPEX()
            self.__report_IC_for_CAPEX()
            self.__CAPEX_report.write("CAPEX"+separation_character+str(self.__CAPEX)+
            separation_character+str(self.__CAPEX/self.currentScenario[
            "installed_capacity[M]"])+'\n')




    def __export_OPEX_report(self):
        pass

    def __export_data_to_json(self):
        with open(self.__name+'_data.json', 'w') as fp:
            json.dump(self.currentScenario, fp, sort_keys=True, indent=4)

    def export_reports(self):
        self.__export_CAPEX_report()
        self.__export_OPEX_report()
        self.__export_data_to_json()

    def exportSimplifiedMatrixWithAllSolutions(self, matrix):
        print "all solutions:", matrix
        with open('simplified_matrix.txt', 'w') as simplified_matrix_file:
            simplified_matrix_file.write(" ".join(self.headersForOptimisation)+"\n")
            for line in matrix:
                simplified_matrix_file.write( " ".join(map(str,line))+"\n")

    def addScenarioToSimplifiedMatrixForOptimisation(self, line):
        self.simplifiedMatrixForOptimisation.append(line)

    def calculateCostsOnSpecificSiteByUsingASingleTurbine(self,
                                                          turbineIndex=0,
                                                          siteIndex=0,
                                                          reportName="report1.txt",
                                                          years_of_operation = 25,
                                                          number_of_scenarios_to_calculate =
                                                          1,
                                                        number_of_turbines = 50, open_mode=
                                                        'a'):
        self.currentScenario = self.scenarioTemplate


        turbineName = self.turbinePortfolio.getNameOfTurbineWithIndex(turbineIndex)
        siteName = self.sitesPortfolio.getSiteNameWithIndex(siteIndex)

        self.currentScenario["turbineName"] = turbineName
        self.currentScenario["siteName"] = siteName
        self.currentScenario["years_of_operation"] = years_of_operation
        self.currentScenario["production_hours"] = 120000
        self.currentScenario["number_of_days"] = 125 * years_of_operation
```

```
        self.currentScenario["load_factor"] = 0.38
        self.currentScenario["constant_FiT"] = 6.62
        self.currentScenario["wind_speed"] = self.sitesPortfolio.getAverageWindSpeedOfSite(
        siteName)
        self.currentScenario["water_depth"] = self.sitesPortfolio.getAverageWaterDepthOfSite(
        siteName)
        self.currentScenario["number_of_turbines"] =  number_of_turbines

        self.currentScenario["power_rate[W]"] = self.turbinePortfolio.
        calculateTheTurbinePerformanceOfTurbineAtWindSpeed(self.currentScenario["turbineName"
        ], self.currentScenario["wind_speed"])
        self.currentScenario["installed_capacity[M]"] = self.calculateInstalledCapacity()

        self.currentScenario["CAPEX[M]"] = self.calculateCAPEX()

        self.currentScenario["income[M]"] = self.
        calculateIncomeOfASingleTurbineOverAPediodWithSpecificWindSpeed(self.currentScenario[
        "turbineName"], self.currentScenario["number_of_days"], self.currentScenario[
        "constant_FiT"], self.currentScenario["wind_speed"]) / 1000000
        self.currentScenario["transmission_costs"] = self.calculateTransmissionCost(self.
        currentScenario["turbineName"], self.currentScenario["number_of_days"], self.
        currentScenario["wind_speed"])
        self.currentScenario["cost_of_foundation[M]"] = self.calculateCostOfFoundation(self.
        currentScenario["turbineName"], self.currentScenario["water_depth"], 40, 30, self.
        currentScenario["wind_speed"])/1000000


        self.currentScenario["predevelopment_and_consenting[M]"] = self.
        calculatePredevelopmentAndConsenting()
        self.currentScenario["production_and_acquisition[M]"] = self.
        calculateCostOfProcurementAndAcquisition()
        self.currentScenario["installation_and_commissioning[M]"] = 0
        self.currentScenario["operation_and_maintenance[M]"] = self.
        calculateCostOfOperationAndMaintenance()
        self.currentScenario["decommissioning_and_disposal[M]"] = 0

        with open(reportName, open_mode) as reportFile:

            data_to_save = [turbineIndex,
                            siteIndex,
                            years_of_operation,
                            number_of_turbines,
                            self.currentScenario["predevelopment_and_consenting[M]"],
                            self.currentScenario["production_and_acquisition[M]"]]
            reportFile.write(" ".join(map(str,data_to_save)) +"\n")

        return self.calculatePredevelopmentAndConsenting(), self.
        calculateCostOfProcurementAndAcquisition(), self.
        calculateCostOfOperationAndMaintenance()


    def estimateCostsOnSpecificSiteByUsingASingleTurbine(self, turbineName="turbine134",
    siteName="site23", reportName="report1.txt", years_of_operation = 25,
    number_of_scenarios_to_calculate = 1, number_of_turbines = 50, open_mode='a'):


        with open(reportName, open_mode) as reportFile:

            reportHeader = self.scenarioTemplate.keys()
            if open_mode == 'w':
                reportFile.write("senario_name "+" ".join(reportHeader) +"\n")

            self.currentScenario = self.scenarioTemplate

            self.currentScenario["turbineName"] = turbineName
            self.currentScenario["siteName"] = siteName
            self.currentScenario["years_of_operation"] = years_of_operation
```

```
self.currentScenario["production_hours"] = 120000
self.currentScenario["number_of_days"] = 125 * years_of_operation
self.currentScenario["load_factor"] = 0.38
self.currentScenario["constant_FiT"] = 6.62
self.currentScenario["wind_speed"] = self.sitesPortfolio.
getAverageWindSpeedOfSite(siteName)
self.currentScenario["water_depth"] = self.sitesPortfolio.
getAverageWaterDepthOfSite(siteName)
self.currentScenario["number_of_turbines"] =  number_of_turbines

self.currentScenario["power_rate[W]"] = self.turbinePortfolio.
calculateTheTurbinePerformanceOfTurbineAtWindSpeed(self.currentScenario[
"turbineName"], self.currentScenario["wind_speed"])
self.currentScenario["installed_capacity[M]"] = self.calculateInstalledCapacity()

self.currentScenario["CAPEX[M]"] = self.calculateCAPEX()

self.currentScenario["income[M]"] = self.
calculateIncomeOfASingleTurbineOverAPediodWithSpecificWindSpeed(self.
currentScenario["turbineName"], self.currentScenario["number_of_days"], self.
currentScenario["constant_FiT"], self.currentScenario["wind_speed"]) / 1000000
self.currentScenario["transmission_costs"] = self.calculateTransmissionCost(self.
currentScenario["turbineName"], self.currentScenario["number_of_days"], self.
currentScenario["wind_speed"])
self.currentScenario["cost_of_foundation[M]"] = self.calculateCostOfFoundation(
self.currentScenario["turbineName"], self.currentScenario["water_depth"], 40, 30,
 self.currentScenario["wind_speed"])/1000000


self.currentScenario["predevelopment_and_consenting[M]"] = self.
calculatePredevelopmentAndConsenting()
self.currentScenario["production_and_acquisition[M]"] = self.
calculateCostOfProcurementAndAcquisition()
self.currentScenario["installation_and_commissioning[M]"] = self.
calculateCostOfInstallationAndCommissioning()
self.currentScenario["operation_and_maintenance[M]"] = self.
calculateCostOfOperationAndMaintenance()
self.currentScenario["decommissioning_and_disposal[M]"] = 0


self.currentScenario["LCOE[M]"] = self.currentScenario[
"predevelopment_and_consenting[M]"]
self.currentScenario["LCOE[M]"] += self.currentScenario[
"production_and_acquisition[M]"]
self.currentScenario["LCOE[M]"] += self.currentScenario[
"installation_and_commissioning[M]"]
self.currentScenario["LCOE[M]"] += self.currentScenario[
"operation_and_maintenance[M]"]
self.currentScenario["LCOE[M]"] += self.currentScenario[
"decommissioning_and_disposal[M]"]


resultsLine = ["scenario_"+str(self.scenario_counter)]
for items in reportHeader:
    resultsLine.append( str(self.currentScenario[items]) )
text = " ".join(resultsLine) + "\n"
reportFile.write(text)

completeScenario = self.currentScenario
self.addToCalculatedScenarios(completeScenario)

lineForSimplifiedMatrixForOptimisation = []
for item in self.headersForOptimisation:
    lineForSimplifiedMatrixForOptimisation.append(self.currentScenario[item])
self.addScenarioToSimplifiedMatrixForOptimisation(
lineForSimplifiedMatrixForOptimisation)
```

```
def workingExample_with_many_runs():
    tp1 = turbinePortfolio.turbinePortfolio()
    sp1 = sitesPortfolio()

    se1 = scenarioEvaluator(tp1, sp1)
    se1.estimateCostsOnSpecificSiteByUsingASingleTurbine(turbineName="T5",  siteName="site1",
     reportName="report1.txt", years_of_operation=25, number_of_scenarios_to_calculate = 1,
    number_of_turbines = 100, open_mode='w')

    list_of_all_sites = sp1.getListOfAllRealSiteNames()
    list_of_all_turbines = tp1.getNamesOfAllRealTurbines()

    for site in list_of_all_sites:
        for turbine in list_of_all_turbines:
            for number_of_turbines in range(50,80, 5):

                se1.estimateCostsOnSpecificSiteByUsingASingleTurbine(turbineName=turbine,
                siteName=site, reportName="report1.txt", years_of_operation=25,
                number_of_scenarios_to_calculate = 1, number_of_turbines = number_of_turbines
                , open_mode='a')

    se1.exportPareFront()

def workingExample_with_a_single_run():
    tp1 = turbinePortfolio.turbinePortfolio()
    sp1 = sitesPortfolio()

    se1 = scenarioEvaluator(tp1, sp1, name='test_single_run4')
    se1.estimateCostsOnSpecificSiteByUsingASingleTurbine(turbineName="T5",  siteName="site1",
     reportName="report1.txt", years_of_operation=25, number_of_scenarios_to_calculate = 1,
    number_of_turbines = 100, open_mode='w')


    se1.exportPareFront()
    se1.export_reports()


def exampleForSensitivityAnalysis():
    tp1 = turbinePortfolio.turbinePortfolio()
    sp1 = sitesPortfolio()

    se1 = scenarioEvaluator(tp1, sp1)
    se1.estimateCostsOnSpecificSiteByUsingASingleTurbine(turbineName="T5",  siteName="site1",
     reportName="report1.txt", years_of_operation=25, number_of_scenarios_to_calculate = 1,
    number_of_turbines = 100, open_mode='w')

    list_of_all_sites = sp1.getListOfAllRealSiteNames()
    list_of_all_turbines = tp1.getNamesOfAllRealTurbines()

    samples = sample3VariablesForFirstExample()

    for sample in samples:
        site = sample[0]
        turbine = sample[1]
        number_of_turbines = sample[2]



        se1.estimateCostsOnSpecificSiteByUsingASingleTurbine(turbineName=turbine,  siteName=
        site, reportName="report1.txt", years_of_operation=25,
        number_of_scenarios_to_calculate = 1, number_of_turbines = number_of_turbines,
        open_mode='a')

    se1.exportPareFront()

if __name__ == "__main__" :
```

```
    workingExample_with_a_single_run()
    print 'successfully ended'
```

```python
'''
Sensitivity Analysis from the database

@author: Vera Mytilinou - Cranfield University 2018
'''

from SALib.sample import saltelli
from SALib.analyze import sobol
from SALib.test_functions import Ishigami
import numpy as np

from dataBrokerForSensitivityAnalysis import dataBroker


file_to_analyse = 'database_for_paper4_all_sites_20180401_130438.db'

def CAPEX_sensitivity_analysis():

  d1 = dataBroker(file_to_analyse)


  data1 = d1.getColumnAsAnArrayFromTable('CAPEX[M]',
  'history_of_all_solutions_evaluated_by_LCC')

  problem = {
    'num_vars': 4,
    'names': ['site_name', 'turbine_name', 'number_of_turbines', 'layout'],
    'bounds': [[1, 18], [1, 4], [1, 8000], [1, 3]]
  }


  Si = sobol.analyze(problem, data1, print_to_console=True)


def OPEX_sensitivity_analysis():
  d1 = dataBroker(file_to_analyse)



  data1 = d1.getColumnAsAnArrayFromTable('OPEX[M]',
  'history_of_all_solutions_evaluated_by_LCC')

  problem = {
    'num_vars': 4,
    'names': ['site_name', 'turbine_name', 'number_of_turbines', 'layout'],
    'bounds': [[1, 18], [1, 4], [1, 8000], [1, 3]]
  }


  Si = sobol.analyze(problem, data1, print_to_console=True)

print('CAPEX:')
CAPEX_sensitivity_analysis()
print('OPEX:')
OPEX_sensitivity_analysis()
```

```
'''
Sensitivity Analysis and utilities

@author: Vera Mytilinou - Cranfield University 2018
'''
import pynolh
from matplotlib.mlab import PCA
import numpy
import numpy as np



def performOrthogonalLatinHypercube():
    dim = 6
    m, q, r = pynolh.params(dim)
    conf = range(q)
    remove = range(dim - r, dim)
    nolh = pynolh.nolh(conf, remove)
    print nolh

def performLatinHypercube(numberOfDimensions = 1, numberOfSamples = 1):

    import pyDOE
    samplePlan = pyDOE.lhs(numberOfDimensions, samples=numberOfSamples, criterion='center')
    print samplePlan
    return samplePlan

def performPrincipalComponentAnalysis():
    data = numpy.array(numpy.random.randint(10,size=(10,3)))
    results = PCA(data)
    print results.fracs

def doExampleOfSensitivityAnalysis():
    performOrthogonalLatinHypercube()
    performPrincipalComponentAnalysis()

def doOrthogonalLatinHypercubeFromPyKriging():
    import pyKriging
    from pyKriging.krige import kriging
    from pyKriging.samplingplan import samplingplan


    sp = samplingplan(3)
    X = sp.optimallhc(20)

    print X





def sample3VariablesForFirstExample():
    import pyKriging
    from pyKriging.krige import kriging
    from pyKriging.samplingplan import samplingplan
    import numpy as np

    def rescale(min, max, b, a, x):
        '''
        scale a range [min,max] to [a,b]
        So, for x tha belongs to [min,max], the rescaled value is:
                 (b-a)(x - min)
         f(x) = --------------  + a
                   max - min
        '''
        return (b-a)*(x - min) / ( max - min ) + a
```

```
    def rescaleAllPointsIn(X):
        number_of_sites = 19
        number_of_turbine_types = 6
        for i in range(X.shape[0]):
            X[i][0] = np.round( rescale(0.0, 1.0, 0, number_of_sites-1, X[i][0]) )
            X[i][1] = np.round( rescale(0.0, 1.0, 0, number_of_turbine_types-1, X[i][1]) )
            X[i][2] = np.round( rescale(0.0, 1.0, 50, 500, X[i][2]) )

        return X

    sp = samplingplan(3)
    X = sp.optimallhc(50)



    X = rescaleAllPointsIn(X)


    return X
```

```
'''
Compile a portfolio of sites with utility functions to query the dataset

@author: Vera Mytilinou - Cranfield University 2018
'''

from jsmin import jsmin
import json
from utilities import get_location_from_available_portfolio

class sitesPortfolio(object):
    '''
    classdocs
    '''

    'in [W]'
    ___round3_total_capacity = 3e6

    __specs_of_all_sites = {
                                        "Moray_Firth_Western_Development_Area":{"average_water_depth":44,
                                        "average_wind_speed":8.82,"distance_to_shore":26,"area":226,
                                        "max_capacity":1.3},
                                        "Moray_Firth_Eastern_Development_Area_1":{"average_water_depth":
                                        44.5,"average_wind_speed":9.43,"distance_to_shore":30.8,"area":
                                        295,"max_capacity":1.3},
                                        "Moray_Firth_Eastern_Development_Area_2":{"average_water_depth":
                                        45.5,"average_wind_speed":9.44,"distance_to_shore":30.8,"area":
                                        295,"max_capacity":1.3},
                                        "Seagreen_Alpha":{"average_water_depth":50,"average_wind_speed":
                                        9.92,"distance_to_shore":36.8,"area":197,"max_capacity":3.5},
                                        "Seagreen_Bravo":{"average_water_depth":50,"average_wind_speed":
                                        10.09,"distance_to_shore":47.3,"area":194,"max_capacity":3.5},
                                        "Creyke_Beck_A":{"average_water_depth":21.5,"average_wind_speed":
                                        10.01,"distance_to_shore":148.2,"area":515,"max_capacity":9},
                                        "Creyke_Beck_B":{"average_water_depth":26.5,"average_wind_speed":
                                        10.04,"distance_to_shore":149,"area":599,"max_capacity":9},
                                        "Teesside_A":{"average_water_depth":25.5,"average_wind_speed":
                                        10.05,"distance_to_shore":214,"area":562,"max_capacity":9},
                                        "Teesside_B":{"average_water_depth":25.5,"average_wind_speed":
                                        10.04,"distance_to_shore":178.3,"area":593,"max_capacity":9},
                                        "Teesside_C":{"average_water_depth":32,"average_wind_speed":10.05
                                        ,"distance_to_shore":176.6,"area":4,"max_capacity":9},
                                        "Teesside_D":{"average_water_depth":35,"average_wind_speed":10.05
                                        ,"distance_to_shore":207.8,"area":4,"max_capacity":9},
                                        "Tranche_D_":{"average_water_depth":37.5,"average_wind_speed":
                                        10.06,"distance_to_shore":245.5,"area":5044,"max_capacity":9},
                                        "Hornsea_Project_1":{"average_water_depth":30.5,
                                        "average_wind_speed":9.69,"distance_to_shore":114.5,"area":407,
                                        "max_capacity":4},
                                        "Hornsea_Project_2":{"average_water_depth":31.5,
                                        "average_wind_speed":9.73,"distance_to_shore":107.7,"area":483,
                                        "max_capacity":4},
                                        "Hornsea_Project_3":{"average_water_depth":49.5,
                                        "average_wind_speed":9.74,"distance_to_shore":132.9,"area":3875,
                                        "max_capacity":4},
                                        "Hornsea_Project_4":{"average_water_depth":44.5,
                                        "average_wind_speed":9.71,"distance_to_shore":87.2,"area":3874,
                                        "max_capacity":4},
                                        "East_Anglia_One":{"average_water_depth":35.5,
                                        "average_wind_speed":9.5,"distance_to_shore":53.8,"area":297,
                                        "max_capacity":7.2},
                                        "East_Anglia_One_North":{"average_water_depth":45.5,
                                        "average_wind_speed":9.73,"distance_to_shore":46.6,"area":206,
                                        "max_capacity":7.2},
                                        "East_Anglia_Two":{"average_water_depth":50,"average_wind_speed":
                                        9.46,"distance_to_shore":40.2,"area":358,"max_capacity":7.2},
```

```
                            "East_Anglia_Three":{"average_water_depth":36,
                            "average_wind_speed":9.56,"distance_to_shore":74.6,"area":301,
                            "max_capacity":7.2}

                           }


    def __read_from_external_file(self, filename_of_the_external_configuration):
        with open(filename_of_the_external_configuration) as _externalJSON:
            config = jsmin(_externalJSON.read());

        validJSON = json.loads(config)
        return validJSON["location_porfolio"]


    def __init__(self, external_portfolio='modelling.json', sites_to_remove=None):
        '''
        Constructor
        '''
        if external_portfolio is not None:
            self.__specs_of_all_sites = self.__read_from_external_file(external_portfolio)

        if sites_to_remove!=None:
            for element in sites_to_remove:
                if element in self.__specs_of_all_sites:
                    del self.__specs_of_all_sites[element]

    def getNumberOfSitesInThePorfolio(self):

        return len(self.__specs_of_all_sites)

    def getSiteNameWithIndex(self, index):
        try:
            return self.__specs_of_all_sites.keys()[index]

        except IndexError as e:
            print e, "site index to try:", index

    def getSiteWithIndex(self, index):
        siteName = self.getSiteNameWithIndex(index)
        return get_location_from_available_portfolio(siteName)

    def getSiteByName(self, siteName):
        return get_location_from_available_portfolio(siteName)


    def getAverageWaterDepthOfSite(self, siteOfInterest):
        return self.__specs_of_all_sites[siteOfInterest]["average_water_depth"]


    def getAverageWindSpeedOfSite(self, siteOfInterest):
        return self.__specs_of_all_sites[siteOfInterest]["average_wind_speed"]


    def getDistanceToShoreOfSite(self, siteOfInterest):
        return self.__specs_of_all_sites[siteOfInterest]["distance_to_shore"]


    def getDistanceToClosestPortOfSite(self, siteOfInterest):
        return self.__specs_of_all_sites[siteOfInterest]["distance_to_closest_port"]


    def getMaxCapacityOfSite(self, siteOfInterest):
        return self.__specs_of_all_sites[siteOfInterest]["max_capacity"]


    def getCurrentCapacityOfSite(self, siteOfInterest):
```

```
        return self.__specs_of_all_sites[siteOfInterest]["current_capacity"]

    def getListOfAllRealSiteNames(self):
        temp_dict = self.__specs_of_all_sites.keys()
        temp_dict.remove('site1')
        temp_dict.remove('site23')
        temp_dict.remove('site57')
        return temp_dict

    def getSiteSpecificationBySiteName(self,siteName):

        return self.__specs_of_all_sites[siteName]
```

```
'''
Prototype wind farm deployment model based on LCC and geo-spatial modelling

@author: Vera Mytilinou - Cranfield University 2018
'''

import math
import json
from jsmin import jsmin
from utilities import get_turbine_from_available_portfolio,
get_location_from_available_portfolio, get_test_turbine_for_the_development_of_models
from capacity_settings_reader import capacity_constraint
from CablingLayoutGenerator import calculate_the_length_of_cables_for_windfarm_of,
CablingLayoutGenerator


class solution_evaluator_by_using_LCC(object):
    __name = None
    __location = None
    __turbine_specifications = None
    __years_of_operation = None
    __number_of_turbines = None
    __solution = None
    __pi = 3.1415
    __rho = 1.23
    __number_of_variables = 3
    __number_of_objectives = 7
    __layout = 'layout1'
    __distance_to_scrap_centre_in_km = 50
    __distance_to_landfill_in_km = 50

    def __load_solution_template_to_an_internal_solution(self):
        with open('solution_template.json', 'r') as fp:
            temp = jsmin(fp.read());

            self.__solution = json.loads(temp)


    def __calculate_power_extracted(self):
        power_coefficient = self.__solution["independent"]["turbine"]["powerCoefficient"]
        windSpeed = self.__solution["independent"]["site_specifications"][
        "average_wind_speed[m/s]"]
        power_extracted = 0.5 * self.__rho * self.__solution["independent"]["turbine"][
        "sweptArea"] * power_coefficient * (windSpeed ** 3)
        return power_extracted/1000000.0

    def __calculate_installed_capacity(self):
        return self.__solution["independent"]["number_of_turbines"] * self.__solution[
        "dependent"]["power_rate[MW]"]

    def __calculate_cost_of_surveys(self):
        installed_capacity = self.__solution["dependent"]["nominal_installed_capacity[MW]"]
        cost_of_environmental_survey = self.__solution["dependent"][
        "cost_of_predevelopment_and_consenting"]["inputs_for_baseline_OWF_Model"][
        "Csurveyeia[GBP/MW]"]
        cost_of_coastal_processes_survey = self.__solution["dependent"][
        "cost_of_predevelopment_and_consenting"]["inputs_for_baseline_OWF_Model"][
        "Csurveycp[GBP/MW]"]
        cost_of_sea_bed_survey = self.__solution["dependent"][
        "cost_of_predevelopment_and_consenting"]["inputs_for_baseline_OWF_Model"][
        "Csurveysb[GBP/MW]"]
        cost_of_met_ocean_survey = self.__solution["dependent"][
        "cost_of_predevelopment_and_consenting"]["inputs_for_baseline_OWF_Model"][
        "Csurveymet[GBP]"]

        result = (cost_of_environmental_survey + cost_of_coastal_processes_survey +
        cost_of_sea_bed_survey) * installed_capacity + cost_of_met_ocean_survey
```

```
        self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["Csurveys"] =
        result
        return result

    def __calculate_cost_of_engineering(self):
        installed_capacity = self.__solution["dependent"]["nominal_installed_capacity[MW]"]
        Cbase = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "inputs_for_baseline_OWF_Model"]["Cbase[GBP]"]
        Cengliner = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "inputs_for_baseline_OWF_Model"]["Ceng[GBP/MW]"] * installed_capacity
        Cengvalid = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "inputs_for_baseline_OWF_Model"]["Cengvalid[GBP]"]
        result =  Cbase + Cengliner + Cengvalid
        self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["Ceng"] = result
        return result

    def
    __calculate_intermediate_cost_of_predevelopment_and_consenting_to_find_the_temporary_CAPEX
    (self):
        self.__calculate_cost_of_surveys()
        self.__calculate_cost_of_engineering()

    def __calculate_temporary_CAPEX(self):
        Csurveys = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "Csurveys"]
        Ceng = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["Ceng"]
        temporaty_CAPEX = Csurveys + Ceng
        temporaty_CAPEX += self.__solution["dependent"]["cost_of_production_and_acquisition"
        ]["value"]
        temporaty_CAPEX += self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["value"]
        self.__solution["dependent"]["temporary_CAPEX[GBP]"] = temporaty_CAPEX

    def __calculate_cost_of_predevelopment_and_consenting(self):
        self.
        __calculate_intermediate_cost_of_predevelopment_and_consenting_to_find_the_temporary_C
        APEX()
        self.__calculate_temporary_CAPEX()

        Csurveys = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "Csurveys"]
        Ceng = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["Ceng"]
        CprojM = 0.03 * self.__solution["dependent"]["temporary_CAPEX[GBP]"]
        self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["CprojM"] =
        CprojM
        Clegal = 0.0013 * self.__solution["dependent"]["temporary_CAPEX[GBP]"]
        self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["Clegal"] =
        Clegal
        Ccontingency = 0.1 * self.__solution["dependent"]["temporary_CAPEX[GBP]"]

        result = CprojM + Clegal + Csurveys + Ceng + Ccontingency
        self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["value"] =
        result

    def __calculate_port_related_costs(self, duration_of_task_in_days):

        specific_values = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"]
        result = specific_values["C_port_rate_I&C[GBP]"]
        C_port_labour = specific_values["N_onsh[Men]"] * specific_values["C_onsh_MH[GBP/day]"
        ] *  duration_of_task_in_days
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["intermediate"
        ]["C_port_labour[GBP]"] = C_port_labour
        result += C_port_labour
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["C_I&C_port"]
        = result
        return result
```

```
    def __calculate_insurance_package(self):
        result = self.__solution["dependent"]["cost_of_installation_and_commissioning"][
        "inputs_for_baseline_OWF_Model"]["C_insu_rate_I&C[GBP/MW]"] * self.__solution[
        "dependent"]["nominal_installed_capacity[MW]"]
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["C_I&C_ins"] =
         result
        return result

    def __calculate_cost_of_commissioning(self):


        daily_hiring_rate = 0
        fuel_consumption_for_each_vessel_per_hour = 0
        mobilisation_and_demobilisation_cost = 0
        time_for_the_activity_as_a_function_of_the_wind_turbine_and_cable = 0
        number_of_vessels = 0


        number_of_workers = 0
        salary_of_workers = 0
        total_instalation_and_commissioning_time = 0

        cost_of_vessel = 0
        cost_of_labour = 0
        cost_of_commissiong = cost_of_vessel + cost_of_labour

        result = self.__solution["dependent"]["cost_of_installation_and_commissioning"][
        "intermediate"]["C_port_labour[GBP]"] + self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["intermediate"][
        "transportation_cost_of_WT[GBP]"]
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["C_comm"] =
        result



        return result

    def
    __calculate_cost_of_installations_of_compomnents_related_to_foundation_and_WT_and_offshore
    _electrical_systems(self):


        types_of_vessel_required_for_installation_of_compomnents_related_to_foundation_and_WT_
        and_offshore_electrical_systems = ["V_hr_AHL[GBP/day]",
                           "V_hr_BA[GBP/day]",
                           "V_hr_CL[GBP/day]",
                           "V_hr_CT[GBP/day]",
                           "V_hr_DP[GBP/day]",
                           "V_hr_JU[GBP/day]",
                           "V_hr_SV[GBP/day]",
                           "V_hr_TV[GBP/day]",
                           "V_hr_T[GBP/day]"]
        result = 0
        duration_in_days = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "T_I&C[years]"] * 365
        off_shore_labour_cost = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "C_off_man[GBP/day]"] * duration_in_days
        for vessel in
        types_of_vessel_required_for_installation_of_compomnents_related_to_foundation_and_WT_
        and_offshore_electrical_systems:
            vessel_rate = self.__solution["dependent"][
            "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][vessel]
            cost_of_vessel = vessel_rate * duration_in_days + self.__solution["dependent"][
            "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
```

```
            "Mob/Demob[GBP]"]
            result += cost_of_vessel + off_shore_labour_cost

        vessel_rate_for_HL = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "V_hr_HL[GBP/day]"]
        cost_of_vessel = vessel_rate_for_HL * duration_in_days + self.__solution["dependent"
        ]["cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "Mob/Demob_HL[GBP]"]
        result += cost_of_vessel + off_shore_labour_cost

        return result

    def
    __calculate_cost_of_installations_of_compomnents_related_to_onshore_electrical_systems(
    self):

        days_to_construct_the_grid = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "T_I&C[years]"] * 365
        C_on_cable = self.__solution["dependent"]["cost_of_installation_and_commissioning"][
        "inputs_for_baseline_OWF_Model"]["C_on_cable_truck[GBP/day]"] *
        days_to_construct_the_grid
        result = C_on_cable + self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "C_on_subs[GBP]"]
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["intermediate"
        ]["C_ones"] = result
        return result

    def __calculate_cost_of_installation_of_components(self):

        result = self.
        __calculate_cost_of_installations_of_compomnents_related_to_foundation_and_WT_and_offs
        hore_electrical_systems()
        result += self.
        __calculate_cost_of_installations_of_compomnents_related_to_onshore_electrical_systems
        ()
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["C_I&C_comp"]
        = result
        return  result


    def __calculate_cost_of_WT_transport(self):

        Vhr = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["Vhr[GBP/day]"]
        N_WT = self.__solution["independent"]["number_of_turbines"]
        N_WT_per_trip = 0.9 * self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["inputs_for_baseline_OWF_Model"][
        "VCapacity[tons]"] /  self.__solution["independent"]["turbine"][
        "total_weight[tonnes]"]


        distance_manufacturing_WT = self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["inputs_for_baseline_OWF_Model"][
        "dist.manufWT[Km]"] + self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["inputs_for_baseline_OWF_Model"][
        "dist.manufF[km]"]
        vessel_speed = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["vessel_speed[knot]"]
        result = Vhr * (N_WT/N_WT_per_trip) * 2 * (distance_manufacturing_WT/vessel_speed)
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "transportation_cost_of_WT[GBP]"] = result
        return result
```

```
    def __calculate_cost_of_wind_turbine(self):

        C_of_WTsubassemblies = 3000000 * math.log(self.__solution["dependent"][
        "power_rate[MW]"]) - 662400
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "C_of_WTsubassemblies[GBP]"] = C_of_WTsubassemblies

        C_of_transport = self.__calculate_cost_of_WT_transport()
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "C_of_transport[GBP]"] = C_of_transport
        result = C_of_WTsubassemblies * self.__solution["independent"]["number_of_turbines"]
        + C_of_transport
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "C_WT[GBP]"] = result
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["CWT"] = result


    def __calculate_cost_of_material_transportation_for_foundation(self):

        Vhr = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["Vhr[GBP/day]"]
        N_WT = self.__solution["independent"]["number_of_turbines"]
        foundation_weight_in_tonnes = self.__solution["independent"][
        "foundation_weight[tonnes]"]
        N_of_foundations_per_trip = 0.9 * self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["inputs_for_baseline_OWF_Model"][
        "VCapacity[tons]"] /  foundation_weight_in_tonnes
        distance_manufacturing_F = self.__solution["independent"]["site_specifications"][
        "Distance_from_the_port_[km]"]
        vessel_speed = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["vessel_speed[knot]"]
        result = Vhr * (N_WT/N_of_foundations_per_trip) * 2 * (distance_manufacturing_F/
        vessel_speed)
        return result

    def __calculate_cost_of_foundation(self):

        power_rate = self.__solution["dependent"]["power_rate[MW]"]
        hub_height = self.__solution["independent"]["turbine"]["hubHeight"]
        rotor_diameter = 2 * self.__solution["independent"]["turbine"]["radius"]
        water_depth = self.__solution["independent"]["site_specifications"][
        "average_water_depth[m]"]
        cost_of_material_for_foundation = 339200 * power_rate * (1 + 0.02*(water_depth - 8
        ))*(1+0.8 * (hub_height *(rotor_diameter*rotor_diameter)/4 - 100000) / 1000000)

        cost_of_material_transportation = self.
        __calculate_cost_of_material_transportation_for_foundation()
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["CSS"] = (
        cost_of_material_for_foundation + cost_of_material_transportation) * self.__solution[
        "independent"]["number_of_turbines"]

    def __calculate_cost_of_cables(self):

        total_length_of_cables = self.__solution["dependent"][
        "total_length_of_array_cables[km]"]
        number_of_lines = 2

        number_of_turbines = self.__solution["independent"]["number_of_turbines"]
        cost_of_cable_protection = number_of_turbines * self.__solution["dependent"][
        "cost_of_production_and_acquisition"]["inputs_for_baseline_OWF_Model"][
        "Cprotect[GBP/WT]"]

        result = 3* cost_of_cable_protection
        result += self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["Ccableunitarray[GBP/m]"] * \
        total_length_of_cables * \
        number_of_lines
```

```
        result += self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["Ccableunitexport[GBP/m]"] * \
        self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["L2[Km]"] * \
        number_of_lines

        result += self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["Ccableunitons[GBP/m]"] * \
        self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["L3[Km]"] * \
        number_of_lines

        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "C_of_cables"] = result

        return result

    def __calculate_cost_of_offshore_substations(self):
        installed_capacity = self.__solution["dependent"]["nominal_installed_capacity[MW]"]
        result = 0
        if installed_capacity < 100:
            result = 0
        else:
            result = 583300 + 107900 * installed_capacity

        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "cost_of_offshore_substation[GBP]"] = result

        return result

    def __calculate_cost_of_power_transmission_system(self):


        cost_of_cables = self.__calculate_cost_of_cables()
        cost_of_offshore_substations = self.__calculate_cost_of_offshore_substations()
        cost_of_onshore_substations = cost_of_offshore_substations/2
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["intermediate"][
        "cost_of_onshore_substation[GBP]"] = cost_of_onshore_substations
        result = cost_of_cables + cost_of_offshore_substations + cost_of_onshore_substations
        self.__solution["dependent"]["cost_of_production_and_acquisition"]["CPTS"] = result

    def __calculate_cost_of_monitoring(self):
        number_of_turbines = self.__solution["independent"]["number_of_turbines"]
        C_SCADA = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["C_SCADA[GBP/WT]"]
        C_CMS = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "inputs_for_baseline_OWF_Model"]["C_CMS[GBP/WT]"]

        self.__solution["dependent"]["cost_of_production_and_acquisition"]["Cmonitoring"] =
        number_of_turbines * (C_SCADA + C_CMS)


    def __calculate_cost_of_production_and_acquisition(self):
        self.__calculate_cost_of_wind_turbine()


        self.__calculate_cost_of_foundation()


        self.__calculate_cost_of_power_transmission_system()

        self.__calculate_cost_of_monitoring()

        self.__solution["dependent"]["cost_of_production_and_acquisition"]["value"] =  self.
        __solution["dependent"]["cost_of_production_and_acquisition"]["Cmonitoring"] + \
            self.__solution["dependent"]["cost_of_production_and_acquisition"]["CPTS"] + \
```

```
            self.__solution["dependent"]["cost_of_production_and_acquisition"]["CWT"] + \
            self.__solution["dependent"]["cost_of_production_and_acquisition"]["CSS"]

    def __calculate_cost_of_installation_and_commissioning(self):
        result = 0
        duration_of_installation_and_commissioning_in_years = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "T_I&C[years]"]
        result += self.__calculate_port_related_costs(365 *
        duration_of_installation_and_commissioning_in_years)
        result += self.__calculate_insurance_package()
        result += self.__calculate_cost_of_commissioning()
        result += self.__calculate_cost_of_installation_of_components()
        self.__solution["dependent"]["cost_of_installation_and_commissioning"]["value"] =
        result

    def __calculate_CAPEX(self):

        CAPEX = self.__solution["dependent"]["cost_of_production_and_acquisition"]["value"]
        CAPEX += self.__solution["dependent"]["cost_of_installation_and_commissioning"][
        "value"]
        CAPEX += self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "value"]
        self.__solution["dependent"]["CAPEX[M]"] = CAPEX / 1000000

    def getCAPEX_in_Millions(self):
        return self.__solution["dependent"]["CAPEX[M]"]

    def getCAPEX(self):
        return self.__solution["dependent"]["CAPEX[M]"] * 1000000

    def __calculate_OPEX(self):
        self.__solution["dependent"]["OPEX[M]"] = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["value"] / 1000000

    def getOPEX_in_Millions(self):
        return self.__solution["dependent"]["OPEX[M]"]

    def getOPEX(self):
        return self.__solution["dependent"]["OPEX[M]"] * 1000000

    def __calculate_DECOMMISSIONING_and_DISPOSAL(self):
        self.__solution["dependent"]["DECOMMISSIONING_AND_DISPOSAL[M]"] =  self.__solution[
        "dependent"]["cost_of_decommissioning_and_disposal"]["value"] / 1000000


    def __calculate_electricity_produced(self):

        number_of_turbines = self.__solution["independent"]["number_of_turbines"]
        years_in_operation = self.__solution["independent"]["years_of_operation"]

        preventive_downtime = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "preventive_downtime[hr/turbine]"]
        corrective_downtime = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "corrective_downtime[hr/year]"]

        downtime_hours = preventive_downtime * number_of_turbines + corrective_downtime *
        years_in_operation
        total_production_hours =  self.__solution["dependent"][
        "production_hours_for_all_turbines_throughout_the_lifetime_of_the_farm"]

        availability = 1.0 * (total_production_hours - downtime_hours ) /
        total_production_hours
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "availability_throught_the_tenure"] = availability
```

```
        power_rate = self.__solution["independent"]["turbine"]["nominal_power_rate[MW]"]
        load_factor = self.__solution["independent"]["load_factor"]
        sum_of_all_losses = self.__solution["independent"]["sum_of_all_losses"]

        result =  number_of_turbines * power_rate * load_factor * availability * ( 1.0 -
        sum_of_all_losses)
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "electricity_produced_throught_the_tenure[MW]"] = result
        return result

    def __calculate_cost_of_lease(self):
        lease = self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "inputs_for_baseline_OWF_Model"]["%lease"]
        electricity_produced = self.__calculate_electricity_produced()

        electricity_price = self.__solution["dependent"]["cost_of_operation_and_maintenance"
        ]["inputs_for_baseline_OWF_Model"]["P_elect[GBP/MWhr]"]

        cost_of_rent = lease * electricity_produced * electricity_price
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "C_rent[GBP]"] = cost_of_rent
        return cost_of_rent


    def __calculate_cost_of_operation(self):
        cost_of_lease =  self.__calculate_cost_of_lease()
        cost_of_operation_insurance = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "C_insu_rate_O_and_M[GBP/MW]"] * self.__solution["dependent"][
        "nominal_installed_capacity[MW]"]
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "C_O_and_M_insurrance[GBP]"] = cost_of_operation_insurance
        cost_of_transmission_charges = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "C_trans[GBP/MW]"] * self.__solution["dependent"]["nominal_installed_capacity[MW]"]
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "C_transmission_charges[GBP]"] = cost_of_transmission_charges
        result = cost_of_lease + cost_of_operation_insurance + cost_of_transmission_charges
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["C_O"] = result
        return result

    def __calculate_cost_of_indirect_maintenance(self):

        C_port_O_and_M = self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "inputs_for_baseline_OWF_Model"]["C_port_O_and_M[GBP/year]"] * self.__solution[
        "independent"]["years_of_operation"]
        number_of_vessels = 2
        C_fixed_vessels = number_of_vessels * self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "C_fix_vessels[GBP/vessel]"]
        C_onshore_labour_O_and_M = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "C_onshore_labour_O_and_M[GBP/turbine]"] * self.__solution["independent"][
        "number_of_turbines"]
        cost_of_weather_forecasting = self.__solution["dependent"][
        "cost_of_operation_and_maintenance"]["inputs_for_baseline_OWF_Model"][
        "cost_of_weather_forecasting[GBP/year]"] * self.__solution["independent"][
        "years_of_operation"]
        indirect_maintenance = C_port_O_and_M + C_fixed_vessels + C_onshore_labour_O_and_M *
        self.__solution["independent"]["number_of_turbines"] + cost_of_weather_forecasting

        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "C_indirect_maintenance[GBP]"] = indirect_maintenance

    def __calculate_cost_of_direct_maintenance(self):
        '''
```

```
        i represents the nature of maintenance (0 for scheduled, 1 for corrective)
        j represents the component
        '''

        distance_travelled_during_maintenance = self.__solution["independent"][
        "site_specifications"]["Distance_from_the_port_[km]"]
        P_d = self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "inputs_for_baseline_OWF_Model"]["P_d"]

        labour_daily_rate = [ [180, 120, 120], [200, 200, 200] ]
        N_men = [ 3, 3, 3]
        C_consumables = [ [13916.5, 652089, 215704 ], [3386, 3548, 18676] ]
        f = [ [1, 0.2, 0.2] , [4.5, 3, 0.05] ]
        cost_of_transportation = [360, 400] #first for i=1 and second for i=2

        C_labour = [ [0,0,0], [0,0,0] ]
        C_transport = [ [0,0,0], [0,0,0] ]

        C_SM = [0,0,0]
        C_CM = [0,0,0]


        #i=0, Scheduled/preventive
        scheduling_index = 0
        #i=1, corrective
        corrective_index = 1

        transportation_time = 0.5
        time_to_setup_the_maintenance_activity = 0.5
        time_required_for_the_maintenance_activity_per_kilometer = 0.02
        hours_a_day = 8
        for i in range(2):
            for j in range(3):
                C_labour[i][j] = N_men[j] * labour_daily_rate[i][j] * (
                distance_travelled_during_maintenance*
                time_required_for_the_maintenance_activity_per_kilometer+
                time_to_setup_the_maintenance_activity+transportation_time)
                C_transport[i][j] = 2 * distance_travelled_during_maintenance *
                cost_of_transportation[i]

        #scheduled/preventive
        for j in range(3):
            C_SM[j] =  C_labour[scheduling_index][j] +  C_transport[scheduling_index][j] +
            C_consumables[scheduling_index][j]

        #corrective
        for j in range(3):
            C_CM[j] =  C_labour[corrective_index][j] +  C_transport[corrective_index][j] +
            C_consumables[corrective_index][j]


        temp_sum1 = 0
        for j in range(3):
           temp_sum1 += f[scheduling_index][j] * C_SM[j]

        temp_sum2 = 0
        for j in range(3):
           temp_sum2 += f[corrective_index][j] * C_CM[j]

        direct_maintenance_cost = (1 - P_d) * temp_sum1 + P_d * temp_sum2


        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["intermediate"][
        "C_direct_maintenance[GBP]"] = direct_maintenance_cost

    def __calculate_cost_of_maintenance(self):
        self.__calculate_cost_of_indirect_maintenance()
```

```
        self.__calculate_cost_of_direct_maintenance()
        result =  self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "intermediate"]["C_indirect_maintenance[GBP]"]
        result += self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "intermediate"]["C_direct_maintenance[GBP]"]
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["C_M"] = result
        return  result

    def __calculate_cost_of_operation_and_maintenenance(self):
        C_O = self.__calculate_cost_of_operation()
        C_M = self.__calculate_cost_of_maintenance()
        self.__solution["dependent"]["cost_of_operation_and_maintenance"]["value"] = C_O +
        C_M

    def __calculate_cost_of_port_preparation_for_decommissioning(self):
        duration_of_port_preparation_for_decommissioning = self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["inputs_for_baseline_OWF_Model"][
        "total_D_and_D_time[days]"]
        result = self.__calculate_port_related_costs(
        duration_of_port_preparation_for_decommissioning)
        result += self.__solution["dependent"]["cost_of_installation_and_commissioning"][
        "inputs_for_baseline_OWF_Model"]["C_port_rate_I&C[GBP]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "cost_of_port_preparation_for_decommissioning[GBP]"] = result
        return result

    def __calculate_cost_of_removal_operations(self):

        types_of_vessel_required_for_removal_operations_during_decommissioning_and_disposal =
         [
                          "V_hr_JU[GBP/day]",

                          "V_hr_CL[GBP/day]",
                          "V_hr_TV[GBP/day]",
                          "V_hr_T[GBP/day]",
                          "V_hr_BA[GBP/day]",
                          "V_hr_CT[GBP/day]",

                          "V_hr_SV[GBP/day]",
                          ]
        result = 0
        duration_of_removal_in_days = self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["inputs_for_baseline_OWF_Model"][
        "total_D_and_D_time[days]"]
        off_shore_labour_cost = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "C_off_man[GBP/day]"] * duration_of_removal_in_days
        for vessel in
        types_of_vessel_required_for_removal_operations_during_decommissioning_and_disposal:
            vessel_rate = self.__solution["dependent"][
            "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][vessel]
            cost_of_vessel = vessel_rate * duration_of_removal_in_days + self.__solution[
            "dependent"]["cost_of_installation_and_commissioning"][
            "inputs_for_baseline_OWF_Model"]["Mob/Demob[GBP]"]
            result += cost_of_vessel + off_shore_labour_cost

        vessel_rate_for_HL = self.__solution["dependent"][
        "cost_of_installation_and_commissioning"]["inputs_for_baseline_OWF_Model"][
        "V_hr_HL[GBP/day]"]
        cost_of_vessel = vessel_rate_for_HL * duration_of_removal_in_days + self.__solution[
        "dependent"]["cost_of_installation_and_commissioning"][
        "inputs_for_baseline_OWF_Model"]["Mob/Demob_HL[GBP]"]
        result += cost_of_vessel + off_shore_labour_cost

        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "cost_of_removal_operations[GBP]"] = result
        return result
```

```
    def __calculate_cost_of_decommissioning(self):

        self.__calculate_the_weight_of_all_components()

        cost_of_port_preparation = self.
        __calculate_cost_of_port_preparation_for_decommissioning()
        cost_of_removal_operations = self.__calculate_cost_of_removal_operations()
        result = cost_of_port_preparation + cost_of_removal_operations
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["C_dmsg[GBP]"] =
         result
        return result

    def __calculate_cost_of_waste_management_processing(self):


        total_length_of_cables = self.__solution["dependent"][
        "total_length_of_array_cables[km]"]
        result = 0
        specifications = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"
        ]["inputs_for_baseline_OWF_Model"]
        result = specifications["cost_of_processing_turbine[GBP/ton]"] * self.__solution[
        "independent"]["turbine"]["total_weight[tonnes]"]
        result += specifications["cost_of_processing_foundation[GBP/ton]"] * specifications[
        "foundation_weight[tons]"]
        result += specifications["cost_of_processing_array_cable[GBP/km]"] *
        total_length_of_cables
        result += specifications["cost_of_processing_met-tower[GBP/ton]"] * specifications[
        "met-tower_weight[tons]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "cost_of_waste_management_processing[GBP]"] = result
        return result

    def __calculate_the_weight_of_all_components(self):


        total_length_of_cables = self.__solution["dependent"][
        "total_length_of_array_cables[km]"]
        specifications = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"
        ]["inputs_for_baseline_OWF_Model"]

        sum_of_weight = self.__solution["independent"]["turbine"]["total_weight[tonnes]"]
        sum_of_weight += specifications["foundation_weight[tons]"]
        sum_of_weight += total_length_of_cables * specifications["array_cable_weight[kg/m]"]/
        1000
        sum_of_weight += specifications["met-tower_weight[tons]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "sum_of_weight_of_all_components[tonnes]"] = sum_of_weight


    def __calculate_cost_of_waste_management_for_transport(self):

        tarrif_per_km = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "inputs_for_baseline_OWF_Model"]["tarrif_per_lorry_km[GBP/km]"]
        specifications = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"
        ]["inputs_for_baseline_OWF_Model"]

        result = tarrif_per_km * ( self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["sum_of_weight_of_all_components[tonnes]"] /
        specifications["lorry_capacity[tons]"] ) * 2 * specifications[
        "distance_to_scrap_centre[km]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "cost_of_waste_management_for_transport[GBP]"] = result
        return result

    def __calculate_cost_of_waste_management_for_landfill(self):
```

```
        result = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "sum_of_weight_of_all_components[tonnes]"] * self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["inputs_for_baseline_OWF_Model"][
        "cost_of_landfill_unit_price[GBP/ton]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "cost_of_waste_management_for_landfill[GBP]"] = result
        return result

    def __calculate_profits(self):

        result = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "sum_of_weight_of_all_components[tonnes]"] * self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["inputs_for_baseline_OWF_Model"][
        "cost_of_scrap_value[GBP/ton]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["intermediate"][
        "profits_in_waste_management[GBP]"] = result
        return result

    def __calculate_cost_of_waste_management(self):

        cost_of_waste_management_processing = self.
        __calculate_cost_of_waste_management_processing()
        cost_of_waste_management_for_transport = self.
        __calculate_cost_of_waste_management_for_transport()
        cost_of_waste_management_for_landfill = self.
        __calculate_cost_of_waste_management_for_landfill()
        profits = self.__calculate_profits()
        result = cost_of_waste_management_processing + cost_of_waste_management_for_transport
         + cost_of_waste_management_for_landfill - profits
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["C_WM[GBP]"] =
        result
        return result

    def
    __calculate_the_actual_occupied_area_of_the_wind_farm_based_on_the_number_of_turbines_per_
    layout(self):

        max_area_per_layout = self.__solution["independent"]["site_specifications"][
        "area[km2]"]
        layout_type = self.__solution["independent"]["site_specifications"]["layout"]
        max_number_of_turbines_per_layout = self.__solution["independent"][
        "site_specifications"]["max_number_of_turbines_for_this_layout"]
        number_of_turbines = self.__solution["independent"]["number_of_turbines"]
        result =  max_area_per_layout * (number_of_turbines * 1.0 /
        max_number_of_turbines_per_layout )
        self.__solution["independent"]["site_specifications"][
        "occupied_area_of_the_wind_farm_based_on_the_number_of_turbines_per_layout[km2]"] =
        result
        return result

    def __calculate_cost_of_site_clearence(self):

        area_for_site_clearence = self.
        __calculate_the_actual_occupied_area_of_the_wind_farm_based_on_the_number_of_turbines_
        per_layout()
        result = area_for_site_clearence * self.__solution["dependent"][
        "cost_of_decommissioning_and_disposal"]["inputs_for_baseline_OWF_Model"][
        "cost_of_site_clearence[GBP/km2]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["C_SC[GBP]"] =
        result
        return result

    def __calculate_cost_of_post_monitoring_activities(self):

        result = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "C_SC[GBP]"]
```

```
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["C_PostM[GBP]"]
        = result
        return result

    def __calculate_cost_of_decommissioning_and_disposal(self):


        C_dmsg = self.__calculate_cost_of_decommissioning()
        C_WM = self.__calculate_cost_of_waste_management()
        C_SC = self.__calculate_cost_of_site_clearence()
        C_PostM = self.__calculate_cost_of_post_monitoring_activities()
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["value"] =
        C_dmsg + C_WM + C_SC + C_PostM

    def __update_solution_based_on_input(self):
        self.__solution["name"] = self.__name
        self.__solution["validity"] = 0
        self.__solution["independent"]["turbine"] = self.__turbine_specifications.values()[0]
        self.__solution["independent"]["turbine"]["name"] = self.__turbine_specifications.
        keys()[0]
        self.__solution["independent"]["turbine"]["type"] = 'T'+str(self.__solution[
        "independent"]["turbine"]["nominal_power_rate[MW]"])
        self.__solution["independent"]["site_specifications"] = self.__location.values()[0]
        self.__solution["independent"]["site_specifications"]["name"] = self.__location.keys
        ()[0]
        self.__solution["independent"]["site_specifications"]["layout"] = self.__layout

        self.__solution["independent"][
        "production_hours_of_a_single_turbine_throughout_its_lifetime"] = self.
        __production_hours_of_a_single_turbine_throughout_its_lifetime
        self.__solution["independent"]["years_of_operation"] = self.__years_of_operation
        self.__solution["independent"]["number_of_turbines"] = self.__number_of_turbines
        self.__solution["independent"]["turbine"]["sweptArea"] = self.__pi * self.__solution[
        "independent"]["turbine"]["radius"] * self.__solution["independent"]["turbine"][
        "radius"]
        self.__solution["independent"]["load_factor"] = float(self.__load_factor)
        self.__solution["independent"]["sum_of_all_losses"] = float(self.__sum_of_all_losses)


        distance_from_the_port = self.__solution["independent"]["site_specifications"][
        "Distance_from_the_port_[km]"]
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "inputs_for_baseline_OWF_Model"]["distance_to_scrap_centre[km]"] =
        distance_from_the_port
        self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "inputs_for_baseline_OWF_Model"]["distance_to_landfill[km]"] = distance_from_the_port

        temp_total_number_of_turbines = self.__solution["independent"]["number_of_turbines"]
        temp_turbine_diameter = 2.0 * self.__solution["independent"]["turbine"]["radius"]
        temp_layout_number = int(self.__solution["independent"]["site_specifications"][
        "layout"].replace('layout',''))
        cable_layout_generator = CablingLayoutGenerator(temp_total_number_of_turbines,
        temp_turbine_diameter, temp_layout_number)


        self.__solution["dependent"]["total_length_of_array_cables[km]"] =
        cable_layout_generator.calculate_the_length_of_cables_for_windfarm_of()


        turbine_type = self.__solution["independent"]["turbine"]["type"]
        site_name = self.__solution["independent"]["site_specifications"]["name"]
        self.__solution["independent"]["site_specifications"][
        "max_number_of_turbines_for_this_layout"] = self.__capacity_constraint.
        query_the_maximum_number_of_turbines(area=site_name, turbine_type = turbine_type,
        layout = self.__layout)
```

```
        self.__solution["independent"]["turbine"]["nominal_power_rate[MW]"] = float(self.
        __solution["independent"]["turbine"]["nominal_power_rate[MW]"])
        self.__solution["dependent"][
        "production_hours_for_all_turbines_throughout_the_lifetime_of_the_farm"] = self.
        __solution["independent"]["number_of_turbines"] * self.__solution["independent"][
        "production_hours_of_a_single_turbine_throughout_its_lifetime"]
        self.__solution["dependent"]["power_rate[MW]"] = self.__solution["independent"][
        "turbine"]["nominal_power_rate[MW]"]
        self.__solution["dependent"]["power_extracted[MW]"] = self.
        __calculate_power_extracted()
        self.__solution["dependent"]["installed_capacity[MW]"] = self.
        __calculate_installed_capacity()
        self.__solution["dependent"]["nominal_installed_capacity[MW]"] = float(self.
        __solution["independent"]["number_of_turbines"] * self.__solution["independent"][
        "turbine"]["nominal_power_rate[MW]"])
        self.__solution["dependent"]["total_power_extracted[MW]"] = self.__solution[
        "independent"]["number_of_turbines"] * self.__solution["dependent"][
        "power_extracted[MW]"]

        self.__calculate_cost_of_production_and_acquisition()
        self.__calculate_cost_of_installation_and_commissioning()
        self.__calculate_cost_of_predevelopment_and_consenting()
        self.__calculate_CAPEX()

        self.__calculate_cost_of_operation_and_maintenenance()
        self.__calculate_OPEX()

        self.__calculate_cost_of_decommissioning_and_disposal()
        self.__calculate_DECOMMISSIONING_and_DISPOSAL()



    def __init__(self, name, location, turbine, number_of_turbines,
    production_hours_of_a_single_turbine_per_year=6000,  years_of_operation=25, load_factor=
    0.535,constant_FiT=6.62, sum_of_all_losses=0.141, number_of_variables=3,
    number_of_objectives = 7, layout='layout1'):
        self.__name = name
        self.__location = location
        self.__turbine_specifications = turbine
        self.__number_of_turbines = number_of_turbines
        if number_of_variables !=3 :
            self.__number_of_variables = number_of_variables

        if number_of_objectives != 7:
            self.__number_of_objectives = number_of_objectives

        if layout != 'layout1':
            self.__layout = layout

        self.__production_hours_of_a_single_turbine_throughout_its_lifetime =
        production_hours_of_a_single_turbine_per_year * years_of_operation
        self.__years_of_operation = years_of_operation
        self.__load_factor = load_factor

        self.__sum_of_all_losses = sum_of_all_losses
        self.__load_solution_template_to_an_internal_solution()
        self.__capacity_constraint = capacity_constraint('modelling.json')


        self.__update_solution_based_on_input()


    def export_to_json(self):
        with open(self.__name+'_solution.json', 'w') as fp:
            json.dump(self.__solution, fp, sort_keys=True, indent=4)
```

```
    def get_P_and_A(self):
        return self.__solution["dependent"]["cost_of_production_and_acquisition"]["value"]

    def get_I_and_C(self):
        return self.__solution["dependent"]["cost_of_installation_and_commissioning"]["value"]

    def get_number_of_turbines_for_minimisation(self):
        return self.__solution["independent"]["number_of_turbines"]

    def get_negative_of_installed_capacity_for_minimisation(self):
        return -self.__solution["dependent"]["installed_capacity[MW]"]

    def get_negative_of_total_power_extracted_for_minimisation(self):
        return -self.__solution["independent"]["number_of_turbines"] * self.__solution[
        "dependent"]["power_extracted[MW]"]

    def get_P_and_C(self):
        return self.__solution["dependent"]["cost_of_predevelopment_and_consenting"]["value"]

    def get_O_and_M(self):
        return self.__solution["dependent"]["cost_of_operation_and_maintenance"]["value"]

    def get_D_and_D(self):
        return self.__solution["dependent"]["cost_of_decommissioning_and_disposal"]["value"]

    def __get_area_name(self):
        return self.__solution["independent"]["site_specifications"]["name"]

    def __get_turbine_type(self):
        return self.__solution["independent"]["turbine"]

    def __get_layout(self):
        return self.__solution["independent"]["site_specifications"]["layout"]

    def check_against_capacity_constraints(self):
        result = False
        target_area = self.__solution["independent"]["site_specifications"]["name"]
        max_turbines_allowd_in_this_solution = self.__capacity_constraint.
        query_the_maximum_number_of_turbines(area=target_area, turbine_type =  self.
        __solution["independent"]["turbine"]["type"], layout = self.__solution["independent"
        ]["site_specifications"]["layout"])
        turbines_in_this_solution = self.__solution["independent"]["number_of_turbines"]

        installed_capacity_in_this_solution = self.__solution["dependent"][
        "installed_capacity[MW]"] * 1000.0
        max_allowed_capacity_in_this_solution = self.__capacity_constraint.
        query_the_maximum_installed_capacity(target_area)
        if  (turbines_in_this_solution <= max_turbines_allowd_in_this_solution) and (
        installed_capacity_in_this_solution <= max_allowed_capacity_in_this_solution):
            result = True
        else:
            pass

        self.__solution["validity"] = result
        return result

    def set_validity(self, value):
        self.__solution["validity"] = value

    def get_validity(self):
        return self.__solution["validity"]


    def __get_all_the_numerical_values_of_the_solution(self):

        text = ""
        text += self.__solution["independent"]["site_specifications"]["name"] + " "
```

```
        text += self.__solution["independent"]["turbine"]["name"] + " "
        text += str(self.__solution["independent"]["number_of_turbines"]) + " "
        if self.__number_of_variables > 3:
            text += str(self.__solution["independent"]["site_specifications"]["layout"]) + " "



        text += str(self.get_P_and_A()) + " "
        text += str(self.get_I_and_C()) + " "
        text += str(self.get_number_of_turbines_for_minimisation()) + " "
        text += str(self.get_negative_of_installed_capacity_for_minimisation())  + " "
        text += str(self.get_P_and_C()) + " "
        text += str(self.get_O_and_M()) + " "
        text += str(self.get_negative_of_total_power_extracted_for_minimisation())+ " "
        if self.__number_of_objectives > 7:
            text += str(self.get_D_and_D())

        return text

    def get_solution(self):
        return self.__solution

    def log_solution(self):
        with open('evaluation_history.log','a') as logfile:
            line = self.__get_all_the_numerical_values_of_the_solution()
            logfile.write(line+"\n")

    def export_solution_in_tuple_format_for_database_insertion(self):
        solution = 22 * [0]

        solution[0] = self.__solution["name"]
        solution[1] = self.__solution["validity"]
        solution[2] = self.__solution["independent"]["years_of_operation"]
        solution[3] = self.__solution["independent"]["number_of_turbines"]
        solution[4] = self.__solution["independent"]["turbine"]["name"]
        solution[5] = self.__solution["independent"]["site_specifications"]["name"]
        solution[6] = self.__solution["independent"][
        "production_hours_of_a_single_turbine_throughout_its_lifetime"]
        solution[7] = self.__solution["independent"]["load_factor"]
        solution[8] = self.__solution["independent"]["foundation_weight[tonnes]"]
        solution[9] = self.__solution["independent"]["sum_of_all_losses"]
        solution[10] = self.__solution["dependent"]["CAPEX[M]"]
        solution[11] = self.__solution["dependent"]["OPEX[M]"]
        solution[12] = self.__solution["dependent"]["cost_of_predevelopment_and_consenting"][
        "value"]
        solution[13] = self.__solution["dependent"]["cost_of_production_and_acquisition"][
        "value"]
        solution[14] = self.__solution["dependent"]["cost_of_installation_and_commissioning"
        ]["value"]
        solution[15] = self.__solution["dependent"]["cost_of_operation_and_maintenance"][
        "value"]
        solution[16] = self.__solution["dependent"]["cost_of_decommissioning_and_disposal"][
        "value"]
        solution[17] = self.__solution["dependent"]["installed_capacity[MW]"]
        solution[18] = self.__solution["dependent"]["nominal_installed_capacity[MW]"]
        solution[19] = self.__solution["dependent"]["power_extracted[MW]"]
        solution[20] = self.__solution["dependent"]["total_power_extracted[MW]"]
        solution[21] = self.__solution["independent"]["site_specifications"]["layout"]

        return solution


def test_solution_generation():

    location_index_1 = get_location_from_available_portfolio("Rampion_(Hastings)")
    turbine1 = get_test_turbine_for_the_development_of_models()
    s1 = solution_evaluator_by_using_LCC("test_solution_1",location_index_1, turbine1,
```

```
    number_of_turbines=100)
    s1.export_to_json()

def test_solution_generation_for_paper4():

    location_index_1 = get_location_from_available_portfolio(
    "Moray_Firth_Western_Development_Area")
    turbine1 = get_turbine_from_available_portfolio('T8')
    s1 = solution_evaluator_by_using_LCC("test_solution_1",location_index_1, turbine1,
    number_of_turbines=100)
    s1.export_to_json()


if __name__ == "__main__":

    test_solution_generation_for_paper4()
    print 'solution evaluation finished successfully'
```

```
{
    "name":null,
    "validity":null,
    "independent":{
        "years_of_operation":null,
        "number_of_turbines":null,
        "turbine":{
                    "name":null,
                    "radius":null,
                    "hubHeight": null,
                    "powerCoefficient": null,
                    "sweptArea": null,
                    "areaForInstalation":null,
                    "total_weight[tonnes]":null,
                    "nominal_power_rate[MW]":null,
                    "type":null
                  },
        "site_specifications":{
                                "name":null,
                                "average_water_depth[m]": null,
                                "average_wind_speed[m/s]": null,
                                "distance_to_shore[km]":null,
                                "area[km2]":null,
                                "max_capacity[GW]": null,
                                "Distance_from_the_port_[km]":null,
                                "round":3,
                                "layout":null,
                                "max_number_of_turbines_for_this_layout":null,

                                "occupied_area_of_the_wind_farm_based_on_the_number_of_turbine
                                s_per_layout[km2]":null
                                 },
        "production_hours_of_a_single_turbine_throughout_its_lifetime":null,
        "number_of_days":null,
        "load_factor":null,
        "constant_FiT":null,
        "foundation_weight[tonnes]":200,
        "sum_of_all_losses":null
    },
    "dependent":{
        "production_hours_for_all_turbines_throughout_the_lifetime_of_the_farm":null,
        "power_extracted[MW]":null,
        "installed_capacity[MW]":null,
        "CAPEX[M]":null,
        "OPEX[M]":null,
        "DECOMMISSIONING_AND_DISPOSAL[M]":null,
        "temporary_CAPEX[GBP]":null,
        "income[M]":null,
        "nominal_installed_capacity[MW]":null,
        "total_length_of_array_cables[km]":null,
        "cost_of_predevelopment_and_consenting":{
            "value":null,
            "inputs_for_baseline_OWF_Model":{
                "Csurveyeia[GBP/MW]":8938,
                "Csurveycp[GBP/MW]":500,
                "Csurveysb[GBP/MW]":19620,
                "Csurveymet[GBP]":4360000,
                "Cbase[GBP]":862500,
                "Ceng[GBP/MW]":529.23,
                "Cengvalid[GBP]":57500,
                "Contigencies[GBP]":null
            },
            "CprojM":null,
            "Clegal":null,
            "Csurveys":null,
```

```
            "Ceng":null,
            "Ccontingency":null,
            "intermediate":{
            }
        },
        "cost_of_production_and_acquisition":{
            "value":null,
            "CWT":null,
            "CSS":null,
            "CPTS":null,
            "Cmonitoring":null,
            "inputs_for_baseline_OWF_Model":{
                "Vhr[GBP/day]":100000,
                "VCapacity[tons]":10286,
                "vessel_speed[knot]":23,
                "dist.manufWT[Km]":1000,
                "Dset[m]":8,
                "dist.manufF[km]":100,
                "Ccableunitarray[GBP/m]":242.2,
                "L1[Km]":133.11,
                "Ccableunitexport[GBP/m]":512.3,
                "L2[Km]":80,
                "Ccableunitons[GBP/m]":67.98,
                "L3[Km]":10,
                "Cprotect[GBP/WT]":7490,
                "C_SCADA[GBP/WT]":10300,
                "C_CMS[GBP/WT]":14420

            },
            "intermediate": {
                "transportation_cost_of_WT[GBP]": null,
                "C_WT[GBP]":null,
                "C_of_WTsubassemblies[GBP]":null,
                "C_of_transport[GBP]":null,
                "C_of_cables":null,
                "cost_of_onshore_substation[GBP]":null,
                "cost_of_offshore_substation[GBP]":null
            }
        },
        "cost_of_installation_and_commissioning":{
            "value":null,
            "C_I&C_port":null,
            "C_I&C_comp":null,
            "C_comm":null,
            "C_I&C_ins":null,
            "intermediate":{
                "C_port_labour[GBP]":null,
                "C_ones":null
            },
            "inputs_for_baseline_OWF_Model":{
                "C_port_rate_I&C[GBP]":13375000,
                "C_onsh_MH[GBP/day]":150,
                "N_onsh[Men]":12, /*number onshore operations*/
                "T_I&C[years]":2,
                "V_hr_JU[GBP/day]":149800,
                "V_hr_HL[GBP/day]":288900,
                "V_hr_AHL[GBP/day]":84400,
                "V_hr_CL[GBP/day]":85600,
                "V_hr_DP[GBP/day]":107000,
                "V_hr_TV[GBP/day]":88275,
                "V_hr_T[GBP/day]":5918.6,
                "V_hr_BA[GBP/day]":1035.75,
                "V_hr_CT[GBP/day]":2071.51,
                "V_hr_SV[GBP/day]":2071.51,
                "C_on_cable_truck[GBP/day]":9330.96,
```

```
            /*Array cable installation rate???*/
            /*Export cable installation rate???*/
            /*Onshore cable inst. rate???*/
            "Mob/Demob[GBP]":138000,
            "Mob/Demob_HL[GBP]":276000,
            "C_off_man[GBP/day]":200,
            "C_on_subs[GBP]":828882.4,
            "C_insu_rate_I&C[GBP/MW]":41600




        }
    },
    "cost_of_operation_and_maintenance":{
        "value":null,
        "C_O":null,
        "C_M":null,
        "inputs_for_baseline_OWF_Model":{
            "%lease":0.02,
            "P_elect[GBP/MWhr]": 50,
            "C_insu_rate_O_and_M[GBP/MW]":14560,
            "C_trans[GBP/MW]":71790,
            "C_port_O_and_M[GBP/year]":561000,
            "C_fix_vessels[GBP/vessel]":1591200,
            "C_onshore_labour_O_and_M[GBP/turbine]":12240,
            "P_d":0.9,
            "preventive_downtime[hr/turbine]":60,
            "corrective_downtime[hr/year]":27567,
            "cost_of_weather_forecasting[GBP/year]":66300
        },
        "intermediate":{
            "electricity_produced_throught_the_tenure[MW]":null,
            "availability_throught_the_tenure":null,
            "C_rent[GBP]":null,
            "C_O_and_M_insurrance[GBP]":null,
            "C_transmission_charges[GBP]":null,
            "C_indirect_maintenance[GBP]":null,
            "C_direct_maintenance[GBP]":null
        }
    },
    "cost_of_decommissioning_and_disposal":{
        "value":null,
        "C_dmsg[GBP]":null,
        "C_WM[GBP]":null,
        "C_SC[GBP]":null,
        "C_PostM[GBP]":null,
        "sum_of_weight_of_all_components[tonnes]":null,
        "inputs_for_baseline_OWF_Model": {
            "total_D_and_D_time[days]":534.44,
            "wind_turbine_weight[tons]":552.5,
            "foundation_weight[tons]":760,
            "array_cable_weight[kg/m]":30.5,
            "met-tower_weight[tons]":570,
            "cost_of_processing_turbine[GBP/ton]":92.04,
            "cost_of_processing_foundation[GBP/ton]":46.02,
            "cost_of_processing_met-tower[GBP/ton]":46.02,
            "cost_of_processing_array_cable[GBP/km]":9102,
            "length_array_cable[km]":133.11,
            "tarrif_per_lorry_km[GBP/km]":0.41,
            "lorry_capacity[tons]":24.00,
            "distance_to_scrap_centre[km]":50,
            "distance_to_landfill[km]":50,
            "cost_of_landfill_unit_price[GBP/ton]":19.77,
            "cost_of_scrap_value[GBP/ton]":205.4,
```

```
                "area_for_site_clearence[km2]":70.14,
                "cost_of_site_clearence[GBP/km2]":51542.4



            },
            "intermediate": {
                "cost_of_port_preparation_for_decommissioning[GBP]":null,
                "cost_of_removal_operations[GBP]":null
            }
        }
    }

}
```

```
'''
Data formatter for platypus

@author: Vera Mytilinou - Cranfield University 2018
'''


def convertBooleanToDecimal(inputList, start=0):
    output = [0] * len(inputList)
    for index in range(len(inputList)):
        if inputList[index] is True:
            output[index] = 1
    return start + int("".join(map(str,output)), 2)



def test_all():
    var1 = [False, False, True, True, True]
    var2 = [True, True]
    var3 = [False, False, False, True, False, False, True, True, False, True, True, True,
    True, True]
    var4 = [False]

    print var1, convertBooleanToDecimal(var1)
    print var2, convertBooleanToDecimal(var2)
    print var3, convertBooleanToDecimal(var3)
    print var4, convertBooleanToDecimal(var4)


if __name__ == "__main__":
    test_all()

    print 'optimisation successfully finished'
```

```
'''
Compile a portfolio of wind turbines with utility functions

@author: Vera Mytilinou - Cranfield University 2018
'''
from jsmin import jsmin
import json
from utilities import get_turbine_from_available_portfolio

class turbinePortfolio(object):
    '''
    classdocs
    '''
    pi = 3.1415
    rho = 1.23
    __specs_of_all_turbines = {
                                "turbine1":{ "radius":34,
                                             "hubHeight": 50,
                                             "powerCoefficient": 0.4,
                                             "sweptArea": 10000,
                                             "object":None,
                                             "areaForInstalation":1000000,
                                             "power":1000000000000000

                                            },

                                "turbine2":{
                                             "radius":56,
                                             "hubHeight": 70,
                                             "powerCoefficient": 0.32,
                                             "sweptArea": 10000,
                                             "object":None,
                                             "areaForInstalation":1000000,
                                             "power":100000000000000
                                            },
                                "turbine134":{ "radius":90,
                                              "hubHeight": 110,
                                             "powerCoefficient": 0.39,
                                             "sweptArea": 10000,
                                             "object":None,
                                             "areaForInstalation":1000000,
                                             "power":1000000000000000

                                            },
                                  'T10':{ 'radius':95, 'hubHeight':125, 'powerCoefficient':0.4,
                                  'sweptArea':10000, 'object':None, 'areaForInstalation':1000000
                                  ,       'power':1000000000000000},
                                   'T8':{ 'radius':82, 'hubHeight':118, 'powerCoefficient':0.4,
                                   'sweptArea':10000, 'object':None, 'areaForInstalation':
                                   1000000,       'power':1000000000000000},
                                   'T7':{ 'radius':85.5, 'hubHeight':110, 'powerCoefficient':0.4
                                   , 'sweptArea':10000, 'object':None, 'areaForInstalation':
                                   1000000,       'power':1000000000000000},
                                   'T6':{ 'radius':76, 'hubHeight':124, 'powerCoefficient':0.4,
                                   'sweptArea':10000, 'object':None, 'areaForInstalation':
                                   1000000,       'power':1000000000000000},
                                   'T5':{ 'radius':63, 'hubHeight':90, 'powerCoefficient':0.4,
                                   'sweptArea':10000, 'object':None, 'areaForInstalation':
                                   1000000,       'power':1000000000000000},
                                   'T3':{ 'radius':45, 'hubHeight':80, 'powerCoefficient':0.4,
                                   'sweptArea':10000, 'object':None, 'areaForInstalation':
                                   1000000,       'power':1000000000000000},


                                }

    listOfTurbines = None
```

```
def calculateMetaSpecificationsForAllTurbines(self):
    '''
    Go through all the turbines and calculate the derived specifications based on the
    manufacturer specifications
    '''
    for turbine in self.__specs_of_all_turbines.iterkeys():
        r = self.__specs_of_all_turbines[turbine]["radius"]
        self.__specs_of_all_turbines[turbine]["sweptArea"] = self.pi * r * r
        self.__specs_of_all_turbines[turbine]["areaForInstalation"] = 2 * (2 * r)


def calculateTheTurbinePerformanceOfEachTurbineAtWindSpeed(self, windSpeed):
    for turbine in self.__specs_of_all_turbines.iterkeys():
        self.__specs_of_all_turbines[turbine]["power"] = 0.5 * self.rho * self.
        __specs_of_all_turbines[turbine]["sweptArea"] * self.__specs_of_all_turbines[
        turbine]["powerCoefficient"] * (windSpeed ** 3)


def calculateTheTurbinePerformanceOfTurbineAtWindSpeed(self, turbine, windSpeed):

    self.__specs_of_all_turbines[turbine]["power"] = 0.5 * self.rho * self.
    __specs_of_all_turbines[turbine]["sweptArea"] * self.__specs_of_all_turbines[turbine
    ]["powerCoefficient"] * (windSpeed ** 3)
    return self.__specs_of_all_turbines[turbine]["power"]

def viewAllThePorfolio(self):
    print self.__specs_of_all_turbines

def __extract_turbines_from_external_file(self, filename_to_import_specifications):
    with open(filename_to_import_specifications) as _externalJSON:
        config = jsmin(_externalJSON.read());

    validJSON = json.loads(config)
    return validJSON["turbine_speficiations"]


def __init__(self, filename_to_import_specifications='modelling.json', turbines_to_remove
=None):
    '''
    Constructor
    '''
    if filename_to_import_specifications is not None:
        self.__specs_of_all_turbines = self.__extract_turbines_from_external_file(
        filename_to_import_specifications)

    if turbines_to_remove!=None:
        for element in turbines_to_remove:
            if element in self.__specs_of_all_turbines:
                del self.__specs_of_all_turbines[element]


    self.calculateMetaSpecificationsForAllTurbines()

def get_specs_of_all_turbines(self):
    return self.__specs_of_all_turbines

def getNameOfTurbineWithIndex(self, index):
    try:
        return self.__specs_of_all_turbines.keys()[index]

    except IndexError as e:
        print e, "turbine index to try:", index

def print_map_of_indices(self):
    pass
```

```
    def getTurbineWithIndex(self, index):
        turbine = None
        turbineName = self.getNameOfTurbineWithIndex(index)
        turbine = get_turbine_from_available_portfolio(turbineName)
        return turbine

    def getTurbineByName(self, turbineName):
        return get_turbine_from_available_portfolio(turbineName)

    def getNamesOfAllRealTurbines(self):
        temp_list = self.__specs_of_all_turbines.keys()
        temp_list.remove("turbine1")
        temp_list.remove("turbine2")
        temp_list.remove("turbine134")
        return temp_list

    specs_of_all_turbines = property(get_specs_of_all_turbines, None, None, None)


def working_example_from_internal_data():
    tp1 = turbinePortfolio()

    tp1.viewAllThePorfolio()

    tp1.calculateTheTurbinePerformanceOfEachTurbineAtWindSpeed(12)

    tp1.viewAllThePorfolio()

def working_example_from_external_data():
    tp1 = turbinePortfolio('modelling.json')

    tp1.viewAllThePorfolio()

    tp1.calculateTheTurbinePerformanceOfEachTurbineAtWindSpeed(12)

    tp1.viewAllThePorfolio()


if __name__ == "__main__":
    working_example_from_external_data()
```

```
'''
Utility functions

@author: Vera Mytilinou - Cranfield University 2018
'''
import json
from time import gmtime, strftime
import logging

def get_turbine_from_available_portfolio(turbine_name):
    with open('modelling.json', 'r') as fp:
        data = json.load(fp)

        return {turbine_name:data["turbine_speficiations"][turbine_name]}

def get_test_turbine_for_the_development_of_models():


    return {"test_turbine_based_on_AD_5-116":{ "nominal_power_rate[MW]":5 ,"radius":63,
    "hubHeight":100, "powerCoefficient":0.4, "sweptArea":10000, "object":None,
    "areaForInstalation":1000000, "total_weight[tonnes]":707.5}}


def get_location_from_available_portfolio(location_name):
    with open('modelling.json', 'r') as fp:
        data = json.load(fp)

        return {location_name:data["location_porfolio"][location_name]}

def convert_boolean_array_to_int(boolean_list):
    output = ""
    for element in boolean_list:
        output += str(1) if element is True else str(0)

    return int(output,2)

def convert_all_variables_to_integers(list_of_variables_to_convert):
    out_list = []
    for element in list_of_variables_to_convert:
        out_list.append(convert_boolean_array_to_int(element))

    return out_list

def test_decoding():
    example = [[False, False, False, True, True], [False, False, False], [False, False, True,
     True, False, True, False, True, False], [False, False, True]]
    print convert_all_variables_to_integers(example)

    example = [[False, True, False, True, False], [True, False, True], [False, True, True,
    False, False, True, False, False, False], [False, True, False]]
    print convert_all_variables_to_integers(example)

    example = [[True, True, True, False, False], [False, False, False], [False, True, True,
    False, False, True, False, False, True], [False, True, True]]
    print convert_all_variables_to_integers(example)

    example1 = [True, True, True, False, False]
    print convert_boolean_array_to_int(example1), ' should be 26'


import json
import csv

def get_leaves(item, key=None):
    if isinstance(item, dict):
        leaves = []
        for i in item.keys():
```

```
            leaves.extend(get_leaves(item[i], i))
        return leaves
    elif isinstance(item, list):
        leaves = []
        for i in item:
            leaves.extend(get_leaves(i, key))
        return leaves
    else:
        return [(key, item)]

def export_json_file_to_flat_csv(json_filename, csv_filename):
    with open(json_filename) as f_input, open(csv_filename, 'wb') as f_output:
        csv_output = csv.writer(f_output)
        write_header = True

        for entry in json.load(f_input):
            leaf_entries = sorted(get_leaves(entry))

            if write_header:
                csv_output.writerow([k for k, v in leaf_entries])
                write_header = False

            csv_output.writerow([v for k, v in leaf_entries])
            print 'exported '+json_filename+" to "+csv_filename


def create_timestamped_name(base_name, extension):
    full_timestamp = strftime("%Y%m%d_%H%M%S", gmtime())
    export_filename = base_name + '_'+ str(full_timestamp) + extension
    return export_filename


formatter = logging.Formatter('%(asctime)s %(levelname)s %(message)s')
def setup_logger(name, log_file, level=logging.INFO):
    """Function setup to create multiple loggers"""

    handler = logging.FileHandler(log_file)
    handler.setFormatter(formatter)

    logger = logging.getLogger(name)
    logger.setLevel(level)
    logger.addHandler(handler)

    return logger

if __name__ == "__main__"  :
    test_decoding()
```

```
'''
Create an offshore wind turbine and calculate additional specifications needed for LCC based
on the specifications of the wind turbine

@author: Vera Mytilinou - Cranfield University 2018
'''
import random

class windTurbine(object):
    '''
    classdocs
    '''

    __sweptArea = None
    __powerCoefficient = None

    def __init__(self, sweptArea=None, powerCoefficient=None):
        '''
        Constructor
        '''
        if sweptArea == None:
            sweptArea = random.uniform(300.0, 400.0)

        if powerCoefficient == None:
            powerCoefficient = random.uniform(0.3, 0.5)

        self.__sweptArea = sweptArea
        self.__powerCoefficient = powerCoefficient


    def get_swept_area(self):
        return self.__sweptArea


    def get_power_coefficient(self):
        return self.__powerCoefficient

    sweptArea = property(get_swept_area, None, None, None)
    powerCoefficient = property(get_power_coefficient, None, None, None)


if __name__ == "__main__":
    wt1 = windTurbine()
```

```
'''
Code to estimate the cabling length

@author: Vera Mytilinou - Cranfield University 2018
'''
import numpy as np
from scipy.spatial.distance import pdist, squareform
import matplotlib.pyplot as plt


def minimum_spanning_tree(matrix_of_coordinates, copy_X=True):
    """matrix_of_coordinates are edge weights of fully connected graph"""
    if copy_X:
        matrix_of_coordinates = matrix_of_coordinates.copy()

    if matrix_of_coordinates.shape[0] != matrix_of_coordinates.shape[1]:
        raise ValueError("matrix_of_coordinates needs to be square matrix of edge weights")
    n_vertices = matrix_of_coordinates.shape[0]
    spanning_edges = []


    # initialize with node
    0:

    visited_vertices = [0]


    num_visited = 1
    # exclude self connections:
    diag_indices = np.arange(n_vertices)
    matrix_of_coordinates[diag_indices, diag_indices] = np.inf

    while num_visited != n_vertices:
        new_edge = np.argmin(matrix_of_coordinates[visited_vertices], axis=None)
        # 2d encoding of new_edge from flat, get correct
        indices
        new_edge = divmod(new_edge, n_vertices)
        new_edge = [visited_vertices[new_edge[0]], new_edge[1]]

        # add edge to tree
        spanning_edges.append(new_edge)
        visited_vertices.append(new_edge[1])
        # remove all edges inside current tree
        matrix_of_coordinates[visited_vertices, new_edge[1]] = np.inf
        matrix_of_coordinates[new_edge[1], visited_vertices] = np.inf

        num_visited += 1


    return np.vstack(spanning_edges)

def calculate_eucledian_distance_between(pointA, pointB):

    distance = np.linalg.norm(np.array(pointA)-np.array(pointB))

    return distance



def calculate_length_of_minimum_spanning_tree(P):
    total_distance = 0.0



    X = squareform(pdist(P))
    edge_list = minimum_spanning_tree(X)
#    plt.scatter(P[:, 0], P[:, 1])
```

```
    for edge in edge_list:
        i, j = edge
        series_of_X_coordinats_from_selected_points_for_plotting = [P[i, 0], P[j, 0]]

        series_of_Y_coordinats_from_selected_points_for_plotting = [P[i, 1], P[j, 1]]


        first_point = [P[i, 0], P[i, 1]]
        second_point = [P[j, 0], P[j, 1]]
#         plt.plot(series_of_X_coordinats_from_selected_points_for_plotting,
series_of_Y_coordinats_from_selected_points_for_plotting, c='r')

        temp_distance = calculate_eucledian_distance_between(first_point, second_point)

        total_distance += temp_distance
#     print 'total distance:', total_distance
#     plt.show()

    return total_distance

def test_mst():
    P = np.random.uniform(size=(13, 2))

    calculate_length_of_minimum_spanning_tree(P)

if __name__ == "__main__":
    test_mst()
```