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The Game of Guwarra: A game theory-based decision-making framework for site selection of offshore wind farms in Australia

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ABSTRACT

Global concerns around climate change and the volatility of conventional fuel prices have prompted researchers and technologists to make significant efforts to identify and exploit alternative energy sources that are cleaner and more sustainable. Wind energy has seen considerable development among these alternative energy sources, mainly due to its abundance and global availability for extraction and the existing knowledge within the aviation and aerospace fields. Many nations, including European countries, already operate offshore wind farms (OWFs) and are progressively carrying out new projects and expanding on other projects. The Australian offshore environment provides unique opportunities for wind energy extraction, particularly along the southern coast of mainland Australia and the regions around Tasmania, where substantially strong winds blow most of the year. A significant challenge to establishing wind farms is the selection of site locations with optimal outputs. This can become a complex decision-making problem if there are numerous options and no information from previous projects. This paper aims to develop a decision-making framework to select the optimal location for installing OWFs while addressing financial, performance-related, and availability-related objectives. This paper adopts a game-theoretical approach to develop a decision-support tool to account for the interdependencies of influencing factors and possible conflicts amongst the parties. The game model is applied to an OWF development case study in the Bass Strait, known for its dominant and strong winds.

1. Introduction

Over the past decade, considerable effort has been devoted to the research and development of clean alternative energy resources to mitigate the environmental risks posed by conventional fuel emissions in the electricity sector. The advent of modern renewable energy technologies, especially for wind and solar applications, has sped up the support for decarbonisation within the power division. In 2020, 27.7% of the total electricity generated in Australia was from renewable sources, including wind, solar, and hydro (Council, 2020). Solar and wind have been the primary drivers in more than doubling the country's renewable generation expansion over the past decade. Emerging technologies are making wind energy a competitive resource for lowering the emission of CO_2 and other greenhouse gases.

In Australia, renewable energy generation by wind technologies was around 36 percent in 2020. In 2020, 10 new wind farms were installed around Australia, adding 1.1 GW of wind capacity. More than half of them are installed in Victoria, known as the home of wind farms in Australia.

The cumulative installed capacity of wind energy in Australia increased from around 1850 MWs in 2010 to more than 6000 MW in 2019 (Council, 2020). The Australian wind resource is strongest in southern parts of the continent, where the maximum average wind speeds of over 12 m/s in the south of Tasmania. The Bass Strait, between Tasmania and Victoria, are comparable to areas such as the North Sea, where mean annual 100 m level wind speeds are in the range of 9–10 m/s (Briggs, 2021). Given the substantial available resources for wind in Australia and the current rate of developments, it is expected that 50% of the energy generated in Australia will be from renewable energy by 2030 (Blakers et al., 2017).

Advanced technologies will continue to make the offshore wind energy industry a key element in the renewable energy strategies of many

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countries. The higher wind speed and minimal land footprint will make the offshore wind energy industry a considerable energy producer. This industry is expected to grow even more rapidly in the following years. Australia is, however, very new to the offshore renewable energy industry with twelve new proposals, two projects in early-stage (Bass offshore windfarm and project Gippsland) and one existing development project, the Star of the South, which is in the environmental assessment phase and estimated to become operational in 2025. Furthermore, research into renewable energy in the Australian offshore environment has been minimal, including Aryai et al. (2021), Messali and Diesendorf (2009) and Boelen et al. (2010).

The challenges for a new offshore wind development project include economic, technical, social, and environmental factors such as substantial initial cost, high operation and maintenance (O&M) costs, farm availability increase, and tighter governmental regulation (Babatunde and Najafi, 2018). Due to the increasing need to find suitable locations for offshore wind farms in Australian waters to achieve the best possible output by considering all parameters, it is necessary to understand the parameters and factors that affect selecting wind turbine locations in different environments. Before selecting a site, developers need to consider a wide range of factors affecting the OWF operational and financial performance to those that impact their surrounding environment and other stakeholders. By incorporating these parameters into their decision-making process, developers will ensure sustainable establishment for the offshore wind farm. Several methodologies have been developed and discussed to identify the most appropriate OWF location for investment while considering the benefits in terms of energy yield and cost. The site selection for offshore wind in Australia has been studied by a number of scientists, such as Messali et al. (2009), who analysed multiple criteria for selecting the most suitable sites. The researchers studied the annual mean wind speed, depth of water, distance from the shore, and locations of existing transmission lines, centers of electricity demand, and protected areas databases to determine the suitability of offshore wind farm sites. A site selection strategy based on offshore wind farms was also presented by Boelen et al. (2010) in relation to a case study around Victoria. Furthermore, their research incorporated multicriteria assessment by dividing its criteria into three different groups: economic factors, environmental factors, and social factors.

More sites selection methodologies with global applications are presented in the literature, such as Mytilinou and Kolios (2018) as well as Mytilinou et al. (2018) for site selection on the UK for fixed platforms. The study by Mytilinou et al. (2018a) used life cycle cost analysis to optimise OWFs according to the criteria considered in the study, where the layout, number of WTs, size and site name were considered. By determining the most effective solutions, they ranked them according to expert preferences. MCDM has also been applied to developing a methodology for renewable energy site selection by Chaouachi et al. (2017). Analytical Hierarchy Process (AHP) was applied to the selection of offshore wind farm sites to provide a new framework for multicriteria assessment. The proposed site selection framework considers the electricity network's operating security aspects, economic investment, operation costs and capacity performances relative to each potential three sites for the Baltic States. Earlier, Cavazzi and Dutton (2016) published a model for assessing offshore wind energy potential in the United Kingdom to compare costs between different offshore developments. Based on the use of technical data and geospatial marine characteristics, development costs, potential energy output, operations and maintenance costs, and financial parameters were considered criteria for developing OWFs. Baseer et al. (2017) integrated AHP with Geographic Information System (GIS) modelling to determine the most suitable locations for wind power plants in Saudi Arabia. Several factors were considered in the analysis, such as economics, aesthetics, and environmental criteria. Mahdy and Bahaj (2017) also used a GIS-based AHP method to identify the offshore wind power potential in Egypt taking several factors into account, including the mean wind power density, soil properties, distance from the coast and water depth.

However, the effects of other factors, including maintenance strategies and asset reliability, have not been thoroughly evaluated. This can only be achieved successfully by capturing the interactions among influencing factors. Although a site may have the optimum energy yield or require minimum investment costs, higher O&M costs may be needed to achieve the desired reliability levels, making it not the optimal farm implementation choice.

Site selection strategies often involve conflicting objectives, including the minimisation of environmental degradation while maximising economic profit. The uncertainties in the information available on offshore environments and conflict among decision-making objectives will increase the complexity of the decision-making process. There is, therefore, a need for a multi-objective decision-making method that incorporates the objectives of each party and serves in finding the alternatives that consider the needs of all involved parties simultaneously.

Decision-making involving multiple criteria is a complex task as many decision-makers have their own views on the individual criteria. Hence, different multi-criteria decision-making (MCDM) methods have been developed that help in evaluating multiple (conflicting) criteria as part of the decision-making process. According to the literature, many studies have investigated MCDM methods for tackling group decision-making issues which are, but not limited to, AHP (Li et al., 2021; Tahri et al., 2015; Yang et al., 2011; Zhu et al., 2020), DEcision Making Trial And Evaluation Laboratory (DEMATEL) (Si et al., 2018; Yazdi et al., 2020a, 2020b), TOPSIS (Diemuodeke et al., 2016; Kaya and Kahraman, 2011), Best Worst Method (BWM) (Deveci et al., 2021; Yazdi et al., 2020c) and ELimination and Choice Expressing the REality (ELECTRE) (Chen et al., 2013; Govindan and Jepsen, 2016; Yadav et al., 2018).

One of the commonly used MCDM methods in the environmental sector is AHP or modified AHP. Chaouachi et al. (2017) proposed an AHP-based framework for selecting offshore wind farms based on investment cost, energy yield, and reliability (dependent on congestion in the electricity network). The main disadvantage of this method is the limited number of decision alternatives (DAs) that can be handled at a time by this method. By taking a fuzzy-based multiple attribute approach, Wu et al. (2018) developed a scheme for optimal site selection of an offshore wind farm in the China Sea considering maritime safety and economic feasibility. Fetanat and Khorasaninejad (2015) proposed a fuzzy logic-derived process based on technical factors and economic aspects of offshore wind farms. However, the method depends on biased judgments. Abaei et al. (2017) developed an MCDM for selecting the most suitable offshore sites for implementing wave energy converter (WEC) devices. The method adopts Bayesian Networks and Influence Diagrams for selecting the most suitable sites for installing WEC devices. In their method, a mathematical approach is used instead of expert judgment on the decision-making process. However, the conflict between decision-makers is not considered. Wu et al. (2016) applied the ELECTRE-III method in offshore wind development problems and structured a framework for OWF site selection using criteria such as wind speed, mean wind power density, effective wind hours, meteorological conditions, marine conditions, beach width, traffic condition and environmental impact. In this case, intuitive fuzzy sets were applied to deal with the vague and imprecise information. Kolios et al. (2016) reviewed several MCDM methods to select the support structure of wind turbines. The research shows that technique for the order of preference by similarity to the ideal solution (TOPSIS) and preference ranking organisation method for enrichment evaluation (PROMETHEE) is more accurate in complex environments compared to the weighted sum method (WSM); weighted product method (WPM); analytical hierarchy process (AHP); and ELECTRE. However, the drawback of the two methods (TOPSIS and PROMETHEE) is that the evaluation of alternatives is subjective and may cause inaccuracies in the ranking and the decision results.

Here, the game theory technique is compared with other MCDM methods to highlight its advantages and disadvantages. Strengths and weaknesses of the most commonly used methods in MCDM, that is, AHP, DEMATEL, TOPSIS, and ELECTRE, have been shown in Table 1.

In managing a complex decision-making problem, such as determining the most suitable location for an OWF, conflicts over decision-makers are inevitable with possible impact on the final outcome of the process. Thus, the owners, developers, operators and regulators will benefit from more than a simple single-objective cost-benefit analysis. For instance, many production and maintenance staff may experience the conflicts that arise between managing a likely major breakdown when production is under pressure (Zuashkiani et al., 2011). Multi-criteria decision-making approaches to resolving this issue typically recommend aggregating different decision-making objectives and developing a compound objective to identify the best solution to the problem. In the available methods, perfect cooperation is assumed to be present among the decision-makers to reach the optimal solutions. Conflicts and imperfect cooperation, however, are intrinsic to project development problems, including site selection. Decision theories usually analyse the processes from the point of view of decision-makers and experts. In other words, the outcome of different methods of the MCDM techniques depends on the preferences of decision-makers over different criteria. Most attempts to develop site selection methods in the offshore environment have paid little attention to the potential conflicts between decision-maker objectives. It should be considered that some conflicts among the parties and the uncertainties associated with the available information can substantially increase the complexity of the decision-making process (Sadiq et al., 2004; Yang et al., 2011). In other words, there is a lack of a framework that can reflect the non-cooperative behaviour of decision-makers, often disregarded by other MCDM methods.

Table 1
Strengths and weaknesses of different MCDM methods.

Methods	Strength	Weakness
AHP	1. Flexible and adaptable. 2. The calculation process is straightforward. 3. Each criterion becomes more focused and transparent with a hierarchical structure. 4. This method is widely used to evaluate technologies and select locations.	1. With more decision-makers involved, the problem becomes more complex. 2. It requires the collection of data based on experience/expertise. 3. The results should be verified by further analysis. 4. It is based on the assumption that the criteria are independent and ignores their interactions and interdependence.
ELECTRE, ELECTRE III	1. It examines quantitative as well as qualitative criteria. 2. Reasons are given to validate final results	1. Lack of adaptability. 2. Only the preference is addressed in this method, without reference to the level of difference between alternatives. 3. Complicated calculation process
TOPSIS	1. It is computationally a simple process. 2. Because of being so easy to apply, it has become one of the most popular MCDM techniques. 3. In comparison to other methods of MCDM, this method is faster. 4. Often used in combination with other methods. 5. Typically, this method is applied to evaluating energy technologies.	1. Modelling situations with conflict can be difficult to handle. 2. It does not consider the difference between positive and negative values.
DEMATEL	1. Assesses the mutual relationship among various factors. 2. The decision-maker can identify which are mutually influencing each other. 3. This analysis can help determine the ranking of alternatives, determine evaluation criteria, and measure the weightings of evaluation criteria.	1. The interdependence between criteria is not considered in the decision-making process. 2. The weights of experts are not taken into account when group assessments are aggregated. 3. The aspirations of decision-makers cannot be considered.
Game Theory	1. Flexible and adaptable. 2. The result can be achieved even when there is no perfect collaboration between decision-makers. 3. Possibility of solving problems regardless of the presence or absence of cardinal information. 4. Enables solving a problem using different units, weighting criteria/decision-makers, and objective aggregation.	1. The assumption that decision-makers act rationally may not always be realistic. 2. The limited application of this method in engineering problems causes a narrow knowledge on the knowledge requirements for enhanced utilisation.

The novelty of the suggested method over traditional MCDM is its ability to capture multiple aspects of a decision-making problem, including the conflict amongst decision-makers and integrate multiple criteria as well. In game theory, every decision-maker (DM) seeks to maximise their own objective while considering how other DM's decisions impact theirs and how their actions influence other DM's decisions (Askari et al., 2019). In other words, the suggested method considers the non-cooperative behaviour, which is often ignored by other MCDM methods. It is not necessary for the outcome predicted by the Game theory to be Pareto-optimal (Madani and Lund, 2011). As the overall outcome depends on all strategic decisions made by DMs, the primary concern of DMs is maximising their own outcome. Compared to the traditional decision-making and optimisation methods, game theory enables the decision-makers to consider different aspects of the conflict between themselves when the preferred outcomes are known as well as when the outcome can be foreseen based on quantitative and qualitative information, even if a large amount of information is unavailable (Kelly, 2003). By adopting a game theory approach, it is possible to simulate the interests and behaviour of various stakeholders more realistically. A novel method for dealing with the uncertainty in decision making is presented in this paper, which can provide important planning and execution insights without a need for only using criteria and DMs weights.

The following sub-section briefly introduces the game theory and the basic concept of game theory, such as games, players, strategies, payoff, and solutions.

1.1. Game theory and engineering applications

Game theory is a powerful method of interdependent decision-making in which the outcome of the decision-making process cannot be determined by one party or actor alone (Samsura et al., 2010). Game theories conceptualise the different strategic choices available for those involved in the decision-making process, making them suitable for the application of OWF site selection.

The main objectives of partnership in decision-making are to share risk, maximise investment portfolios and optimise short and long-term strategies. Hence, the presence of multiple players and the impact that each distinct strategy has over the final outcomes make the OWF site selection an interesting field for the game theory applications. The team members in the decision-making of OWF site selection consist of investors who are cost-oriented, operators who are offshore facilities' service providers interested in higher turbine availability, and consumers who are network or transmission system operators interested in the mere output. Each strategy proposed by decision-makers may impact the outcome of OWF site selection. So, in the decision-making process using game theory, different alternatives by the decision-makers and associated conflicts can be considered. This attribute makes the theory an attractive decision-making platform for OWF site selection.

The modern game theory began in 1921 when Borel introduced the term "game theory". In 1928, von Neumann provided a major contribution to the field by introducing the minimax theorem for the matrix game (Myerson, 1991; Ungureanu, 2018). However, Game theory was applied in economics by Von Neumann and Morgenstern (1944) and developed by Nash (1950), who made it a valuable tool by developing a key concept, the Nash equilibrium, which is applicable in many different areas. Shapley (1953) presented a vital solution concept by defining a value for cooperative games. Thomas Schelling contributed further to the literature by applying the game theoretical framework in the context of conflict and cooperation known as Schelling's Strategy of Conflict (Schelling, 1960). After 1960, game theory played a crucial role in a wide range of science fields, especially economics. It has been widely used in various applications in engineering for modelling decision-making processes. More details on the application of game theory in engineering projects can be found in Kapliński and Tamošaitienė (2010) and Piraveenan (2019).

An interactive decision theory can be used in a situation where decision-makers influence the decision of other players. In such cases, the interactive decision model can provide a solution by solving the utility maximisation problem. Myerson (1991) defines game theory as "a model of conflict and cooperation between intelligent and rational decision-makers". Shoham and Leyton-Brown (2008) define game theory as a study of interaction among self-interested decision-makers. Before proceeding, the basic concept of game theory should be explained. A typical game defined in game theory consists of a set of players, being a collection of rational and intelligent individuals who have decisions to make; a player strategy set, which refers to the collection of strategies from which they can choose; and a player payoff function indicating how the player evaluates a strategy profile (Harrington, 2009; Myerson, 1991).

Amongst different decision-making methods, game-theoretical models can be classified into non-cooperative and cooperative games, depending on the behaviour of decision-makers. A game is non-cooperative when every player tends to maximise their own payoff, while cooperative games are when the players try to look for joint actions that work optimally for the group. In a non-cooperative game, decision-makers should consider the conflict to achieve the best outcome from the process. Furthermore, it should be noted that each player, when making any decision, either may or may not be perfectly informed about some or all of the events that have already occurred in the game, defining the game as *perfect information* or *imperfect information.* To set up a game, the decision-making team needs to consider other game characteristics, including being simultaneous or sequential (Hanley and Folmer, 1998; Harrington, 2009).

According to Yang et al. (2013), in environmental decision making, in which more than one aspect should be considered, a multi-objective, non-cooperative game should be developed. Non-cooperative game theory can be helpful for handling conflicts without accurate quantitative information and when only qualitative information is available (Madani, 2010). As a result, a non-cooperative game would be counter to an effect of uncertainties in data for the offshore environment.

In localisation decision-making, in which more than one objective is considered, a multi-objective non-cooperative game should be proposed. Two-person zero-sum games play a central role in the whole theory of games. A two-person zero-sum game consisting of two players (Player 1 and Player 2) and two sets of pure strategies. $S_1 = \{a_1, \dots, a_m\}$ and $S_2 = \{b_1, \dots, b_n\}$ denote the two sets of pure strategies where m number of strategies are available to player 1 and n strategies available to player 2. To a strategy choice for each of the players, $a_i$for player 1 and $b_j$for player 2, there is a certain outcome denoted by $x_{ij} = b_j(a_i)$, known as the payoff (Luce and Raiffa, 1989). In the two-person zero-sum game, one player's gain is equal to the losses of the other player. The existing payoffs of a typical game can be a matrix, as shown by Eq. (*1*).

$$U(x) = \begin{array}{c c} & \begin{array}{ccc} b_1\dots & b_j\dots & b_n \end{array} \\ \begin{array}{c} a_1 \\ a_i \\ a_m \end{array} & \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & x_{ij} & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{1}$$

where $U(x)$ is the payoff matrix of player1,x_{ij} is the payoff of player 1 when player 1 proposes the strategy i, and player 2 proposes the strategy j. Then, the payoff matrix of player 2 is $-U(x)$.

There are several concepts to solve a game theory based on the type of the game being played in different situations, including the *Nash* equilibrium and *Stackelberg* equilibrium, which are applied in non-cooperative games, as well as the stable set (von Neumann-Morgenstern solution) and Shapely value, which are applied in cooperative games. Nash equilibrium is frequently used to solve the non-cooperative game and for finding the best strategies to choose by all players. It should be noted that the best strategy in this concept does not mean the strategy that gives the highest payoff for every player. Nash equilibrium gives the optimal solution strategy for each player depending on the strategy of other players.

A two-person zero-sum game either has a Nash equilibrium when a saddle point is found or a mixed strategy. If the min-max value equals the max-min value, then the game is known to have a saddle point (or equilibrium), and the corresponding strategies are said to be optimum strategies. The amount of payoff at an equilibrium point is the game value (v) (Hillier, 2012).

With a game that does not have an equilibrium point, the mixed strategy is chosen to solve the game. A mixed strategy for player 1 and player 2 is determined by vectors P and Q, where p_i (q_j) represents the probabilities of the row-player choosing $a_i(b_j)$, where $\sum_{i=1}^{m} p_i = 1(\sum_{j=1}^{n} q_j = 1)$.The mixed strategy can be symbolised by the vector of probabilities that optimise the pairing of player 1 and player 2 ($P^*$and Q^*), representing the optimal weights of player 1 and player 2. Any game with mixed strategies can be solved by transforming the problem into a linear programming problem. The solution in mixed strategies is used to construct a weighted sum of the primary objectives, leading to a solution for the decision-making problem. More details on explaining the game theory and its solution concepts can be found in Bauso (2016); Myerson (1991); Osborne (2004), and Harrington (2009).

Some existing works apply game theory in the decision-making process of engineering projects. Yang et al. (2013) used game theory to model decision-making by a diverse group of players in offshore oil and gas operation and transformed uncertain qualitative and quantitative data into rough numbers using rough set theory. The multicriteria game is solved using the generalised maximin solution concept. In their study, players are the operators, regulators, and service engineers who focus on cost, environmental issues, and technical feasibility. Samsura et al. (2010) proposed game-theoretical modelling to identify the key strategic decisions of land and property development projects by showing the different payoffs for stakeholders due to their chosen strategies. Their study model looks at the decision-making processes as a game in an extensive form with four players under two scenarios and identifies the key strategic decisions of land and property development projects by showing the different payoffs for all stakeholders during the project. Madani (2010) reviewed the fundamental game theory concepts and utilised game theory in a water system. The research presents some simple two-by-two water resource games and reviews the applicability of game theory to water resource management and conflict resolution through a series of non-cooperative water resource games. The review identifies the behaviour of the involved parties relating to water resource problems and describes the interactions of different parties who give priority to their objectives. Asgari et al. (2014) present a game-theoretical framework for resource management in construction projects. Their paper strategically forms a cooperative game to investigate the cooperation between sub-contractors for sharing resources and maximising profit. Kose et al. (2017) applied game theory and geographical information systems (GIS) to find a layout plan for troops to maximise the probability of identifying enemies. The game used in their research was a two-person zero-sum game. Peldschus et al. (2010) present the min-max solution for two-person zero-sum game theory methods applied for the sustainable assessment of alternatives in the construction industry. Aplak and Sogut (2013) applied the Game Theory analytical model to the decision-making processes within energy management context, considering the industry and environment as the two players in the game with conflicting strategies. Optimal strategies of competitors (players) were found by analysing the critical criteria. Collins and Kumral (2020) employed the Game Theory based on a multi-criteria technique to examine the environmental sustainability issues in the mining industry by developing five games to investigate maximising both the overall sustainability and environmental sustainability.

However, there is limited research on applying game theory to decision-making problems in the offshore environment, especially in site selection problems in engineering applications with different alternatives available to each decision-maker.

The main objective of this paper is developing a decision-making

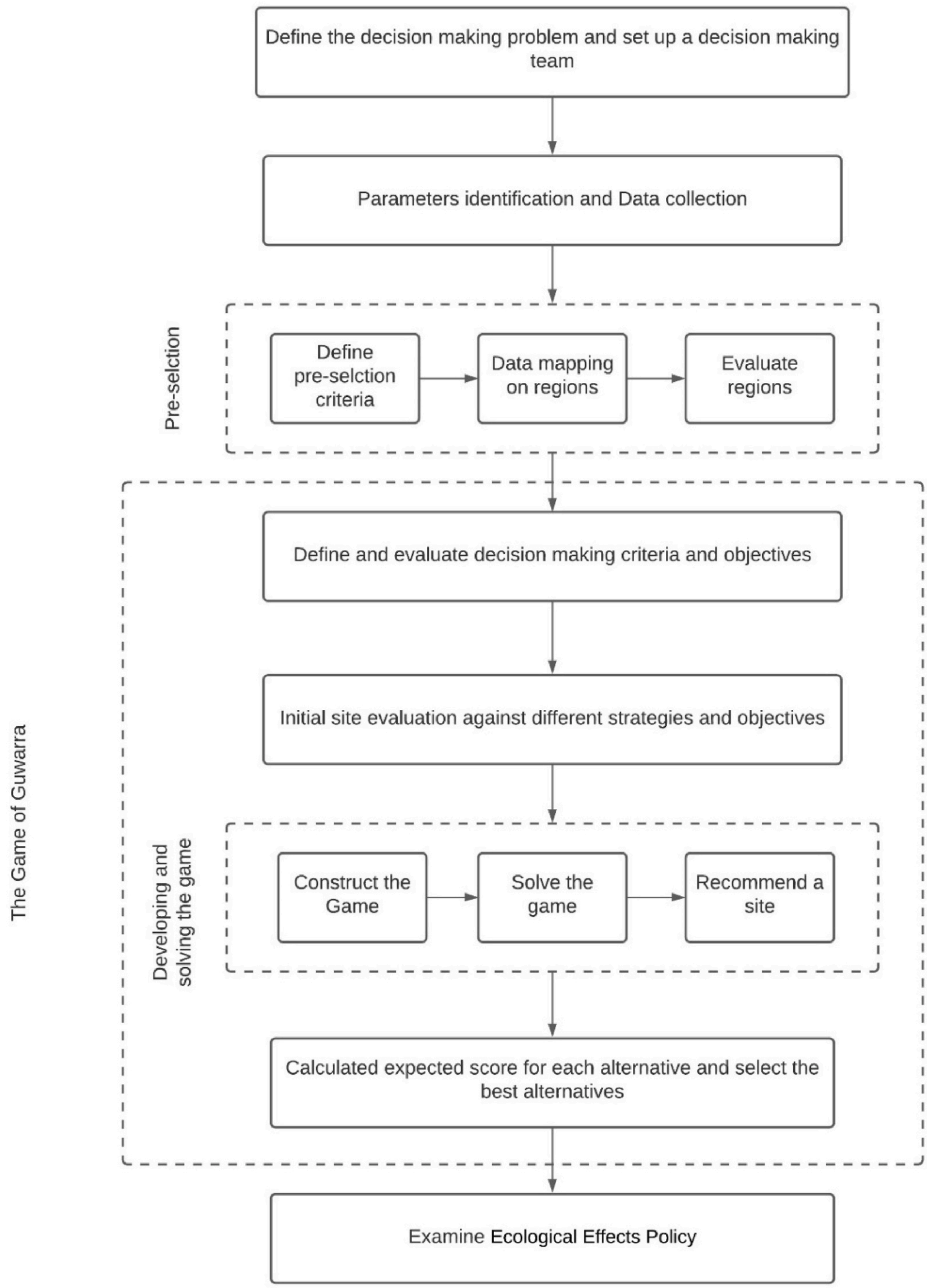

Fig. 1. The proposed methodology for selecting optimum OWF sites.

framework to select the optimal location for installing offshore wind farms while considering different objectives, address the conflicts among the preferences of decision-makers and the uncertainties associated with the available information, which collectively increase the complexity of this decision-making problem. This paper adopts a game-theoretical approach for selecting optimal OWF locations by identifying the critical factors affecting the decision-making process and investigating various objectives of the key decision-makers. The decision-makers involved in a project may have different, and at times conflicting, goals when selecting a site; specifically, investors may seek minimum investment cost, while operators prefer higher availability of OWF, including turbines and Balance of Plant (BoP). A wide range of factors, including available wind power, prevailing weather conditions, distance to ports/grid, and structural reliability, are considered. Understanding these factors and their associated uncertainties will help decision-makers select an optimum location for establishing an offshore wind farm. Furthermore, marine life is affected by the construction of a wind farm. This paper recommends a policy to counter the adverse effects of wind farm deployment on the marine environment and examines the cost of adopting the policy by developing a game-theoretical approach. This paper also examines the impact of a new policy or regulation and evaluates the environmental impacts of different foundation types in a case study selecting the site of an offshore wind farm installation in the Bass Strait. It is anticipated that this knowledge will help minimise the operational risks associated with the infrastructure and enhance operational reliability and profitability. The developed model will help all stakeholders involved in the decision-making process to make informed decisions when selecting a site for an offshore wind farm by estimating the payoffs of each alternative decision concerning different strategies.

2. Methodology

The main focus of this study is to develop a methodology to select the optimal location for installing an OWF considering different decision-maker objectives. The proposed site selection framework aims to identify the criteria affecting the optimal selection of offshore wind sites and the criteria affecting the performance of the site. The framework also explores the possibility of decision-making under environmental regulations that aims to minimise adverse impacts on marine life.

The main steps of the developed methodology are depicted in Fig. 1. The methodology starts by setting up the decision-making team and defines the problem. The team includes a group of decision-makers who have different preferences. After determining the objectives of decision-makers, the criteria and attributes are identified, the next step is to exclude those restricted zones where a wind farm could not be located. This is followed by identifying the factors based on decision-maker objectives. The alternatives are then defined by evaluating the initial site against different strategies and objectives. The n alternatives and m objectives game is defined by a matrix, and an optimisation model based on maximin theory is developed to solve the game. The total expected payoffs (TEPs) are obtained for each alternative, where the highest TEP represents the optimum decision. Finally, the impact of the ecological effect's policy on communities from the various foundation types' installation and presence is examined. The cost of adopting the policy by developing a game-theoretical approach is investigated.

The decision-making parties involved in the project are considered as a team that aims to maximise the payoff of the site selection game while accounting for various preferences and objectives.

2.1. Influential factors identification and data requirements

A wide range of factors, human-related and natural constraints, and environmental restrictions must be considered when locating a wind farm. These factors determine the required location or those affected by the location characteristics, as shown in Fig. 2. For instance, the mean wind speed influences the expected power output of the farm; water depth affects the support structure of the turbines and its cost; seabed soil classification affects the design/cost of support structures; and distance to port and grid, which are integral factors, influencing the cost, grid connection conversion, and maintenance of offshore wind farms.

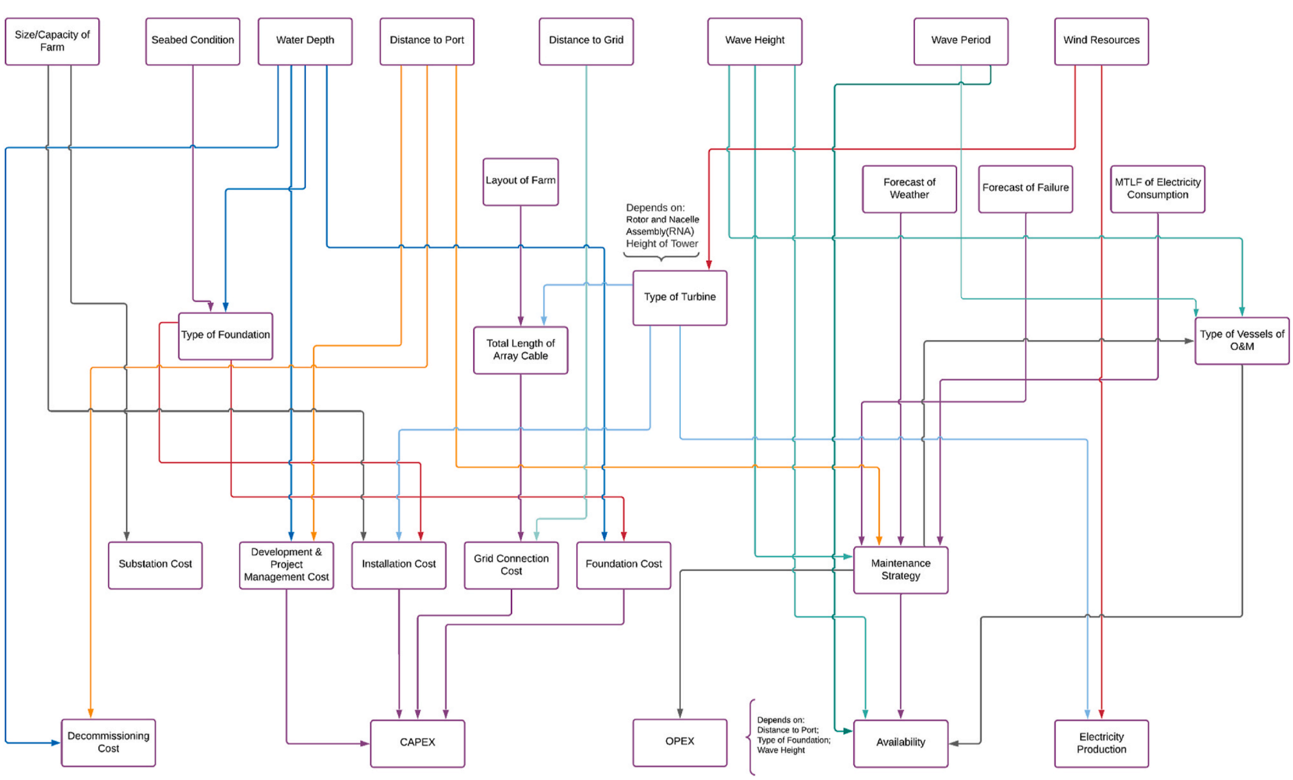

Fig. 2. Parameters and criteria that affect selection of OWF location.

As discussed previously, many decision-makers are involved in an OWF development project, each with different priorities and objectives. The objectives of a decision-maker can interact with those of other parties. To achieve the best outcome, all the major objectives and their interactions should be accounted for. It should be noted that decision-makers may choose specific strategies to increase their outcome, which will likely affect the outcome of other decision-makers. For example, a decision-maker may introduce a specific strategy, for instance, utilising a mother vessel for maintenance activities instead of Crew Transfer Vessel (CTV), to decrease the maintenance crew's transfer time and increase turbine availability to accept the selection of a site which can also increase the overall life cycle cost of the OWF. This paper categorises the primary goals of decision-makers into cost objectives, availability objectives, and production objectives. As shown in Fig. 2, there may be overlaps between these objectives (e.g., availability and performance), highlighting the need to incorporate the interactive effects during the site selection process. The selection of the most suitable wind farm location necessitates a comprehensive set of influential factors. Selecting the right factors is essential for identifying potential regions according to a series of criteria (factors and constraints). The factors are those parameters that affect DMs' preferences, and constraints are restricted areas based on technical constraints and environmental limitations. The factors that influence decision-makers' priorities in the site evaluation process should be collected. Table 2 lists some criteria involved in OWF site selection based on a comprehensive literature review.

2.2. Pre-selection

Once the data have been collected, potential regions for an OWF site should be identified. Some regions, such as anchoring areas, those near active submarine cables, and/or oil and gas infrastructures, are unsuitable for developing an offshore wind farm (Cavazzi et al., 2016). The identified regions will be filtered based on their characteristics and relevant technical and environmental protection limitations and regulatory standards in the pre-selection phase. For instance, in the European context, any offshore wind farm has to be at minimum 0.5 nautical miles away from oil and gas platforms, based on UK marine guidance. For every technical constraint and environmental limitation, specific distance thresholds are assigned to create geographical filters for the pre-selection process.

Table 2
Source of data and influencing criteria in OWF site selection process.

Data	Criteria type	Source of data
Submarine cables	Constraint	Australian Ocean Data Network. Dataset: (Orr and Skeers, 2014)
Power stations	Factor	Australian Renewable Energy (ARENA) (CSIRO, 2014)
Transmission network	Factor	As above
Ports	Factor	As above
Recreation zone	Constraint	As above
Protected area	Constraint	As above
Fishing zone	Constraint	As above
Wind speed	Factor	Global Wind Atlas
Water depth	Factor	General Bathymetric Chart of the Oceans (Smith, 2004)
Wave height	Factor	ARENA
Seabed nature	Factor	ARENA
Fishes	Factor & Constraint	Australian Ocean Data Network
Birds	Factor & Constraint	
Flora & fauna	Factor & Constraint	Australian Ocean Data Network
Coral reef	Constraint	Global Distribution of Coral Reefs (Anonymous, 2015)
Oil and gas platforms	Constraint	Australian Ocean Data Network Dataset: (Orr et al., 2014)
Seismic risk	Constraint	NOAA National Centers for Environmental Information (NCEI) (Weather, 2018)
Ship route	Constraint	Spatial at Australian Maritime Safety Authority (AMSA, 2020)
Oil and gas pipeline	Constraint	Australian Ocean Data Network Dataset: (Manager Client and New, 2017)

Table 3
Environmental and biophysical constraints in OWF site selection.

Features	Acceptable range	Source of data
Water depth	>5 m	General Bathymetric Chart of the Oceans (Smith, 2004)
Coral reef	>10 km	Global Distribution of Coral Reefs (Anonymous, 2015)
Mangrove	>10 km	
Sandbar of shallow water	Avoided	General Bathymetric Chart of the Oceans
Seismic risk	Avoided	
Sediment thickness	Within the exclusive economic zone (EEZ)	
Cyclone	Within the EEZ	

Table 4
Existing infrastructure and human-related constraints.

Features	Acceptable range	Source of data
Visual impact	>8 km	Danish Energy Agency Agency (2017)
Oil and gas field	Avoided	Australian Ocean Data Network Dataset: (Orr et al., 2014)
Oil and gas platform	>0.5 nautical miles	Australian Ocean Data Network Dataset: (Orr et al., 2014)
Oil and gas pipeline	>0.5 nautical miles	Australian Ocean Data Network Dataset: (Manager Client et al., 2017)
Shipping routes	>500 m	Australian Ocean Data Network Dataset: (Manager Client et al., 2017)
Submarine communication cable	>0.5 nautical miles	Australian Ocean Data Network Marine and Amospheric (2016)

In the Australian context, for any offshore wind project to obtain a license, new legislation must be introduced to ensure sustainable development is underway. The Department of Industry has been working on this legislation since January 2020. The present paper reviews previous studies and expert reports to pinpoint the technical and regulatory limitations of offshore site implementation, such as offshore report published by Danish Energy Agency that present the Danish regulatory framework for offshore wind (Agency, 2017); Messali et al. (2009) which was the first published study to evaluate the potentials of offshore wind power in Australia; Gavériaux et al. (2019) that Defined area of available zones for an installation of a renewable energy system in Hongkong; offshore wind energy report published by Blue Economy CRC, outlining the opportunity that exists for Australia in the offshore wind industry Briggs (2021); and Hundleby et al. (2017) that considered offshore wind energy potential in Europe. Table 3 and Table 4 provide a summary of the constraints and limitations. Data is further analysed, restriction zones are excluded, and constraints are applied on the map to determine the unrestricted areas to implement an OWF.

2.3. Define and evaluate decision-making objectives

In this stage, the decision-making team defines their objectives, evaluates existing criteria, and assesses available alternatives. Although self-interested decision-makers are on the team to enhance their own benefits, their objectives may have interactions and conflicts. In the following sub-section, each of the major objectives in the developed game is presented in detail.

2.3.1. Cost objective

The cost of an offshore wind project mainly falls under the investment and operational costs during the life cycle of an OWF. In recent decades, researchers, governments, and consultant companies such as the European Wind Energy Association (EWEA), National Renewable Energy Laboratory (NREL), and International Renewable Energy Agency (IRENA) have carried out assessments of offshore wind energy costs. Some of these studies focus on the part of the wind farm life cycle such as the installation phase (Kaiser and Snyder, 2012), operation and maintenance (Castro-Santos and Diaz Casas, 2014; Myhr et al., 2014), or identified the various cost factors involved in the life cycle of floating wind turbines. However, Shafiee et al. (2016) proposed a framework for life cycle cost (LCC) modelling and the analysis of OWFs to compare the cost of different projects simultaneously. The LCC is a comprehensive measurement to compare various investment options calculated over a given period. Both initial and future costs have to be taken into account, which can be calculated by Eq. (2). An offshore wind project's life cycle cost, which is an indicator of the cost objective, consists of capital expenditure (CAPEX), operation and maintenance expenditure (OPEX), and decommissioning costs.

$$LCC = CAPEX + OPEX + Decom\ Cost \tag{2}$$

CAPEX occurs at the beginning of the process of OWF and is mainly comprised of the cost associated with turbines, foundation, grid connections, installation and development and project management cost (Equation (3)). The development of an OWF typically begins around five years before installation. The cost of development is related to the project management cost, legal costs, survey cost and contingencies cost. The cost of turbines, which includes the cost of Rotor Nacelle Assembly (RNA) and the cost of the tower, is the most significant investment in a wind farm at around thirty percent of the OWF CAPEX. Foundation costs are sensitive to water depth. Monopiles and gravity-based foundations are used in water depths less than 30 m. Large steel monopiles are used for turbines located in regions with less than 50 m of water depth, and jackets and tripods are used as options for foundations with a depth of less than 60 m (Horwath, 2020). Floating structures have been used for water depths beyond 50 m. Grid connection costs mainly depend on the length of the cable, which is determined by the distance between the offshore site and shore and the distance to the onshore substation grid. The distance from the shore also affects the type of export cable used. A high-voltage alternating current is chosen if the distance from shore is less than 55 km, and for longer distances, high-voltage direct-current cables are used. Installation costs are affected by the OWF capacity, intra-array cable length, cable cost, transportation cost (wet tow and dry tow), and foundation type. The cost of a substation is a function of wind farm capacity. Therefore, if there is increased water depth and distance to shore, there will be an increase in the installation cost.

$$CAPEX = C_T + C_F + C_G + C_S \ + C_I + C_{D\&P}, \tag{3}$$

where C_T, is the cost of turbines, C_F is the turbine foundation cost, C_G is the grid connection cost, $C_I$is the installation cost, C_S is the cost of offshore substations, and $C_{D\&P}$ is the cost of development and project management.

OPEX of an OWF is divided into operation, maintenance, port activities, license fees, and other costs (Röckmann et al., 2017). O&M costs represent 53% of the OPEX. For an OWF, O&M cost can be affected by many variables, including the distance to the shore and significant wave height. Distance to the nearest port with required facilities and the length of suitable weather windows also significantly influence the OPEX of a farm.

There can be some strategies to lower the O&M costs of a wind farm, such as changing the turbine type from requiring drivetrain to the direct-drive turbine (i.e., eliminating a high maintenance cost component); and increasing the spare part inventory level, for instance for gearboxes, which are one of the most expensive parts of the wind turbine in terms of capital and maintenance. However, in some cases, these strategies are more costly and can only be accepted by the industry if they promise more revenue.

The maintenance method/strategy chosen by the asset management team is another factor that can affect the cost of maintenance and farm availability. The maintenance strategy can be based on corrective maintenance, preventive maintenance, opportunistic maintenance, condition-based maintenance, or a combination of these. Selection of maintenance approach depends on the type and extent of a repair action, crew and vessel availability, likelihood of suitable weather window and in the case of proactive maintenance, medium-term load forecasting of electricity consumption. Monitoring systems and sensors are incorporated in WTs to detect a failure before it occurs, providing repair opportunities (Tuyet and Chou, 2018). Implementation of every O&M strategy depends on the existing wind and wave conditions. Various techniques to forecast wind speed and wave height have been proposed, including data-driven and physical models. Pandit et al. (2020) proposed a data-driven model for weather forecasting in offshore environments and found that more accurate weather forecasts can decrease O&M costs by up to 3%. As presented in Fig. 2, predicting the electric power demand for the medium-term is a tool to choose the strategy for the maintenance of the farm by trading-off the cost between the maintenance approach and purchasing electricity from other states. Eshragh et al. (2020) developed a model to forecast peak demand in the medium term for three main Australian states. The methodology would be helpful to plan the logistics, including hiring vessels, crew, and maintenance tasks for a farm.

To quantify the investment cost more realistically, a net present value (NPV) approach has been used by applying Equation (4). To capture the total value of a potential investment of a farm during its lifetime, the net present value is applied.

$$NPV = \sum_{i=1}^{n} \frac{C_i}{(1+r)^i}, \tag{4}$$

where C_i, r, and n represent the cash flow at the time *i*, annual interest rate, and the number of years over which the investment takes place, respectively. This metric can inform the operators and decision-makers about the current trends in the relative costs of OWF and the project competitiveness.

2.3.2. Availability objective

The reliability of an offshore wind farm is defined as the ability of an OWF to perform the required functions under given conditions for a lifetime (Gonzalez et al., 2017). The reliability of a wind farm can be affected by many factors, including the adopted maintenance strategy (Sarker and Faiz, 2016; Scheu, 2012; Scheu et al., 2018, 2019)), access method, type of turbine, and balance of plant availability. Electricity demand from the farm for each month is another factor affecting the availability of the wind farm. Mid-term load forecasting of electricity consumption is used to plan the maintenance time, especially when the farm maintenance strategy is opportunistic maintenance. To assess the reliability of an OWF, different metrics are considered, such as mean time between failure (MTBF), mean time between repair (MTTR), mean time to failure (MTTF), failure rate, and availability. Availability is the comprehensive indicator used to show the effectiveness of strategies chosen for reliability. Availability is defined as the "ability to be in a state to perform as and when required, under given conditions, assuming that the necessary external resources are provided" (BSI, 2010), and it can be calculated by Equation (5):

$$\text{Availability} = \frac{\text{Mean Time Between Failure}}{\text{Mean Time Between Failure} + \text{Mean Down Time}}, \quad (5)$$

where Mean Downtime is a summation of Mean Time to Repair, Mean Logistic Delay Time and Mean Waiting Time for Spare Parts (Wing and Crow, 1990). The wind farm downtimes are divided into unplanned maintenance downtime or repair time, crew and vessel unavailability, spare parts unavailability, and unsuitable weather. Therefore, increasing the distance to shore causes a higher transportation time and may decrease availability. There are some strategies to use to improve the availability of offshore wind farms, such as using faster transport vessels, redundancy for critical components or eliminating them by using other technologies (e.g., direct train turbines), increasing the level of maintenance inventory, or coordinating with suppliers and distributors to shorten the lead time.

In the case study of this research, changing the type of vessel is examined to improve the availability. The vessel's range depends on the voyage, weather conditions, and availability of vessels. Two main options exist for the vessel choice for performing maintenance activities: onshore-based marine access such as CTVs and offshore-based maritime access such as mother vessels. Offshore-based vessels, which accommodate a large number of technicians and spare parts, can significantly decrease the transfer time to the farm, especially when corrective maintenance is needed. The drawback is that the vessel is very costly compared to a CTV, and staying offshore for a long time can affect human cognitive performance and contribute to human errors. The vessels may either be purchased by the service provider, chartered for a fixed period or hired on the spot (when needed). Each of these options will invoke different costs, where the benefit of having a number of vessels available is that maintenance or repairs can be scheduled immediately, hence minimising the impact of failure on farm availability. Having idle vessels will imply costs for the owners/operators during periods with few or no maintenance activities. Spare parts and logistics are other factors that influence wind farm availability. When an unexpected failure occurs that requires replacement, the unavailability of spare parts can lead to extended downtime and significant production losses. From a warehousing and logistics perspective, the service provider needs to balance keeping the necessary spare parts in stock and simultaneously reducing warehousing costs, including rent, utilities, insurance, and personnel costs. The sea state condition is another factor affecting wind farm availability due to its impact on on-site accessibility. For an OWF, significant wave heights at the wind farm location and between the site and the operation port are good indicators of site accessibility. Vessel operability is also affected by wave period. However, wave height has higher importance than the wave period. So, in this study, wave height is considered for site accessibility.

Weather windows significantly influence the cost and availability by limiting accessibility to the turbines for maintenance, increasing the transfer time, and increasing the downtime when corrective maintenance is needed. Regarding weather conditions, the sites can be placed in an environment categorised as mild when significant wave heights are less than 1 m, moderate when significant wave heights are between 1 and 2.5 m, and extreme when significant wave heights are more than 2.5 m. The sites in extreme environments have significantly higher costs and lower availability than moderate sites, which have a significant wave height between 1 and 2.5 m for more than 60% of the time (Beiter et al., 2016). By making some alternative strategies available to the decision-makers, they are able to maximise the outcome of their decision while selecting their preferred alternative.

2.3.3. Production objective

The performance of a wind farm can be calculated by the annual energy production (AEP), which represents the fraction of the total energy delivered over a year (MWh/year). It can be affected by many different factors such as wind speed, wind direction, and turbine design, including its swept area, hub height and power rating. For the assessment of wind energy potential, the wind characteristics at the desired locations must be fully understood. When developing a wind farm, a crucial step is making an AEP prediction. The available energy to each turbine is the key indicator for analysing the performance of the different alternatives. Several studies of forecasting wind power suggest that the wind direction is less important than wind speed in wind energy generation (Anuradha et al., 2016). Therefore, the wind speed magnitude is modelled probabilistically for each site in this paper. The average wind speed is used to calculate the energy available to each turbine. Wind speed data are collected, and the distribution of wind speed was estimated using a Weibull distribution. There are some sources for collecting offshore wind speed data, such as historical data, wave-buoys, remote sensing from satellites, national weather ships, coastal meteorological stations, and statistical distribution (Foley et al., 2012). Previous studies have shown that the Weibull distribution is a good representation of hourly wind speed variations at a location (Shu et al., 2015; Yue et al., 2019). The Weibull distribution is fitted to wind speed data to calculate the shape and scale parameters for a specific location. The cumulative Weibull distribution with a shape factor of 2 is the most common value used to describe the hourly variation of wind speed at many locations (Cavazzi et al., 2016; Neill and Hashemi, 2018). After collecting the wind speed data and the distribution of wind speed is estimated, the Weibull distribution is then used to calculate AEP using the power curve of the wind turbine. AEP is usually calculated as Equation (6).

$$\text{AEP} = \text{T} \sum \text{F}(\text{u}) \times \text{PC}(\text{u}), \quad (6)$$

where T is the total number of hours per year, and $\text{F}(\text{u})$ and $\text{PC}(\text{u})$ are the Weibull distribution of the wind speed data and the power produced by a wind turbine in a given wind speed (i.e., the power curve), respectively (Yue et al., 2019).

The strategies for improving electricity production in wind farms are changing to incorporate high-rated turbines and turbines with large rotors and small generators (Sedaghat et al., 2019). However, at high wind speeds, the power output is not dependent on the rotor diameter (Preindl and Bolognani, 2011). The wind farm layout is usually designed to allow for more optimal power production from the farm (Park and Law, 2016). Additionally, different hub height wind turbines can change wind farm power output (Chen et al., 2017). The adopted metric (AEP) can inform decision-makers about the current trends in the relative performance of offshore wind farms and the project's competitiveness. The potential AEP is estimated for this objective to determine the possible electricity production for each site, depending on the wind speed and type of turbine.

2.4. Site selection decision model

Selecting a wind farm site is perhaps the most complex decision that will have long-term impacts on a wide range of stakeholders, and all the feasible strategies should be considered during the decision-making process. After considering all elements and existing conditions influencing the development of an OWF, potential sites are determined based on the goal of the project. The decision-making model consists of initial site evaluation against different strategies and objectives, developing and solving the game, calculating the expected score of each alternative, and selecting the best options. Subsequently, the decision-making team determines sites and investigates all the strategies and techniques available for each site. After developing and solving the game, the optimal location of a wind farm is selected from between these sites by considering all possible scenarios and limitations.

Firstly, a model is presented that shows the site evaluation against different strategies and objectives of the decision-making process. This model is the initial step of the game-theoretical approach that helps solve the decision-making process to determine the elements of game theory, i.e., alternatives (row player), objectives (column player) and payoffs. The outcome of this step uses the game players' strategies and payoff of the game matrix. In previous sections, the objectives have been determined, and this step aims to define the alternatives of the game. Decision-makers are supposed to be able to choose from a set of different strategies. New strategies that improve availability or production may affect the cost and help the decision-makers choose the best strategies for each site. The alternative which does not involve added strategies is referred to herein as base-case. The decision-making team defines the base case scenario to develop an OWF. Every stakeholder in the team can either accept the base scenario or make counteroffers to gain more outcomes. In the definition of the base case, the size of the farm, type of turbines and body of the plant, type of structure in different water depths, type of access vessels at different distances to shore, etc., have been defined based on previous experiences and studies. For example, assume decision-maker 1 (DM 1) chooses a site that is located 60 km from shore in an area with a 30-m water depth. For a place with these criteria, the decision-making team decides to construct monopile structures as a foundation for the turbine and uses CTVs to access the site. This assumption is used as the base case for this site, and DM 2 (who focuses on availability) either accepts the base case or uses mother vessels to decrease the access time. Changing the vessel type of the wind turbine affects the payoff of DM 2 and may increase the cost of the site and affect DM 1's outcome. Then, DM 3 has the option to apply the base case or offer a new strategy. In the decision-making process, players adopt a plan to achieve their objectives in their strategy and partially control the outcome of the process. Players have different valuation systems over the set of possible outcomes and different preferences over outcomes.

In this process, the decision-makers have bargaining power if the strategy is feasible. In other words, as the decision-makers are rational, and if a strategy defined by the decision-making team is not feasible, they just accept the base case.

Table 5 shows the different payoffs for available $i = (1, \dots, m)$ alternatives (sites and strategies) and $j = (1, \dots, n)$ objectives for the development of a wind farm. In terms of DM objectives, there are three objectives defined for this game which are LCC, availability and AEP, and their values are AUD/MW, Percentage, and MWh/Year per MW. As mentioned before, to calculate the cost objective, the net present value of the summation of capital expenditure, O&M expenditure, and decommission cost $(\mathrm{LCC_i} = \mathrm{NPV}\ (\mathrm{CAPEX_i} + \mathrm{OPEX_i} + \mathrm{Decom\ Cost_i}))$ needs to be determined. Also, it is assumed that the difference between decommissioning costs for all sites with all types of turbines is negligible. Accordingly, $\mathrm{CAPEX_i}$ and $\mathrm{OPEX_i}$ will be changed by modifying the strategies of other DMs, so, $\mathrm{CAPEX_i}$ and $\mathrm{OPEX_i}$ are calculated to find the $\mathrm{LCC_i}$ for each alternative. If DM 1 chooses site i and both DM 2 and 3 accept the base case, the CAPEX, OPEX, availability and annual electricity production would be $\mathrm{Capex_i}$, $\mathrm{Opex_i}$, $\mathrm{R_i}$, and $\mathrm{AEP_i}$ respectively. If DM 2 accepts the base case while DM 3 offers an alternative strategy (in this study, choosing a 10-MW wind turbine instead of 5 MW to increase the production), the CAPEX, OPEX, availability, and annual electricity production (AEP) would be $\mathrm{Capex_i} + \ \mathrm{C_t}$, $\mathrm{Opex_i} + \ \mathrm{Cm_t}$, $\mathrm{R_i} + \vartheta \mathrm{R_i}$, and $\mathrm{AEP_i} + \ \mathrm{A_i}$ respectively. Where $\mathrm{C_t}$is the cost of the difference between the type of turbines that is added to Capex, $\mathrm{Cm_t}$, is the cost that would be added to Opex because of the change of the type of turbines. Furthermore, using a higher-rated turbine may affect the availability (ϑ%) and annual production of electricity ($\mathrm{A_i}$ MWh/year). It should be considered that the value of $\mathrm{C_t}$, $\mathrm{Cm_t}$, ϑ, and $\mathrm{A_i}$ can be negative, positive, or zero. For instance, a strategy implemented to select a higher rate turbine may have an impact on the availability of the farm. Therefore in Table 5, the availability of alternative 2 is represented by $\mathrm{R_i} + \vartheta \mathrm{R_i}$ where ϑ can be 0, positive or negative. α and β that are the percentage of farm availability change when using a new type of maintenance vessel depending on the vessel mobilisation time that causes an increase in availability. Furthermore, several factors affect the power generation efficiency of wind energy extracted from wind turbines. These factors do not stop the turbine and should be addressed before causing failure in the wind turbine during running conditions. Dust accumulation is one of the factors affecting wind turbine performance (Deb et al., 2017). Also, blade contamination by insects can reduce the power output of turbines by up to 55% (Dalili et al., 2009). Therefore, the wind turbine blades should frequently be cleaned using robots without stopping turbine operation completely. So, θ and λ are the percentage of farm performance change when using new type of vessels that affect the mobilisation time of tasks that increase the performance without stopping the turbine.

After determining the strategies applicable to each farm and quantifying the outcome of each objective for all the alternatives, the next step is to develop an optimisation model to solve the game and aims to develop an optimisation model based on the maximin objective to solve the game.

The solution concept is adopted from the model developed by Peldschus et al. (2010). A two-person zero-sum game is defined in a

Table 5
Objective payoff relationships for the available alternatives (for site *i* and its strategies) to develop a wind farm. α: percentage of farm availability change when faster CTV is used; β: percentage of farm availability change when mother vessels are used; C_{v+}: difference between two types of CTV; C_{mv}: difference between CTV defined in the base case and mother vessel; θ: percentage of Change in AEP when faster CTV is used; and λ: percentage of change AEP when mother vessels are used.

Alternative	Description	Elements of Objective 1		Objective 2	Objective 3
		CAPEX	OPEX	Availability	Annual Energy Production
Alternative 1	• Owner chooses Site *i* • Operator accepts the base case, • Consumer chooses Base Case Scenario	$\mathrm{CAPEX_i}$	$\mathrm{OPEX_i}$	$\mathrm{R_i}$	$\mathrm{AEP_i}$
Alternative 2	• Owner chooses Site *i*; • Operator accepts the base case, • Consumer makes an offer to use a higher rated turbine	$\mathrm{CAPEX_i} + \ \mathrm{C_t}$	$\mathrm{OPEX_i} + \ \mathrm{Cm_t}$	$\mathrm{R_i} + \vartheta \mathrm{R_i}$	$\mathrm{AEP_i} + \ \mathrm{A_i}$
Alternative 3	• Owner chooses Site *i*; • Operator makes an offer to change the O&M vessels to increase accessibility and increase the availability, • Consumer makes an offer to use a higher rated turbine	If the site is more than 70 km from the shore: $\mathrm{CAPEX_i} + \ \mathrm{C_t}$ If the site is less than 70 km from the shore: $\mathrm{CAPEX_i} + \ \mathrm{C_t}$	$\mathrm{OPEX_i} + \ \mathrm{Cm_t} + \mathrm{C_{mv}}$ $\mathrm{OPEX_i} + \ \mathrm{Cm_t} + \mathrm{C_{v+}}$	$\mathrm{R_i} + \vartheta \mathrm{R_i} + \beta \mathrm{R_i}$ $\mathrm{R_i} + \vartheta \mathrm{R_i} + \alpha \mathrm{R_i}$	$\mathrm{AEP_i} + \ \mathrm{A_i} + \theta\,(\mathrm{AEP_i} + \ \mathrm{A_i})$ $\mathrm{AEP_i} + \ \mathrm{A_i} + \lambda\,(\mathrm{AEP_i} + \ \mathrm{A_i})$
Alternative 4	• Owner chooses Site *i*; • Operator makes an offer to change the O&M vessels to decrease access time and increase the availability, • Consumer accepts the base case	If the site is more than 70 km from the shore: $\mathrm{CAPEX_i}$ If the site is less than 70 km from the shore: $\mathrm{CAPEX_i}$	$\mathrm{OPEX_i} + \ \mathrm{C_{mv}}$ $\mathrm{OPEX_i} + \ \mathrm{C_{v+}}$	$\mathrm{R_i} + \ \beta \mathrm{R_i}$ $\mathrm{R_i} + \ \alpha \mathrm{R_i}$	$\mathrm{AEP_i} + \theta\,(\mathrm{AEP_i})$ $\mathrm{AEP_i} + \lambda\,(\mathrm{AEP_i})$

matrix. Let $S_A = \{a_1, a_2, \ldots, a_i, \ldots, a_m\}$ and $S_O = \{o_1, o_2, \ldots, o_j, \ldots, o_n\}$ denote sets of alternatives and objectives, respectively. In this particular setup of the game theories, players are not the individuals who make the decision, rather an element of the game that enables the playing. The row players in this game are decision alternatives (DAs), and the column players are DM objectives (i.e., the cost, availability, and production objectives in the current method). When the row player chooses the alternative a_i and the column player chooses the objective o_j, $x_{ij} = o_j(a_i)$ shows the payoff. Then the matrix $U(X)$ is considered as a payoff matrix for a zero-sum matrix game, and the row player chooses one of the alternatives from *Set* S_A, and the column player chooses one of the objectives from Set S_O. It should be noted that all objectives are maximised by the game, and because some of the objectives are cost values, they must be normalised to make them comparable. Usually, to allow for comparability of the values, they are normalised on an interval between zero and one. There are several options for the normalisation of the characteristic values. Generally, a distinction can be made between linear and non-linear transformations (Peldschus et al., 2010). Next, the initial decision-making matrix is normalised, and a normalised matrix is prepared (matrix $\overline{U}(X)$). The normalised decision-making matrix is then solved according to the (maximin) principle.

The solution (equilibrium) of the game either has a Nash equilibrium, if $\text{Maximum (Row Minimum)} = \text{Minimum (Column Maximum)}$, or has a mixed strategy. So, the most suitable site can be identified either by the saddle point (pure Nash equilibrium) or by aggregating the normalised payoff with the corresponding weight from the vector $Q^* = \{q_1, \ldots, q_j, \ldots, q_n\}$. q_j is also the optimal weight of the objective obtained in this game; thus, the conflict between three different groups of DMs are solved. The best alternative is identified by obtaining the total expected payoff of the three DM objectives. The total expected payoff (TEP) is obtained by Equation (7).

$$\text{TEP}_i = \sum_{i=1}^{n} \sum_{j=1}^{m} q_j x_{ij}, \tag{7}$$

where $x_{ij}$is the payoff of alternative i on objective$j$, and q_j is the optimal weight of an objective. The highest-ranked alternative is the best site for implementing an OWF.

2.5. Assessment of ecological effects

This section examines the impact of the ecological effect's policy on communities from the various foundation types' installation and presence. The cost of adopting the policy by developing a game-theoretical approach is investigated.

Over the past 20 years, local governments and legislators have introduced a series of legal rules to decrease the environmental impacts from development activities in the offshore renewable energy sector. Offshore structures and operations, in general, have a significant impact on their surrounding environment, and wind farms are no exception. The developed framework in this paper considers evaluating the environmental effects from various farm development strategies (related to site selection and implementation), enabling the stakeholders to incorporate significant environmental protection policies in the decision-making process. The paper offers a policy to ensure sustainable development and consider environmental impacts in the development phase, especially the environmental impacts that occur during the construction and operation of an OWF to ensure more sustainable development for the project.

In this paper, three types of environmental impacts that three forms of wind turbine foundations (monopile, jacket, floating) may have on the ecological communities are evaluated. These effects include wake and scour effects and habitat loss, and artificial reef. Scouring is an essential effect of OWTs on the environment, similar to every other subsea structure. Compared to monopiles, jacket foundations cause less scouring due to their having a smaller contact area with the seabed. Floating OWTs introduce the minimum wave effect and scouring to the seabed, compared to monopiles and jackets (Horwath, 2020). Impacts of habitat loss due to foundation installation and operation are expected to be most significant for foundations with the largest footprint (Horwath, 2020), such as monopile, but are relatively smaller for the jacket and almost negligible for floating foundations. Soft-bottom habitat loss could affect marine mammals such as grey whales that use soft-bottom habitats for feeding areas, feeding on infauna and epifauna. Foundations can act as artificial reef-like structures, which can have positive ecological effects. Artificial reefs provide better protection and food availability to fishes (English et al., 2017). The artificial reef effects could be larger with a jacket foundation than monopiles because of the greater surface area associated with a lattice structure and may be greater with some types of floating foundations depending on the depth and surface area of their anchoring systems (English et al., 2017; Horwath, 2020).

The above factors can be of great significance during the lifetime of an OWF. Hence, a site selection process for OWF must closely evaluate the likely impacts during the installation, operation, and decommissioning activities. More importantly, if the regulatory authorities introduce specific policies to reduce such effects, the presented decision-making method can identify the alternatives that assist with this objective. This can be done by selecting the appropriate WT support structure. An approach based on the qualitative matrix is used as a qualitative metric to help decision-makers choose options with the lowest hazard level for the environment. To demonstrate the application of the new policy in the decision-making process, the policy is applied to all DA determined in the previous stage.

In this section, an extensive-form game with perfect information processes is used for calculating the effect of this policy. In an extensive form game, decision-makers, which are players of the game, decide sequentially whereby the first player makes a decision, the second one responds, and so on. Such a problem can be structured as a game tree with a set of players (nodes) and a directed graph (arrows connecting the nodes). Each decision node is labelled as belonging to a player in the game, and each player has a payoff function.

A frequently used solution concept for extensive-form games with perfect information is the Subgame *Nash Perfect Equilibrium* (SNPE). In terms of Nash equilibrium in the extensive-form game, it should be considered that every subgame perfect Nash equilibrium is a Nash equilibrium. Still, not every Nash equilibrium is a subgame perfect Nash equilibrium (Harrington, 2009). The backward induction method would be used to find an SNPE with a searching process after equilibriums at the end of the tree in a sub-tree and rolling back through several sub-trees to the root of the tree and analysing for equilibriums leads to an SNPE.

Fig. 3 represents the game tree. Player 1 first chooses between EcEP or not for the site *i*. If no EcEP is involved in this stage, player 2 has the option of accepting the base case or rejecting it and offering a new strategy to improve the payoff. Then, player 3 has the option to accept the base case or reject/offer. In Fig. 3, LCC_i, R_i, and AEP_i are life cycle cost, availability and annual electricity production of site$i$. c_i, r_i, a_i are the amount added to LCC_i, R_i, and AEP_i changing the decision of player 2 and player 3. E_CIs the cost deducted from the LCC, if the DMs choose less impact foundations. It can be categorised to $Ec^J$and Ec^F for jacket and floating foundation. In other words, the Ec^Jwould be deducted from the LCC, and if the DM choose floating, the Ec^F, $Ec^F > Ec^J$, would be

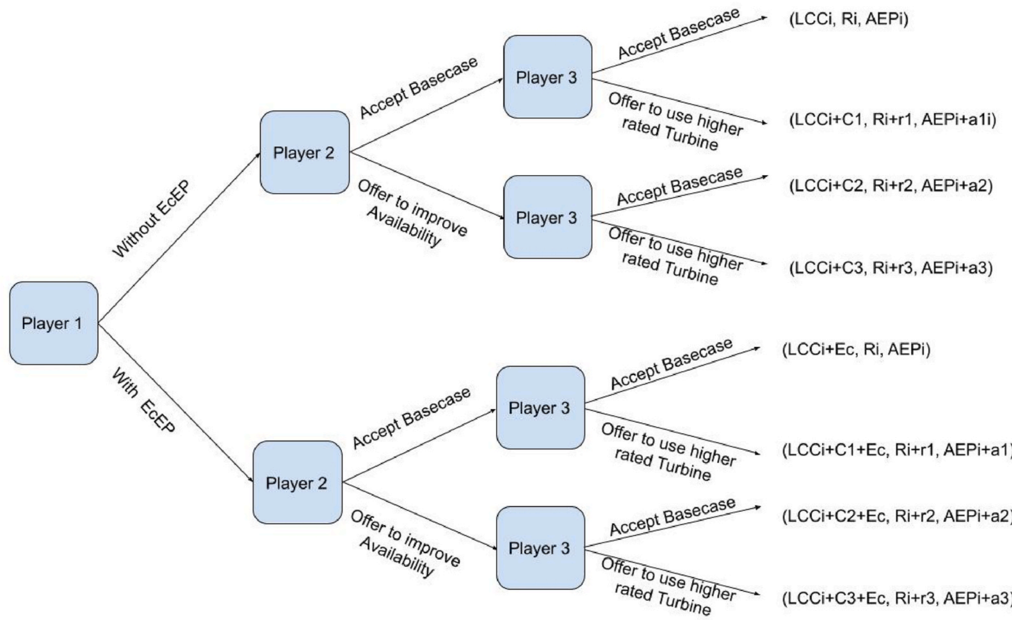

Fig. 3. Proposed Game tree for adopting the Ecological Effects Policy (EcEP).

deducted from the LCC.

3. Application of methodology: an OWF in Tasmanian waters

The application of the developed methodology is demonstrated using a case study to find the optimum location of an OWF site in the Bass Strait, which is known for its strong and constant wind, suitable soil and water conditions, and proximity to the national electricity distribution grid. To determine the best OWF location, a decision-making team consisting of investors, operators and consumers are set up, and the baseline cases are defined within the team. The proposed methodology is applied to an offshore wind farm consisting of 100, 5 MW wind turbines in an area of 100km^2. The wind turbines have a 116-m rotor diameter and 100-m hub height with monopile foundation in water less than 30 m depth; jacket type foundation in water depth between 30 m and 60 m; and floating type foundation in water depth more than 60 m. WTs are positioned in a layout of 10 rows by 10 columns, and the array cable length is calculated as a function of the number of WTs in a farm. In this case study, it is assumed that the change of diameter of the turbine does not affect the distance between each two WTs. Also, the offshore substation is placed in the middle of the wind farm, and the distance from the coast to the onshore grid connection point is 20 km. Since this paper aims to compare different locations and strategies in the Bass Strait, the rental charges, transmission charges etc. Are considered the same for all sites. After setting up the game team and identifying the influencing parameters and data collection, the excluded areas are identified. Different DMs' objectives are then determined for all areas in the Bass Strait. Subsequently, the game theory model is applied to find the best location. In the next section, the details of the case study and the obtained data are presented.

3.1. Preselection steps

The proposed methodology is applied to assess the areas suitable for offshore wind farm development in the Bass Strait regarding human-based and natural constraints. This results in certain parts of the region being excluded from the options, with the main exclusions being marine parks and the area near oil and gas platforms in the north of Bass Strait. Fig. 4 illustrates the results of this process where excluded areas in the East-southern Australian waters are accounted for.

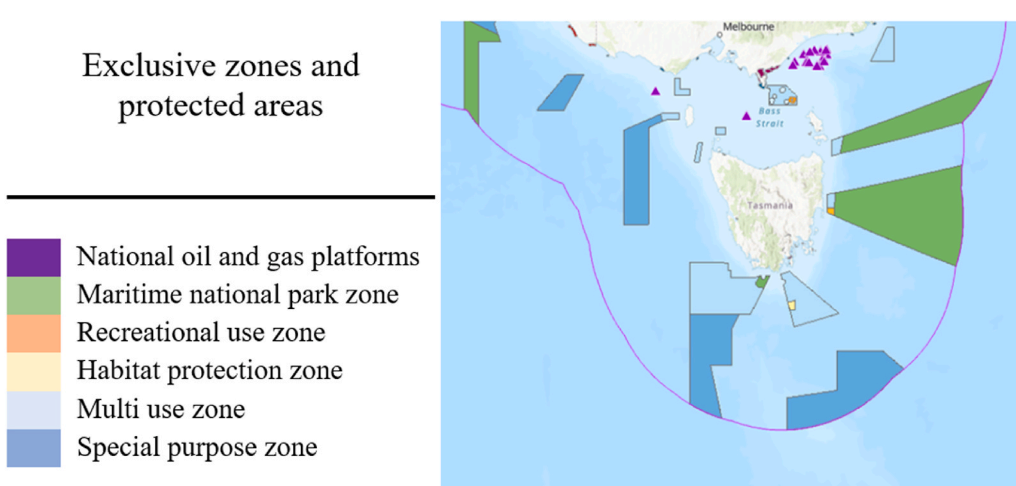

Fig. 4. Excluded areas for implementing an OWF in the East-southern Australian waters.

3.2. The Game of Guwarra

As previously mentioned, decision-makers have their own priorities in the wind farm development project. Variability in decision-making goals is considered here with three major objectives, including project cost, OWF availability and production capacity.

Although the next sub-sections provide a detailed summary of the mathematical methods used to estimate the payoffs of each objective, readers are referred to the works of Shafiee et al. (2016), Beiter et al. (2016), Cavazzi et al. (2016), and Bosch et al. (2019) for more information on CAPEX and OPEX calculations. These cost components of the OWF life cycle are modelled on a per-megawatt basis and in Australian dollars for the sake of this case study.

The cost of a turbine is one of the largest proportions of CAPEX in OWF development projects. Although it is not possible to find exact data about turbine cost because of competition among manufacturers, the values presented in this paper are the estimated material cost of a wind turbine as reported by Shafiee et al. (2016) and converted to Australian dollars. Turbine models are ranked by their power density. Since the average wind speed in the area of interest is more than 8.5 m/s, Class II turbines are suitable for the farm. The 5-MW wind turbine with a hub height of 100 m is chosen for this case study.

Foundation costs are dependent on the type of foundation as well as water depth. The foundation types considered in this study are monopile, jacket, and floating which are suitable for water depth ranges of 0–30 m, 30–60 m, and >60 m, respectively. It should be noted that the water depths in the regions of interest are less than 120 m. The values of foundation cost depend on the material cost and cost of transportation of foundation from port to the site in different calculated water depths based on the method used by Bosch et al. (2019). The foundation cost ranges from 612 k AUD/MW for a depth of up to 15 m to more than 1000 k AUD/MW for a water depth of up to 100 m. Shallow bedrock, boulders, or coarse gravel layers are considered as poor seabed conditions unsuitable for monopiles. Due to the unavailability of site-specific seabed data from hydrographic surveys, factors such as geotechnical considerations of offshore wind farm foundations were not incorporated in the assessment framework. In this study, the geological condition is assumed to be suitable for OWT installation of all types of foundations. The spatial distribution of the foundation cost is shown in Fig. 5.

The grid connection costs depend on the distance to the coast. Connection to the grid is estimated to cost from around 242 k AUD/MW for OWFs within 15 km of the onshore connection point to above 780 k AUD/MW for sites as much as 90 km away from shore. The length of the export cables equals the distance between the site and the shore. The length of onshore cables is the distance from the land to the grid connection point, which is assumed to be constant for all the potential sites in this case study (20 km for this study). The distances of these farm sites to the shore are less than 80 km. The spatial distribution of the grid connection cost is shown in Fig. 6.

Similarly, installation costs are calculated per MW of installed capacity, using a cost methodology from Cavazzi et al. (2016) and influenced by distance to the shore. The costs include transportation, the expenditure for erecting support structures and WTs, intra-array cable cost, and intra-array installation cost. The length of the intra-cables depends on the area of the farm and its layout. The farm area is assumed to be 100km^2 for all the alternatives in this case study. The costs range from 350 k AUD/MW for an area within 20 km of shore with 10 m water depth to around 600 k AUD/MW for a site within 100 km of the coast.

In addition, the installation cost is sensitive to the water depth as it changes the type of foundation, especially floating foundations. Floating foundations are in the early phase of development, and the breakdown costs for them are limited. However, the recent development of simulation codes is helpful to find estimate costs of these type of structures. According to Ghigo et al. (2020), the installation cost of floating foundations is 2 m AUD/MW to 3 m AUD/MW. Myhr et al. (2014) mentioned that the installation costs for different types of floating foundations are between 1.5 m AUD/MW and 2.5 m AUD/MW. Also, in their study, the installation costs of monopile and jacket type foundations were estimated as 430 k AUD/MW and 525 K AUD/MW. Thus, in consideration of installation cost, both distance to the coast and water depth should be considered. It should also be noted that the installation cost depends on the equipment costs and labour costs which are known to be the same for all options. The costs related to distance to shore and water depth have been used to obtain the scale factors for different water depth range and distances to the coast. Although the presented cost model may not represent the exact costs of OWF site selection (e.g. not including offshore or onshore substation costs), these components are most likely to be very similar between different sites in the particular regions of this case study hence not resulting in significant changes to the site-selection process.

The project development and management costs are other components of CAPEX cost, which depend on farm capacity (estimated at around 3% of the CAPEX) (Shafiee et al., 2016). After calculating the

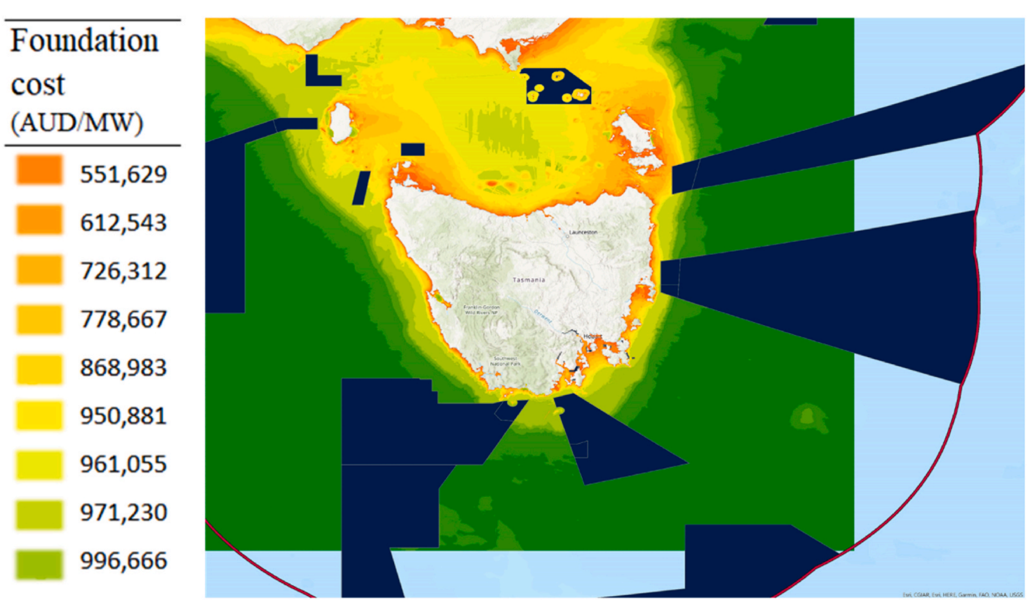

Fig. 5. Foundation costs of the base-case OWF as a function of water depth.

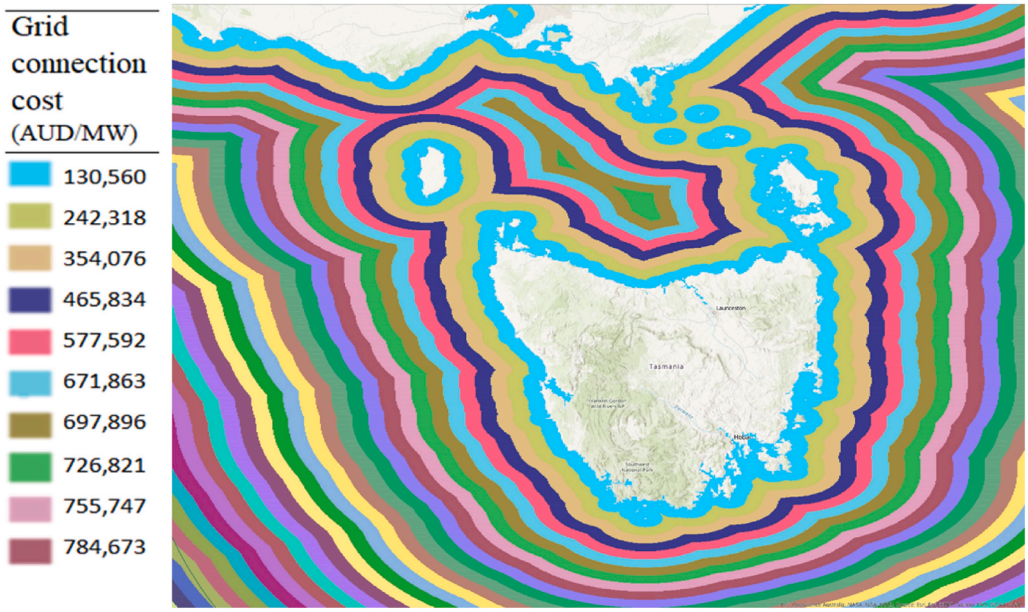

Fig. 6. Grid connection costs of an OWF as a function of distance to the shore.

Table 6
The obtained scale factor for cost increases as a function of water depth and distance to the coast.

		0–10	10–20	20–30	30–40	40–50	50–60	60–70	70–80	80–100	100–150	150–200	200–300	300–500	>500
Water depth (m)	10–20	1.00	1.04	1.08	1.12	1.16	1.19	1.20	1.21	1.23	1.26	1.32	1.40	1.56	1.79
	20–30	1.05	1.09	1.13	1.17	1.21	1.25	1.26	1.27	1.29	1.33	1.39	1.47	1.64	1.88
	30–40	1.11	1.16	1.20	1.25	1.29	1.33	1.34	1.35	1.37	1.41	1.47	1.56	1.74	2.00
	40–50	1.15	1.20	1.25	1.29	1.34	1.37	1.39	1.40	1.42	1.46	1.52	1.62	1.81	2.07
	50–60	1.19	1.24	1.28	1.33	1.38	1.42	1.43	1.44	1.47	1.51	1.57	1.67	1.86	2.13
	60–70	1.67	1.82	1.89	1.95	2.02	2.08	2.10	2.12	2.15	2.21	2.31	2.45	2.74	3.13
	70–80	1.67	1.93	2.01	2.08	2.15	2.21	2.23	2.25	2.29	2.35	2.46	2.61	2.91	3.34
	80–120	1.68	2.02	2.09	2.17	2.24	2.31	2.33	2.35	2.39	2.46	2.56	2.72	3.04	3.48

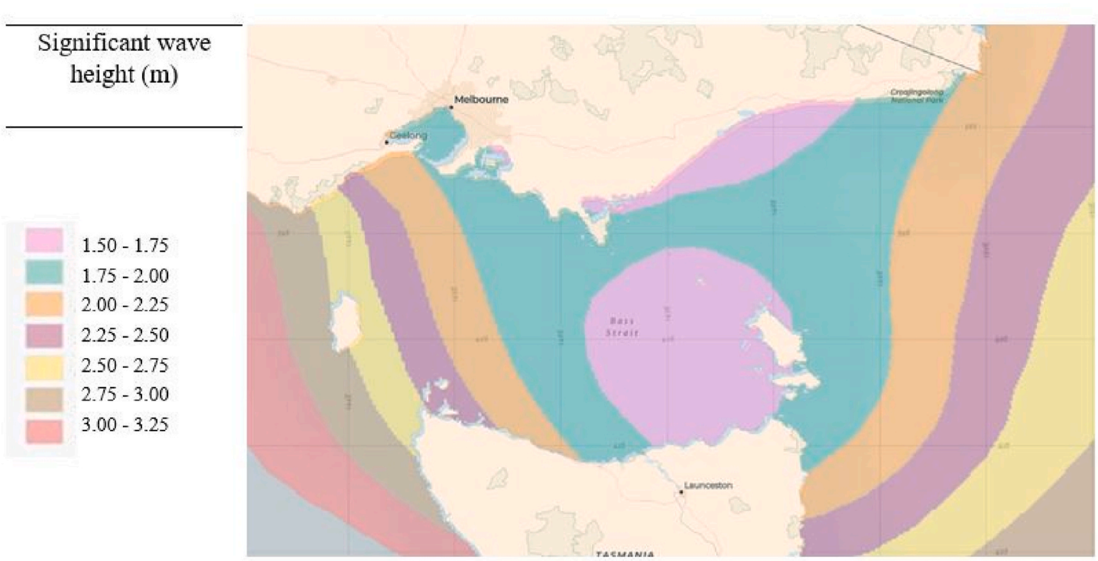

Fig. 7. Spatial distribution of long-term mean significant wave height in the Bass Strait. (Data source: Commonwealth Scientific and Industrial Research Organisation (CSIRO, 2015)).

components of initial costs, the CAPEX cost is evaluated. The costs increase both by increasing distance to the coast and water depth. The approximated scale factors which drive offshore wind farm investment cost as a function of both water depth and distance to the coast are shown in Table 6.

The OPEX of an offshore wind farm is divided into cost of operation, maintenance, port activities, license fees and other costs (Röckmann et al., 2017). Some of these, such as port activities and license fees, are fixed costs and assumed to be constant for all alternatives within this study. Hence, in this section, only variable costs are discussed. The variables affecting OPEX can be categorised into deterministic factors such as component costs, labour costs, and downtime rate, or uncertain factors such as suitability of weather windows, maintenance strategy, and failure rates of component and system. Wave height data and distance to shore are the most important parameters in estimating the OPEX of an offshore wind farm.

The significant wave height and maximum wave height data for the regions of this case study (Bass Strait) have been collected from the Australian Renewable Energy Agency (CSIRO, 2014), as presented in Fig. 7. In this paper, the base case of availability-oriented strategies is defined as accessing the OWF with small CTVs to perform repair and service activities. These vessels are the least costly option for crew transport; however, they have the capacity and operational limits. For instance, most CTVs can only operate in maximum wave heights of less than 2 m.

As the wave height in some locations of Bass Strait is more than 2 m, using the small CTVs may affect the farm availability. Therefore using the larger CTVs, which can travel in higher wave heights (2.5 m), or mother vessels (service offshore vessels) with a travel weather limit of 3 m, increases the accessibility. Due to their lower cost, though, small CTVs with cost reduction goals may still be preferred by decision-makers. The estimated O&M costs for a farm in different distances to the shore and based on the use of CTV are mostly adopted from Beiter et al. (2016) and Carroll et al. (2017) and converted to Australian dollars for the sake of consistency.

The availability of an offshore wind farm, as is the case with the O&M costs, depends on the wave height and distance to shore. It is assumed that the vessels used in the base case are CTVs, which transfer the maintenance crew from the port to the site. Although CTVs are the cheapest vessels for the O&M of offshore wind farms, they can only operate in a wave height threshold of less than 2 m. As the wave height in some parts of the Bass Strait is more than 2 m, using the CTVs, which have a high price and low speed, would decrease the accessibility and availability. The available strategies for the DM2 to increase the availability of the farm is changing utilised vessels to increase accessibility and improve the availability of the farm. It is assumed that mother vessels are used for farms that are more than 70 km from shore. Although mother vessels increase the yearly O&M cost by around 54,000 AUD/MW (Phillips et al., 2013), it is expected that a decrease in the mobilisation time causes an increase in the availability of the farm by 2.8% (Kolios et al., 2019). Another strategy for sites that are less than 70 km from shore is using larger and faster CTV, which is called CTV+ in this study. The availability for different distances to the shore by using CTV is identified based on Beiter et al. (2016) and Carroll et al. (2017) by considering the distance to the shore, weather windows and type of utilising vessels.

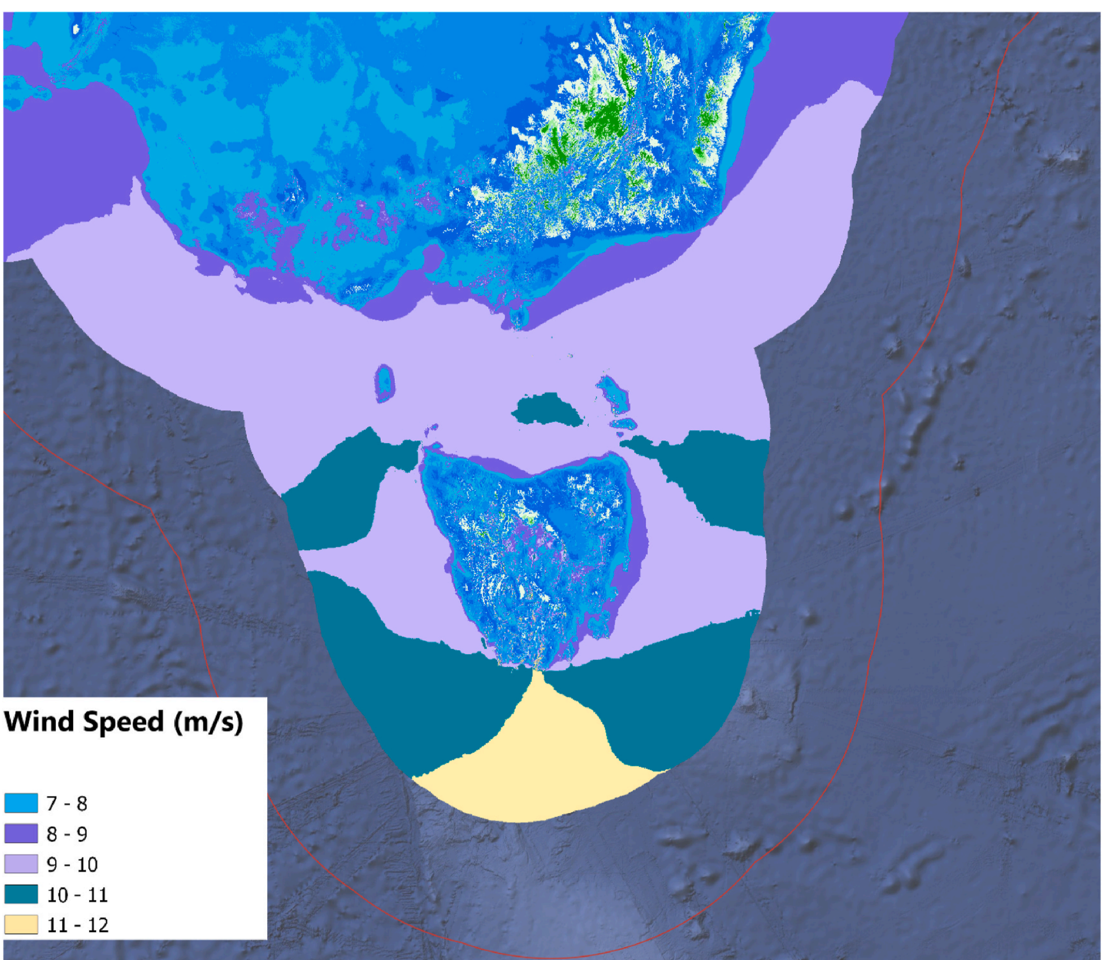

Fig. 8. The average wind speed at 100 m altitude in the Bass Strait and Tasmanian waters.

Table 7

The specifications of potential OWF sites considered in the Game of Guwarra. M: Monopile, J: Jacket, F: Floating.

site	Geographic coordinates		Wind Speed	Wave Height	Water Depth	Distance to Shore
	Latitude	Longitude	m/s	m	m	km
Site 1	−38.79	146.92	8.06	1.5–1.75	30 (M)	40
Site 2	−39.82	146.34	10.03	1.75–2.0	65 (F)	60
Site 3	−40.67	146.73	9.74	1.75–2.0	50 (J)	50
Site 4	−40.42	144.33	11.27	2.5–2.75	55 (J)	30
Site 5	−40.68	146.08	9.50	1.75–2.0	20 (M)	60

Table 8

Case study parameters and their corresponding values.

Definition	Variable	Value
Added capital costs for upgrading turbine type	C_t	200,000 AUD/MW
Added O&M costs for upgrading turbine type	Cm_t	26,000 AUD/MW
Added costs to change CTV to mother vessel	C_{mv}	6000 AUD/MW
Added costs to upgrade CTV to CTV+	C_{v+}	650 AUD/MW
Percentage of farm availability change by using CTV+	α	0.4%
Percentage of farm availability change by using mother vessel	β	2.8%
Percentage of AEP change by using CTV+	θ	0.4%
Percentage of AEP change by using mother vessels	λ	1.0%
O&M costs growth rate	O	5.0%
Discount rate	i	8.0%

In addition to CAPEX and OPEX, other costs that affect the LCC are decommissioning costs, which are usually calculated as a fraction of the main LCC components. If life extension and repowering at the end of an OWF life (i.e. 20 years in this study) are not feasible, the WTs will be decommissioned, costing the industry about 60–70% of the installation costs (Adedipe and Shafiee, 2021; Bosch et al., 2019). In this case study, the decommissioning cost is assumed to be 330,000 AUD/MW.

In order to quantify the value of project cash flow, an NPV-based approach is taken through which the LCC is estimated. The discount rate is considered to be 7%. It is also believed that during the first five years of operation, the maintenance costs will be covered by a service contract provider. Therefore, the O&M costs are calculated from the sixth year of commissioning the project. It must be noted that this does not cover the foundations, array cables, the offshore substation, and transmission infrastructure.

As a key variable in assessing the suitability of a site, the amount of energy available to the wind turbines is used as the indicator of power production potential at that site. The exemplar turbine used for the base case is a 5 MW wind turbine with a cut-in wind speed of 3 m/s, cut-out wind speed of 24 m/s and rated wind power of 5 MW at 11 m/s. The available strategy to DM 3 to increase power production potential is using 10 MW wind turbines with cut-in wind speed, cut-out wind speed and rated wind power of 4 m/s, 26 m/s and 12 m/s, respectively. To calculate the available energy at each site, the average wind speed at 100 m is used. Wind speed data are collected from time series in Vortex (2021) and validated by the Global Wind Atlas (DTU, 2021). The Weibull distribution is then fitted to the wind speed data set, and scale and shape parameters are calculated. The AEP is estimated by multiplying the wind speed distribution with the corresponding power of each wind speed in the power curve. The spatial distribution of wind speed in the Bass Strait is presented in Fig. 8.

Table 9

Decision alternatives (DAs) considered in the site selection case study. *Si*: represents Site *i* where the DM can choose from $i = \{1, 2, 3, 4, 5\}$; Accept: represents the scenario in which Player 2 accepts the base case; Offer when Player 2 makes an offer to increase the payoff; 5 MW: represents the scenario in which Player 3 accepts the base case to use the 5 MW wind turbines and; 10 MW: when Player 3 offers to use 10 MW wind turbines for the project and the capacity of the farm increase from 500 MW to 1 GW.

	DM 1:	DM 2:	DM 3:
	Owner	Operator	Consumer
Decision Alternatives (DA)	LCC/MW	Availability	AEP/MW
DA1: S1-Accept-5MW	$ 4,124,000	93.00%	373,606
DA2: S1-Offer-5MW	$ 4,132,500	93.37%	375,100
DA3: S2-Accept-5MW	$ 6,725,500	89.50%	503,258
DA4: S2-Accept-10MW	$ 7,225,500	89.50%	551,258
DA5: S2-Offer-5MW	$ 6,805,000	92.01%	508,291
DA6: S2-Offer-10MW	$ 7,305,000	92.01%	556,771
DA7:S3-Accept-5MW	$ 5,417,000	91.50%	444,691
DA8: S3-Accept-10MW	$ 5,917,000	91.50%	484,691
DA9: S3-Offer-5 MW	$ 5,426,000	91.87%	446,469
DA10: S3-Offer-10MW	$ 5,926,000	91.87%	486,629
DA11: S4-Accept-5MW	$ 5,192,000	85.60%	528,844
DA12:S4-Accept-10MW	$ 5,692,000	85.60%	568,844
DA13: S4-Offer-5MW	$ 5,272,000	88.00%	530,959
DA14: S4-Offer-10MW	$ 5,772,000	88.00%	571,119
DA15: S5-Accept-5MW	$ 4,681,000	91.50%	429,088
DA16: S5-Offer-5MW	$ 4,690,000	91.87%	433,379

For this practical example, five sites in the suitable regions were identified by the pre-selection process in the case study. The attributes of these five sites are listed in Table 7. Without the help of the Game theoretical decision-support tool, each decision-maker tends to maximise their payoff by selecting one of these five sites. For instance, the wind farm owners may attempt to persuade the stakeholders to choose the site with the minimum required CAPEX, which is most probably a site that is closer to shore and with minimum water depth (due to the large influence on costs). The buyers of energy may, on the other hand, want to convince the team to select the site with maximum power production potentials. For the operators of a wind farm minimising maintenance challenges and farm availability is perhaps more important; hence their preference may be a site closer to a suitable port and with calmer sea conditions. Thus, DMs' objectives, life cycle cost, availability, and AEP are calculated for all potential sites considered in this study.

Table 8 lists the variables required for the payoffs and objectives. The O&M growth rate and discount rate are used for calculating the NPV of the cost. In these calculations, all available DAs to the decision-making team are considered. It should be noted that some sites can have a limited number of improvement strategies. For example, in this case study, 10 MW turbines are not suitable for Sites 1 and 5 because of their water depth and the implications on the WT foundation. The 16 DAs are shown in Table 9. These DAs are determined by including the improvement strategies which may be applicable for each site.

A strategic game is a model of interactive decision-making process consisting of a set of players, where each player has a set of strategies as well as preferences over these. The initial decision-making matrix, the possible alternatives and the objectives of decision-makers are presented in Matrix 1. The main application of the game matrix is the selection of the alternative. To describe the problem, the alternatives are assigned to the row player, and the objectives are assigned to the column player.

Matrix 1. (*The initial decision-making matrix*)

Row Player

$U(x) =$ ***Column Player***

	LCC	Availability	AEP
A1	\$ 4,124,000	93.00%	373,606
A2	\$ 4,132,500	93.37%	375,100
A3	\$ 6,725,500	89.50%	503,258
A4	\$ 7,225,500	89.50%	551,258
A5	\$ 6,805,000	92.01%	508,291
A6	\$ 7,305,000	92.01%	556,771
A7	\$ 5,417,000	91.50%	444,691
A8	\$ 5,917,000	91.50%	484,691
A9	\$ 5,426,000	91.87%	446,469
A10	\$ 5,926,000	91.87%	486,629
A11	\$ 5,192,000	85.60%	528,844
A12	\$ 5,692,000	85.60%	568,844
A13	\$ 5,272,000	88.00%	530,959
A14	\$ 5,772,000	88.00%	571,119
A15	\$ 4,681,000	91.50%	429,088
A16	\$ 4,690,000	91.87%	433,379

As the three objectives in Matrix 1 have different characteristics (i.e. LCC is to be minimized while availability and AEP are to be maximised), they should be normalised so that the decision-making model can make comparisons between them. The initial decision-making matrix was normalised to values between 0 and 1 by applying the linear normalisation method (Peldschus et al., 2010; Zavadskas et al., 2008).

If maximising an objective is preferred,

$$U_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{8}$$

and if the aim is to minimise the objective:

$$U_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{9}$$

Matrix 2. (*Decision matrix with normalised payoff values*)

Row Player

$\overline{U}(x) =$ ***Column Player***

A1	1.0000	0.9521	0.0000
A2	0.9973	1.0000	0.0076
A3	0.1822	0.5018	0.6564
A4	0.0251	0.5018	0.8994
A5	0.1572	0.8242	0.6819
A6	0.0000	0.8242	0.9274
A7	0.5934	0.7591	0.3599
A8	0.4362	0.7591	0.5624
A9	0.5907	0.8062	0.3689
A10	0.4335	0.8062	0.5722
A11	0.6642	0.0000	0.7860
A12	0.5071	0.0000	0.9885
A13	0.6391	0.3084	0.7967
A14	0.4820	0.3084	1.0000
A15	0.8249	0.7591	0.2809
A16	0.8221	0.8062	0.3026

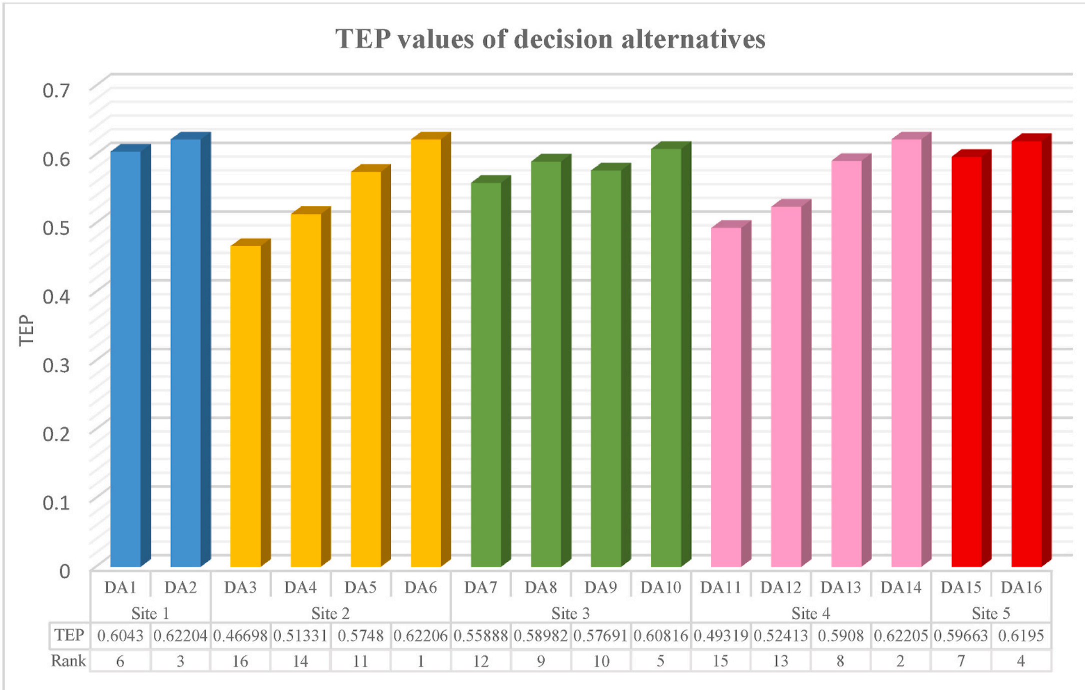

Fig. 9. DAs ranked based on their estimated TEP values.

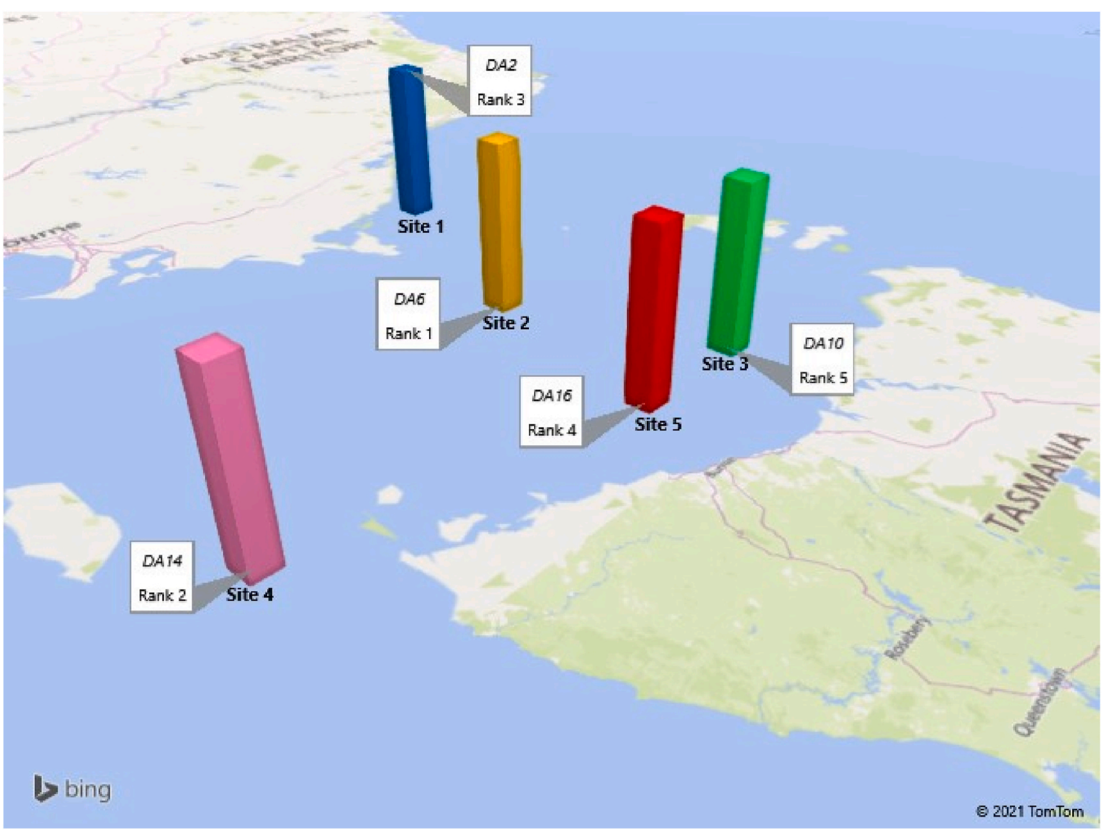

Fig. 10. The highest ranked DAs of each five site locations considered for OWF installation in the Bass Strait.

It can be seen in Matrix 2, the normalised matrix, that there is no dominant strategy according to all objectives. That is, through a comparison of the DAs, none of them can be excluded from the process because of their low payoffs with respect to every objective. Generally, the optimum DA can be identified as the equilibrium point of the entire set; however, there is no equilibrium point in this game since the data does not satisfy the equilibrium condition given by Equation (10).

Table 10
Qualitative matrix for impact assessment of each type of foundation.

Environmental factors	Monopile	Jacket	Floating
Artificial reef	7	5	3
Wake and scour effects	7	5	3
Habitat loss	7	3	5
The score of each potential foundation	21	18	11

$$\text{Maximum (Minimum of a row)} = \text{Minimum (Maximum of a column)} \tag{10}$$

Therefore, the game has no saddle point. A mixed strategy is then used to determine the alternative with the highest payoff with respect to all three objectives.

As explained in the methodology, the probability of objectives (q_j) is calculated to determine the optimal weight of objectives and obtained TEPs. This calculation is done by transforming the problem into a linear programming problem, and the obtained values are the arrays of vector Q* (Equation (11))

$$Q^* = \{0.29283, 0.32713, 0.38003\} \tag{11}$$

This means to find the optimum alternative, the first objective (LCC) is to be weighed 0.293, the second objective (farm availability) 0.3271 and the third objective (AEP) 0.38. The *TEP* of each alternative is then obtained by aggregating the normalised values of each strategy of row player (objectives) with their corresponding weight from Q*.

Fig. 9 demonstrates the estimated TEPs of all alternatives that were available to the decision-making model. DA6, in which the owner selects Site 2, and the operator offers to use MV to increase availability, and the consumer offers 10 MW wind turbines to increase the capacity of the farm to 1 GW, has shown to have the highest expected payoff and represent the optimum choice. The TEP for this alternative is estimated to be $TEP(DA_6) = 0.62206$. The second rank DA14, in which the highest AEP is expected compared to the other DAs, and select site 4, utilize CTV+ and install 10 MW wind turbines.

DA3, which is to select Site 1, the highest availability, utilize CTV for O&M activities and install 5 MW turbines, is ranked 3 in this table.

As mentioned in Table 7, Site 2 has more average wind speed, and as a result, wind turbines installed in site 2 can extract more energy compared to sites 1, 3 and 5. By Considering each objective individually and given the extracted data from the Bass Strait, DA6 costs more than other alternatives, while it ranks third in both availability and AEP among other DAs. Using mother vessels and high-rated turbines improves the availability and AEP of DA6, making it the best place to implement a WF. Although DA12 and DA14 enable great power production capacities and have lower costs than Alternative 6, the harsher sea at their sites is estimated to have a significant impact on availability, which should not go unnoticed. Fig. 10 illustrates high ranked DAs of five sites considered for OWF installation in the north coast of Tasmania that proposed as the studied locations.

This highlights the strength of the presented methodology, which can determine the optimal trade-off between the important decision-making criteria and the project stakeholders and provides a ranking for DAs to reach an agreement about the relative importance of criteria in MCDM problems. Such balance will ensure that the project is being planned with the highest possible outcome for the stakeholders collectively. Even in the absence of initial evaluations, the proposed method provides actual weights and can be applied to decision-making problems with many alternatives and objectives.

3.3. Ecological Effects Policy (EcEP)

This part shows how providing a new policy affects the cost of developing a wind farm. A simple matrix based on the qualitative matrix (Table 10) is used to evaluate the environmental impacts of different foundations. The numeric value ranges are 3 for small magnitude, 5 for moderate magnitude, and 7 for large magnitude. It is assumed that the weight and importance of the criteria are the same.

Although monopiles are the cheapest foundation options for developing a farm, they have a higher considerable anticipated impact than jackets and floating foundations.

The EcEP encourages decision-makers to choose floating, jacket and monopile, in that order. It is assumed that there is a reward if the farm follows the EcEP. If the decision-makers choose a jacket, the Ec^J would be deducted from the LCC, and if the decision-makers choose floating, the Ec^F, $Ec^F > Ec^J$ would be deducted from the LCC.

To demonstrate the application of the new policy, this recommended policy is applied to site 5, as an example. According to Seidel (2021), the

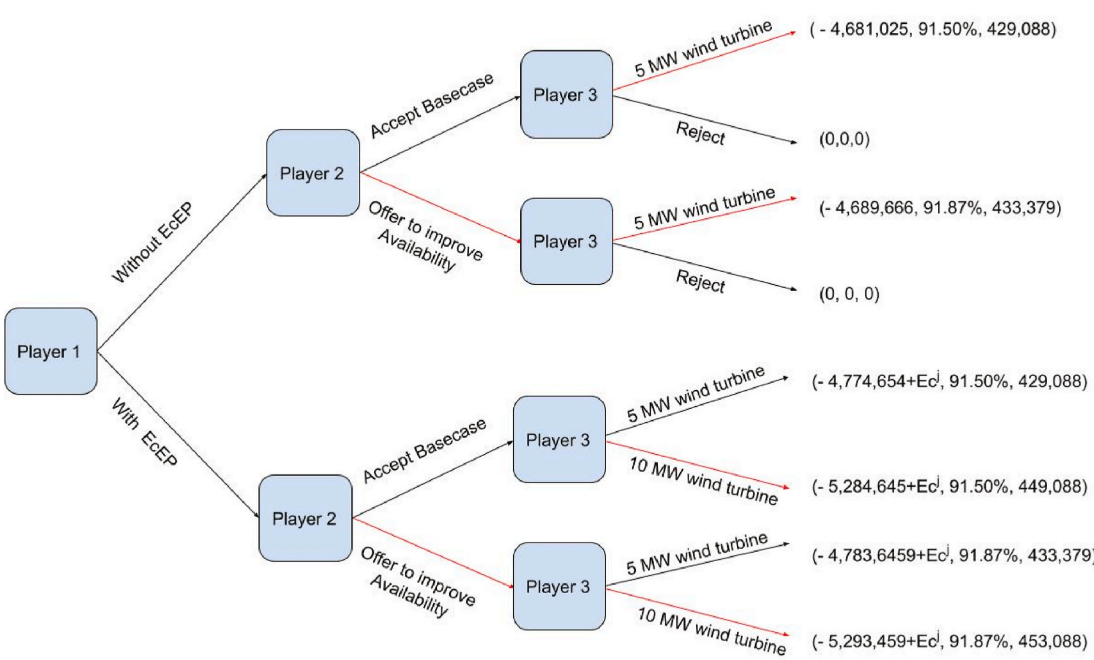

Fig. 11. Proposed Game tree for adopting the Ecological Effects Policy (EcEP).

jacket is assessed to be 2% more expensive than a monopile in a 22-m water depth. We assume the availability and annual electricity production are the same as using monopile. In contrast, the decision-makers can use a 10-MW wind turbine when they decide to use a jacket foundation. In this section, an extensive-form game with perfect information processes is used as a model for calculating the effect of this policy. It is assumed that players decide sequentially wherein the first player makes a decision, the second one responds and so on. Fig. 11 represents the game tree. An owner (player 1) first chooses between E*c*EP or not for site 5. If no E*c*EP is involved in this stage, player 2 (operator) has the option of accepting the base case or rejecting the base case and offering a new method, faster O&M vessels in this case. Player 2 receives 0.4% more benefit if they reject the base case and accept the offer, while player 1 receives less payoff. Player 3 has the option to accept the base case or reject/offer. As mentioned earlier, monopiles cannot be used for large turbines such as the 10-MW turbines that are assumed to improve the production of the farm. Because the players are rational and do not choose unfeasible options, player 3 (consumer) only has the option to accept the base case, the 5-MW turbines, or reject, so when player 3 refuses, the payoff for all players is 0. As is the case in the previous steps, if player 1 chooses the E*c*EP for site 5, player 1 can choose jacket instead of monopile, so the initial cost will be increased because the cost of the foundation and installation in this water range is higher when the jacket foundation is chosen. However, there is a reward for player 1 for selecting the E*c*EP. Player 2 will choose one of the following actions: They either choose the base case or make an offer to increase availability. Furthermore, because player 1 chooses the jacket, it is an option for player 3 to increase the rate of wind turbines to 10 MW and increase the electricity production.

When using the SPNE, the red arrows show the solution to choose the best answer and subgame Nash equilibrium for player 2 and player 3. The SPNE of the game depends on the payoff of player 1 to choose the best location. In other words, the best answer is between "without E*c*EP, Offer, WT:5 MW" and "With E*c*EP, Offer, WT: 10 MW". Player 1 will choose the E*c*EP if the payoff for player1 choosing E*c*EP is less than when player 1 chooses no E*c*EP. In this example, if $-5293459 + Ec^J \leq -4689666$or $Ec^J \geq 603{,}793.32$ AUD/MW. Therefore, if there is a commitment by the government, for example, to buy the electricity of farms that have adopted the E*c*EP, the environmental damage to marine life would decrease, especially for large-scale farms. The value of Ec^F, Ec^J or the value that would be added to the feed-in tariff (FIT) can be determined with the provider model.

Analysis of selecting optimal OWF locations in the Bass strait, using the proposed approach, suggests the ranked for all DAs by considering conflicts over decision-makers and comparing the cost of each site with and without considering environmental impacts by adopting E*c*EP. The suggested methodology can consider different aspects of the conflict and incorporate various characteristics of the decision-makers without aggregation of objectives and assist decision-makers by providing some understanding into decision-making process that would not be possible with traditional decision-making approaches.

4. Conclusion

Considerable effort has been made on the research and development of clean and alternative energy resources, which have led to significant achievements in the decarbonisation of the energy sector. As one of the important role-players of this movement, the offshore wind industry is projected to grow dramatically until 2030 and beyond. This paper develops a method to accelerate the advances of this industry by improving decision-making in project development, with a particular focus on site selection and reducing the environmental impacts of OWF projects on marine life.

This paper presents a game theory decision-making methodology for offshore renewable energy applications. The parties involved in the project may have different objectives when selecting an offshore site. That is, owners or investors may seek less investment, while operators may prefer higher availability and site accessibility. The consumer, meanwhile, may prioritise production. Such conflicts among the parties' interests and the uncertainties associated with available information can substantially increase the complexity of the decision-making process. It is, therefore, necessary to carefully specify the objectives and preferences of each major decision-maker for achieving optimal results. This paper adopts a game-theoretical approach to develop a decision-support tool to account for the interdependencies of influencing parameters and possible conflicts amongst the parties. The method has the general applicability in multi-objective decision-making to select the most suitable sites for implementing offshore wind farms. This methodology can be conducted in the decision-making process with objectives that affect the decision-making teams. The proposed method can be used when a group of decision-makers with conflicting objectives are to solve a complex multi-dimensional problem. For instance, in multi-purpose offshore facilities, if wave energy converters are added to the farm to produce wave energy at the offshore wind site, the annual electricity production from waves would be another objective, and the developed methodology could provide notionally true weights to the new objective. Based on data, the optimum location and decision alternative 6, site 2, with the strategy of using MV and 10-MW wind turbines is determined. This model's priority is to select the optimum location for the implementation of offshore wind farm equipment. Further, the proposed method can be applied to decision-making problems with any number of alternatives/objectives. Its practical realisation is limited only by the capabilities of the solver of the linear programming problem formulated to solve the corresponding zero-sum game. This paper recommends a policy to counter the adverse effects of wind farm deployment on the marine environment and examines the cost of adopting the policy by developing a game-theoretical approach. The results underscore the importance of considering the government's value commitment in encouraging decision-making teams to use foundations with less environmental impact.

This research may be expanded in various directions. In terms of wind farm availability, this research does not take foundation availability, offshore substation availability, or electrical network congestion into account, which could be addressed in future studies. Furthermore, wake effects and intra-network electric losses were considered to remain constant throughout the analysis, which could be counted as variables in future studies. One of the most significant constraints of research in the offshore wind sector is data availability. Further improvements can be made in decision-making models for this industry if more data becomes available from ongoing local projects.

CRediT authorship contribution statement

Nima Golestani: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft. **Ehsan Arzaghi:** Conceptualization, Supervision, Methodology, Writing – review & editing. **Rouzbeh Abbassi:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Vikram Garaniya:** Conceptualization, Funding acquisition, Supervision, Project administration, Writing – review & editing. **Nagi Abdussamie:** Supervision, Writing – review & editing. **Ming Yang:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abaei, M.M., Arzaghi, E., Abbassi, R., Garaniya, V., Penesis, I., 2017. Developing a novel risk-based methodology for multi-criteria decision making in marine renewable energy applications. Renew. Energy 102, 341–348.
Adedipe, T., Shafiee, M., 2021. An economic assessment framework for decommissioning of offshore wind farms using a cost breakdown structure. Int. J. Life Cycle Assess.
Agency, D.E., 2017. Danish Experiences from Offshore Wind Development.
AMSA, 2020. Spatial at Australian Maritime Safety Authority.
Anonymous, 2015. Global Distribution of Coral Reefs. Australian Ocean Data Network.
Anuradha, Keshavan, RAMU, T.S., SANKAR, V., 2016. Probabilistic modeling and forecasting of wind power. Int. J. Perform. Eng. 12, 353–368.
Aplak, H.S., Sogut, M.Z., 2013. Game theory approach in decisional process of energy management for industrial sector. Energy Convers. Manag. 74, 70–80.
Aryai, V., Abbassi, R., Abdussamie, N., Salehi, F., Garaniya, V., Asadnia, M., Baksh, A.-A., Penesis, I., Karampour, H., Draper, S., Magee, A., Keng, A.K., Shearer, C., Sivandran, S., Yew, L.K., Cook, D., Underwood, M., Martini, A., Heasman, K., Abrahams, J., Wang, C.-M., 2021. Reliability of multi-purpose offshore-facilities: present status and future direction in Australia. Process Saf. Environ. Protect. 148, 437–461.
Asgari, S., Afshar, A., Madani, K., 2014. Cooperative game theoretic framework for joint resource management in construction. J. Construct. Eng. Manag. 140, 04013066.
Askari, G., Gordji, M.E., Park, C., 2019. The behavioral model and game theory. Palgrave Communications 5.
Babatunde, S.A., Najafi, F.T., 2018. Overcoming the Challenges of Implementing Offshore Wind Farm Development in the US through Education and Research.
Baseer, M.A., Rehman, S., Meyer, J.P., Alam, M.M., 2017. GIS-based site suitability analysis for wind farm development in Saudi Arabia. Energy 141, 1166–1176.
Bauso, D., 2016. Game Theory with Engineering Applications. SIAM.
Beiter, P., Musial, W., Smith, A., Kilcher, L., Damiani, R., Maness, M., Sirnivas, S., Stehly, T., Gevorgian, V., Mooney, M., 2016. A Spatial-Economic Cost-Reduction Pathway Analysis for US Offshore Wind Energy Development from 2015–2030. National Renewable Energy Lab.(NREL), Golden, CO (United States).
Blakers, A., Lu, B., Stocks, M., 2017. 100% renewable electricity in Australia. Energy 133, 471–482.
Boelen, M., Bishop, I., Pettit, C., 2010. Selecting Offshore Renewable Energy Futures for Victoria. Ekscentar, pp. 63–67.
Bosch, J., Staffell, I., Hawkes, A.D., 2019. Global levelised cost of electricity from offshore wind. Energy 189, 116357.
Briggs, C., Hemer, M., Howard, P., Langdon, R., Marsh, P., Teske, S., Carrascosa, D., 2021. Offshore Wind Energy in Australia. Blue Economy Cooperative Research Centre, p. 92.
BSI, 2010. BS EN 13306:2010, Maintenance — Maintenance Terminology. BRITISH STANDARD INSTITUTE, London.
Carroll, J., McDonald, A., Dinwoodie, I., McMillan, D., Revie, M., Lazakis, I., 2017. Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. Wind Energy 20, 361–378.
Castro-Santos, Laura, Diaz Casas, Vicente, 2014. Life-cycle cost analysis of floating offshore wind farms. Renew. Energy 66, 41–48. https://doi.org/10.1016/j.renene.2013.12.002.
Cavazzi, S., Dutton, A., 2016. An Offshore Wind Energy Geographic Information System (OWE-GIS) for assessment of the UK's offshore wind energy potential. Renew. Energy 87, 212–228.
Chaouachi, A., Covrig, C.F., Ardelean, M., 2017. Multi-criteria selection of offshore wind farms: case study for the Baltic States. Energy Pol. 103, 179–192.
Chen, N., Xu, Z., Xia, M., 2013. The ELECTRE I multi-criteria decision making method based on hesitant fuzzy sets. Int. J. Inf. Technol. Decis. Making 1–37.
Chen, Y., Li, H., Jin, K., Elkassabgi, Y., 2017. Investigating the possibility of using different hub height wind turbines in a wind farm. Int. J. Sustain. Energy 36, 142–150.
Collins, B.C., Kumral, M., 2020. Game theory for analyzing and improving environmental management in the mining industry. Resour. Pol. 69, 101860.
Council, C.E., 2020. Clean Energy Australia Report 2020.
CSIRO, A.R.E.A., 2014. Australian Renewable Energy. Australian Renewable Energy.
CSIRO, A.R.E.A., 2015. In: Organisation, C.S.a.I.R. (Ed.), Australian Region GEOSAT Wave Dataset - CAMRIS - Mean Significant Wave Height.
Dalili, N., Edrisy, A., Carriveau, R., 2009. A review of surface engineering issues critical to wind turbine performance. Renew. Sustain. Energy Rev. 13, 428–438.
Deb, D., Patel, M., Singh, H., 2017. Automated Cleaning of Wind Turbine Blades with No Downtime, 2017. IEEE International Conference on Industrial Technology (ICIT), pp. 394–399.
Deveci, M., Özcan, E., John, R., Pamucar, D., Karaman, H., 2021. Offshore wind farm site selection using interval rough numbers based Best-Worst Method and MARCOS. Appl. Soft Comput. 109, 107532.
Diemuodeke, O., Hamilton, S., Addo, A., 2016. Multi-criteria assessment of hybrid renewable energy systems for Nigeria's coastline communities. Energy, Sustainability and Society 6.
DTU, T.U.o.D., 2021. Global Wind Atlas 3.
English, P., Mason, T., Backstrom, J., Tibbles, B., Mackay, A., Smith, M., Mitchell, T., 2017. Improving Efficiencies of National Environmental Policy Act Documentation for Offshore Wind Facilities Case Studies Report, 26. US Dept. of the Interior, Bureau of Ocean Energy Management, Office of Renewable Energy Programs, Sterling. OCS Study BOEM.
Eshragh, A., Ganim, B., Perkins, T., Bandara, K., 2020. The Importance of Environmental Factors in Forecasting Australian Power Demand arXiv pre-print server.
Fetanat, A., Khorasaninejad, E., 2015. A novel hybrid MCDM approach for offshore wind farm site selection: a case study of Iran. Ocean Coast Manag. 109, 17–28.
Foley, A.M., Kerlin, C., Leahy, P.G., 2012. Offshore Wind Resource Estimation Using Wave Buoy Data. IEEE.
Gavériaux, L., Laverrière, G., Wang, T., Maslov, N., Claramunt, C., 2019. GIS-based multi-criteria analysis for offshore wind turbine deployment in Hong Kong. Spatial Sci. 25, 207–218.
Ghigo, A., Cottura, L., Caradonna, R., Bracco, G., Mattiazzo, G., 2020. Platform optimization and cost analysis in a floating offshore wind farm. J. Mar. Sci. Eng. 8, 835.
Gonzalez, E., Nanos, E.M., Seyr, H., Valldecabres, L., Yürüşen, N.Y., Smolka, U., Muskulus, M., Melero, J.J., 2017. Key performance indicators for wind farm operation and maintenance. Energy Procedia 137, 559–570.
Govindan, K., Jepsen, M.B., 2016. ELECTRE: a comprehensive literature review on methodologies and applications. Eur. J. Oper. Res. 250, 1–29.
Hanley, N., Folmer, H., 1998. Game Theory and the Environment. Edward Elgar.
Harrington, J., 2009. Games, Strategies and Decision Making. Macmillan.
Hillier, F.S., 2012. Introduction to operations research. Tata McGraw-Hill.
J. Horwath, S.H., Grismala, R., Diller, E., 2020. Comparison of environmental effects from different offshore wind turbine foundations ICF International.
Hundleby, G., Freeman, K., Barlow, M., 2017. Unleashing Europe's Offshore Wind Potential-A New Resource Assessment. BVG Associates.
Kaiser, M.J., Snyder, B.F., 2012. Modeling offshore wind installation vessel day-rates in the United States. Marit. Econ. Logist. 14, 220–248.
Kapliński, O., Tamošaitienė, J., 2010. Game theory applications IN construction engineering and management/lošimu TEORIJOS TAIKYMAS STATYBOS inžinerijos ir VALDYMO SRITYSE. Technol. Econ. Dev. Econ. 16, 348–363.
Kaya, T., Kahraman, C., 2011. Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. Expert Syst. Appl. 38, 6577–6585.
Kelly, A., 2003. Decision making using game theory: an introduction for managers. Decision Making Using Game Theory: an Introduction for Managers.
Kolios, A., Mytilinou, V., Lozano-Minguez, E., Salonitis, K., 2016. A comparative study of multiple-criteria decision-making methods under stochastic inputs. Energies 9, 566.
Kolios, A., Walgern, J., Koukoura, S., Pandit, R., Chiachio-Ruano, J., 2019. Open O&M: Robust O&M Open Access Tool for Improving Operation and Maintenance of Offshore Wind Turbines. Research Publishing Services.
Kose, E., Erbas, M., Ersen, E., 2017. An integrated approach based on game theory and geographical information systems to solve decision problems. Appl. Math. Comput. 308, 105–114.
Li, H., Díaz, H., Guedes Soares, C., 2021. A failure analysis of floating offshore wind turbines using AHP-FMEA methodology. Ocean Eng. 234, 109261.
Luce, R.D., Raiffa, H., 1989. Games and Decisions: Introduction and Critical Survey. Dover Publications.
Madani, K., 2010. Game theory and water resources. J. Hydrol. 381, 225–238.
Madani, K., Lund, J.R., 2011. A Monte-Carlo game theoretic approach for Multi-Criteria Decision Making under uncertainty. Adv. Water Resour. 34, 607–616.
Mahdy, M., Bahaj, A., 2017. Multi criteria decision analysis for offshore wind energy potential in Egypt. Renew. Energy 118.
Manager Client, S., New, B., 2017. Oil and Gas Pipelines. Geoscience Australia.
Marine, C., Amospheric, R., 2016. Maritime Cables. CSIRO.
Messali, E., Diesendorf, M., 2009. Potential sites for off-shore wind power in Australia, 33, 335–348.
Myerson, R.B., 1991. Game Theory: Analysis of Conflict. Harvard University Press.
Myhr, A., Bjerkseter, C., Ågotnes, A., Nygaard, T.A., 2014. Levelised cost of energy for offshore floating wind turbines in a life cycle perspective. Renew. Energy 66, 714–728.
Mytilinou, V., Kolios, A., 2018. Techno-economic Optimisation of Offshore Wind Farms Based on Life Cycle Cost Analysis on the UK, 132. Renewable Energy.
Mytilinou, V., Lozano-Minguez, E., Kolios, A., 2018. A framework for the selection of optimum offshore wind farm locations for deployment. Energies 11, 1855.
Nash, J.F., 1950. Equilibrium points in n-person games. Proc. Natl. Acad. Sci. Unit. States Am. 36, 48–49.
Neill, S.P., Hashemi, M.R., 2018. Chapter 4 - offshore wind. In: Neill, S.P., Hashemi, M.R. (Eds.), Fundamentals of Ocean Renewable Energy. Academic Press, pp. 83–106.
Orr, K., Skeers, N., 2014. Offshore Oil and Gas Platforms. Geoscience Australia.
Osborne, M.J., 2004. An Introduction to Game Theory. Oxford university press, New York.
Pandit, R.K., Kolios, A., Infield, D., 2020. Data-driven weather forecasting models performance comparison for improving offshore wind turbine availability and maintenance. IET Renew. Power Gener. 14 (13), 2386–2394.
Park, J., Law, K.H., 2016. A data-driven, cooperative wind farm control to maximize the total power production. Appl. Energy 165, 151–165.
Peldschus, F., Zavadskas, E., Turskis, Z., Tamosaitiene, J., 2010. Sustainable assessment of construction site by applying game theory. Eng. Econ. 21, 223–237.
Phillips, j., Fitch-Roy, O., reynolds, p., gardner, p., 2013. A Guide to UK Offshore Wind Operations and Maintenance.
Piraveenan, M., 2019. Applications of game theory in project management: a structured review and analysis. Mathematics 7, 858.
Preindl, M., Bolognani, S., 2011. Optimization of the generator to rotor ratio of MW wind turbines based on the cost of energy with focus on low wind speeds. In: IECON Proceedings (Industrial Electronics Conference).

Röckmann, C., Lagerveld, S., Stavenuiter, J., 2017. Operation and maintenance costs of offshore wind farms and potential multi-use platforms in the Dutch North Sea. In: Buck, B.H., Langan, R. (Eds.), Aquaculture Perspective of Multi-Use Sites in the Open Ocean: the Untapped Potential for Marine Resources in the Anthropocene. Springer International Publishing, Cham, pp. 97–113.
Sadiq, R., Husain, T., Veitch, B., Bose, N., 2004. Risk-based decision-making for drilling waste discharges using a fuzzy synthetic evaluation technique. Ocean Eng. 31, 1929–1953.
Samsura, D.A.A., Van Der Krabben, E., Van Deemen, A.M.A., 2010. A game theory approach to the analysis of land and property development processes, 27, 564–578.
Sarker, B.R., Faiz, T.I., 2016. Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy. Renew. Energy 85, 104–113.
Schelling, T., 1960. Te Strategy of Conflict. New York.
Scheu, 2012. Maintenance strategies for large offshore wind farms. Energy Procedia 24.
Scheu, M., Matha, D., Schwarzkopf, M.-A., Kolios, A., 2018. Human exposure to motion during maintenance on floating offshore wind turbines. Ocean Eng. 165, 293–306.
Scheu, M.N., Tremps, L., Smolka, U., Kolios, A., Brennan, F., 2019. A systematic Failure Mode Effects and Criticality Analysis for offshore wind turbine systems towards integrated condition based maintenance strategies. Ocean Eng. 176, 118–133.
Sedaghat, A., Alkhatib, F., Eilaghi, A., Sabati, M., Borvayeh, L., Mostafaeipour, A., 2019. A new strategy for wind turbine selection using optimization based on rated wind speed. Energy Procedia 160, 582–589.
Seidel, M., 2021. FEASIBILITY OF MONOPILES FOR LARGE. OFFSHORE WIND TURBINES.
Shafiee, M., Brennan, F., Espinosa, I.A., 2016. A parametric whole life cost model for offshore wind farms. Int. J. Life Cycle Assess. 21, 961–975.
Shapley, L.S., 1953. A value for n-person games. Contributions to the Theory of Games 2, 307–317.
Shoham, Y., Leyton-Brown, K., 2008. Multiagent Systems: Algorithmic, Game-Theoretic, and Logical Foundations. Cambridge University Press.
Shu, Z.R., Li, Q.S., Chan, P.W., 2015. Statistical analysis of wind characteristics and wind energy potential in Hong Kong. Energy Convers. Manag. 101, 644–657.
Si, S.-L., You, X.-Y., Liu, H.-C., Zhang, P., 2018. DEMATEL technique: a systematic review of the state-of-the-art literature on methodologies and applications. Math. Probl Eng. 2018, 3696457.
Smith, D.T., 2004. Polygonised General Bathymetric Chart of the Oceans (GEBCO) Bathymetric Data. Australian Antarctic Data Centre.
Tahri, M., Hakdaoui, M., Maanan, M., 2015. The evaluation of solar farm locations applying Geographic Information System and Multi-Criteria Decision-Making methods: case study in southern Morocco. Renew. Sustain. Energy Rev. 51, 1354–1362.
Tuyet, N.T.A., Chou, S.Y., 2018. Maintenance strategy selection for improving cost-effectiveness of offshore wind systems. Energy Convers. Manag. 157, 86–95.
Ungureanu, V., 2018. Introduction.
Von Neumann, J., Morgenstern, O., 1944. Theory of Games and Economic Behavior (Commemorative Edition)-2007. Princeton university press.
Vortex, 2021. Modeled Wind Resource Data for the Wind Industry.
Weather, U.B.-D.D., 2018. Climate. NOAA National Centers for Environmental Information (NCEI).
Wing, T.E., Crow, L.H., 1990. A Model for Mean-Time-To-Repair and Mean-Logistics-Delay-Time at the System Level. IEEE.
Wu, B., Yip, T.L., Xie, L., Wang, Y., 2018. A fuzzy-MADM based approach for site selection of offshore wind farm in busy waterways in China. Ocean Eng. 168, 121–132.
Wu, Y., Zhang, J., Yuan, J., Geng, S., Zhang, H., 2016. Study of decision framework of offshore wind power station site selection based on ELECTRE-III under intuitionistic fuzzy environment: a case of China. Energy Convers. Manag. 113, 66–81.
Yadav, G., Mangla, S.K., Luthra, S., Jakhar, S., 2018. Hybrid BWM-ELECTRE-based decision framework for effective offshore outsourcing adoption: a case study. Int. J. Prod. Res. 56, 6259–6278.
Yang, M., Khan, F.I., Sadiq, R., 2011. Prioritization of environmental issues in offshore oil and gas operations: a hybrid approach using fuzzy inference system and fuzzy analytic hierarchy process. Process Saf. Environ. Protect. 89, 22–34.
Yang, M., Khan, F.I., Sadiq, R., Amyotte, P., 2013. A rough set-based game theoretical approach for environmental decision-making: a case of offshore oil and gas operations, 91, 172–182.
Yazdi, M., Khan, F., Abbassi, R., Rusli, R., 2020a. Improved DEMATEL methodology for effective safety management decision-making. Saf. Sci. 127, 104705.
Yazdi, M., Nedjati, A., Zarei, E., Abbassi, R., 2020b. A novel extension of DEMATEL approach for probabilistic safety analysis in process systems. Saf. Sci. 121, 119–136.
Yazdi, M., Nedjati, A., Zarei, E., Abbassi, R., 2020c. A reliable risk analysis approach using an extension of best-worst method based on democratic-autocratic decision-making style. J. Clean. Prod. 256, 120418.
Yue, C.-D., Liu, C.-C., Tu, C.-C., Lin, T.-H., 2019. Prediction of power generation by offshore wind farms using multiple data sources. Energies 12, 700.
Zavadskas, E.K., Turskis, Z., Tamošaitienė, J., 2008. Contractor selection OF construction IN a competitive environment. J. Bus. Econ. Manag. 9, 181–187.
Zhu, G.-N., Hu, J., Ren, H., 2020. A fuzzy rough number-based AHP-TOPSIS for design concept evaluation under uncertain environments. Appl. Soft Comput. 91, 106228.
Zuashkiani, A., Rahmandad, H., Jardine, A., 2011. Mapping the dynamics of overall equipment effectiveness to enhance asset management. J. Qual. Mainten. Eng. 17, 74–92.