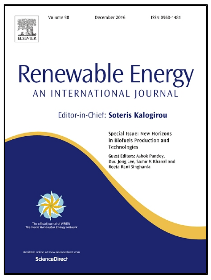

Developing a Novel Risk-based Methodology for Multi-Criteria Decision Making in Marine Renewable Energy Applications

Mohammad Mahdi Abaei, Ehsan Arzaghi, Rouzbeh Abbassi, Vikram Garaniya, Irene Penesis

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Research Highlights

- Application of Bayesian network (BN) and influence diagram (ID) to multi-criteria decision making (MCDM)
- Development of a novel methodology for improvement of power generation efficiency in renewable energy applications
- Integration of theoretical influencing parameters and the costs associated with power generation in decision making process for marine renewable energy site selection
- Development of a utility function for representation of wave energy converter (WEC) implementation

Developing a Novel Risk-based Methodology for Multi-Criteria Decision Making in Marine Renewable Energy Applications

Mohammad Mahdi Abaei, Ehsan Arzaghi, Rouzbeh Abbassi*, Vikram Garaniya, Irene Penesis

National Centre for Maritime Engineering and Hydrodynamics, Australian Maritime College, University of Tasmania, Launceston, Tasmania, Australia

* Corresponding Author: Email: Rouzbeh.abbassi@utas.edu.au

Abstract

Research and development of alternative energy resources such as wave energy has always attracted significant attention due to their abundant and sustainable nature. The uncertainties associated with the marine environment and the significant costs required for implementation of Wave Energy Converters (WECs) require a sound decision making methodology. This paper presents a novel risk-based methodology for selecting sites for WEC installation to minimize the overall economic risk. It provides WEC developers, investors, governments and policy makers a methodology for evaluating influencing parameters for potential site locations whilst also optimizing wave energy extraction. A Bayesian network is developed to model the probabilistic influencing parameters and then it is extended to an influence diagram for estimating the expected utility of installing the WEC equipment for a selected location. To demonstrate the application of the developed methodology, three sites in the south coast of Tasmania are considered. Based on actual sea state data, the optimum location for installing WEC equipment is determined as location 2 and the economic risk associated with energy extraction is minimized by suggesting a specific wave height ($H_S = 5$m) as a design criteria.

Key word:
Decision Making, Renewable Energy, Wave Energy Converter, Bayesian Network, Influence Diagram, Expected Utility

1. Introduction

Significant efforts are currently being invested in the research and development of clean and alternative energy resources, mainly due to the long-term detrimental emissions of fossil fuels and volatility of global oil price. The abundant resources of marine environment that covers 2/3 of the planet's surface is a viable form of renewable energy. Moreover, the practicality of power generation from the ocean in close proximity to the coastal areas yet occupying no land makes it an attractive option for supplying the world's energy needs (Council, 2011).

Wave energy is one of the major forms of marine renewable energy with potentials for significantly low emission power generation. Research has shown that the world's biggest waves, averaging 6m and reaching up to 20m, occur most frequently in the Southern Ocean including the region south of Australia between 40^{o} and 50^{o} S (Cornett, 2008; Lewis et al., 2011; Mørk et al., 2010). According to Harries et al. (Harries et al., 2006), in the southern and western coastal regions of Australia, the mean power in wave fronts varies from 30 to 70 kW/m, with peaks of 100 kW/m. The greatest wave energy resource in Australia is therefore located along its southern coastline from the southwest of Western Australia to the southern coastline of Victoria and on the west coast of Tasmania, where the average inshore wave energy densities range up to 84 kW/m (Harries et al., 2006).

Waves are predominantly generated by the energy transfer from atmospheric activities across the ocean. As a consequence of dispersion process, waves are separated as they travel at the ocean surface developing swells with long wavelengths. Although, swell characteristics are influenced by strong currents and interactions with seabed, they are relatively predictable regular waves and ideal for energy extraction Wave Energy Converter (WEC) devices. The dominant length and period of waves are directly related and the capacity of power generation is dependent on the amount of wave energy present in that area. Therefore, in order to improve the efficiency of power generation, it is essential to investigate the capacity of potential sites considering properties of sea state in each area. This results in reducing the economic risk associated with deployment of WEC equipment.

Recently, Wimmler et al. (2015) provides an extensive review of research on multi-criteria decision making (MCDM) applied to the renewable energy sector and storage problems such as power generation optimization, technology, policy and site selection. However, their research only reported few studies conducted about marine and offshore applications, none of which are focused on wave energy exploitation. Carballo et al. (2014) developed a tool for computing the total energy that can be generated by any WEC in coastal locations across Rias Baixas Region, Spain. They employed a MATLAB-based tool called WEDGE (Wave Energy Diagram Generator), that can construct a high resolution energy diagram based on which a WEC-site selection can be conducted. They suggested that comprehensive decision making for wave energy exploitation requires thorough knowledge of other factors such as the installation and operational cost, energy dissipation due to seabed topography and bathymetry as well as potential environmental aspects. Fetanat and Khorasaninejad (2015) applied a fuzzy-based MCDM methodology for site selection of offshore wind farm on the Persian Gulf, Iran. Several parameters including depth, height, environmental issues, proximity to facilities and economic aspects are considered as the decision making criteria. They asserted that integrating interdependent relationships among the criteria increases the accuracy of the analysis, however, their method is inevitably influenced by uncertainty of expert judgment. The complexity of their methodology also highlights a need for a more straightforward approach towards decision making. Khakzad and Reniers (2015b) developed a Bayesian network (BN) based methodology for calculating the risk of major accidents in chemical plants and combined the results with Analytic Hierarchy Process to design the layout of a storage plant in order to minimize the risks. Khakzad and Reniers (2015a) later adopted an influence diagram (ID) as an extension to BN for multi attribute decision analysis in a case study of fuel tank fireproofing. Their methodology is found promising for selecting the optimum decision alternative while considering several parameters such as fireproofing cost, economic and individual risks. They stated that the inclusion of more factors in the analysis is also facilitated by the developed BN based method. Other researches have used BN to decision problems in the field of medical science and biology such as mildew control and animal breeding. Image analysis and classification are other fields which are benefited from this technique. BN is designed as a knowledge representation of the problem domain, explicitly encoding the probabilistic dependence between the variables in the model. Since the model building focuses on the causal relationships between the variables, a Bayesian network automatically reveals the analyst's intuitive and analytical understanding of the problem (Friis-Hansen, 2000). This facilitates validation of the behavior of the model and makes it easier to convey its essentials to third parties (Friis-Hansen, 2000). Another advantage of BN is that if one of the variables in the domain is observed, then the probability distributions of the remaining variables in the model are easily updated accordingly.

This paper is aimed at developing a novel decision making methodology for selecting a location for installing WEC devices. This methodology must incorporate technical, economic and environmental aspects in the decision making process. As the wave energy transmission through WEC devices contributes to the power generation, parameters such as energy flux and wave breaking play a significant role in the efficiency of energy extraction process. These factors are associated with high level of uncertainty mainly due to their dependence on sea state environment with continuous fluctuations. Moreover, shipping traffic in certain areas can result in strict limitations for installation and operational activities. This factor also varies significantly based on transportation congestion in each location. Stochastic models are therefore considered to take into account these uncertainties. Improvement of power generation efficiency based on these stochastic variables is investigated. For this purpose, a BN is implemented to model the integrated probabilistic influencing parameters. The developed BN is then extended to an influence diagram for the decision making process. The decision-making framework considers the risk factors for marine renewable energy site selection and the costs associated with power generation. Furthermore, the case study details the process of determining locations for WEC installations in south coast of Tasmania is thoroughly discussed.

2. Application of Bayesian network in decision making

2.1 Bayesian Network (BN)

An extensive review of BN and probabilistic knowledge elicitation including wide range of applications in risk and reliability analysis is provided by Barber (2012), Scutari (2014) and Benson (2015). BNs are graphical models for reasoning under uncertainty that use causal relationships (represented by directed edges) among components of a system (represented by chance nodes). BN estimates the joint probability distribution of a set of random variables based on the conditional independencies and the chain rule, stated in Equation 1:

$$P(X_1,X_2,\ldots,X_n) = \prod_{i=1}^{n} P(X_i|pa(X_i)) \tag{1}$$

where $pa(X_i)$ is the parent set of variable X_i. As an example, the joint probability distribution of the random variables X_1 - X_4 shown in Figure 1 is estimated by $P(X_1,X_2,X_3,X_4) = P(X_1)P(X_2)P(X_3|X_1,X_2)P(X_4|X_3,X_2)$

Figure 1

In case new information becomes available for one or more chance nodes, BN is able to update the joint probability based on the Bayes' theorem:

$$P(X|E) = \frac{P(X,E)}{\sum_X P(X,E)} \tag{2}$$

Friis-Hansen (2000) provides a more detailed explanation of BN concepts and its inference algorithms. The application of BN in the field of risk and reliability is explored by many researchers (Abbassi et al., 2016; Bhandari et al., 2016; Yeo et al., 2016).

2.2 Influence Diagram (ID)

As an extension to BN, influence diagrams (ID) are formed by adding decision and utility nodes to the network (see Figure 2).

Figure 2

Decision nodes hold a number of decision alternatives considered by the user. The parents of a decision node provide the information required for making the decision hence an edge pointing to a decision node is an information arc instead of expressing probabilistic dependence (Friis-Hansen, 2000). Consisting numeric values rather than probabilities, utility nodes demonstrate the decision makers' preference over each configuration of decision alternative and the utility's parent nodes. For instance, if there exists n states for node X_4 and m alternatives for the decision node, the utility table requires $n \times m$ numeric values. The expected utility of decision alternative d_i is then estimated by Equation 3 where the decision with maximum expected utility will provide the optimum decision.

$$EU(d_i) = \sum_{X_4} P(X_4)\, U(d_i, X_4) \tag{3}$$

These utility values are determined based on experts' knowledge or utility functions. Jensen and Nielsen (2007) provide an extensive information about influence diagrams which are widely used in decision making applications. To name a few, Nielsen and Sørensen (2010) used ID as a decision making tool for optimizing the operation and maintenance (O&M) costs of offshore wind turbines. Eleye-Datubo et al. (2006) illustrated the applicability of BN and ID in decision making problems through a marine vessel evacuation in an accident and a collision scenario of a floating, production, storage and offloading installation. They asserted that IDs can assist in integration of a large number of interacting issues and their effects on the decision. They also reported that by providing practical solutions for optimization tasks, IDs can be used as robust marine decision-support tools.

3. Developed Methodology

The risk-based decision making methodology developed in this study assists as a tool for important decision making in installation of marine renewable energy devices. The resulting decisions maximize the profitability of power generation considering the limit states of all influencing factors explained later in section 3.2. The developed methodology consists of four different steps as presented in Figure 3 and discussed in the following sections.

Figure 3

3.1 Influencing Parameters

In order to maximize power generation efficiency, the major parameters that influence the decision making about site location are determined. As shown in Figure 3, these parameters are the energy flux, wave breaking and shipping traffic.

Long-term variation of sea state must be considered as metocean criteria for design and operation of offshore structures (Vrouwenvelder, 1997) using the short-term sea state characteristic which is usually described by the variation of significant wave height (H_S) and zero-crossing wave period (T_z). A joint probability distribution of H_S and T_z as $P(H_S,T_z)$ is adopted from the actual areas between which the decision making is conducted. From this joint distribution, $P(H_S)$ is estimated using a Rayleigh distribution (Dean & Dalrymple, 1991) and consequently the conditional probability of $P(T_z|H_S)$ is modelled. To achieve the long-term extreme values of wave heights, Gumbel distribution given below from Sørensen (1986) is adopted.

$$P\left(H_m \middle| h_s,T_z\right) = exp\left(-\nu_0 T_z\, exp\left[-\frac{1}{2}\left(\frac{h_s}{\sigma}\right)^2\right]\right) \tag{4}$$

where $\nu_0 = \sqrt{\frac{m_2}{m_0}}$, $\sigma = \sqrt{m_0}$ and m_i, $i = 0, 2$ is the i-th JONSWAP spectral moment. σ is the standard deviation of wave heights.

To design an offshore structure for the purpose of energy extraction, it is necessary to consider the energy dissipation due to wave breaking. To maximize the amount of energy available for extraction, the location of the wave breaking line must be predicted. For this purpose, the distance from the shore to the breaking line X_b, which depends on the bathymetry of seabed and the wave characteristics is estimated using Equation (5) by Dean and Dalrymple (1991),

$$X_b = \frac{1}{mg^{1/5}K^{4/5}}\left(\frac{{H_m}^2 C_0 \, Cos\, \theta_0}{2}\right)^{2/5} \tag{5}$$

where m is the sea bathymetry slope, g is the acceleration due to gravity, K is a coefficient for considering the effect of seabed slope on the wave breaking height and equals $K = 0.8$ according to Dean & Dalrymple (1991) and $\theta_0 = 0^{\circ}$ for normally incident waves. C_0 is the wave phase velocity estimated as $C_0 = \frac{gT_z}{2\pi}$ assuming that $h/\lambda > 0.5$ where h and λ are the water depth and wave length, respectively.

It is also assumed that the shipping traffic exponentially reduces as the distance from the shore increases, hence to model this parameter exponential distributions are considered.

3.2 Limit state function

According to Kamphuis (2010), limit state functions are widely used in the context of probabilistic design with failure function $G = R - L$. In this methodology, however, the concept of limit state is applied to determine the probability of the event $G \leq 0$ in which L is a function of stochastic variables such as H_S and T_z while R represents a pre-defined threshold constant value. Thus, limit state functions are defined to assess the variation of energy flux, wave breaking and shipping congestion in different locations as;

$$G_{Energy\ Flux} = E_{th} - E.C_g \tag{6}$$

$$G_{\ Wave\ Breaking} = X_{th} - X_b \tag{7}$$

$$G_{Shipping\ Traffic} = D_{th} - D_{tr} \tag{8}$$

where E_{th}, X_{th} and D_{th} are constant thresholds; $E = \frac{1}{8}\rho g H_s^2$ is the average energy per unit length ; $C_g = \frac{g}{2\pi}T_z$ is the wave group velocity and D_{tr} is the variable distance from the shoreline.

3.3 Utility Analysis

For establishment of the decision making process, the influencing parameters are ranked by their level of contribution to power production in each location. As presented in Table 1, the ranking process can be performed for any number of factors and location alternatives, however, in this paper energy flux, wave breaking and shipping traffic are only considered.

Table 1

Consequently, a utility function based on the profit making potentials is derived expressing the preference of stakeholders over all the decision alternatives as:

$$Utility = \begin{cases} C_P(1 - C_C)\gamma_P & for\ high\ energy\ zone \\ C_L\gamma_L & for\ low\ energy\ zone \end{cases} \quad (9)$$

where C_P is profit coefficient proportional to $H_s^2 T_z$ per unit energy generated. C_C and C_L are cost and loss coefficients, respectively. Cost coefficient C_C grows exponentially by increasing the distance from the shore mainly due to the higher costs associated with energy extraction in more extreme sea states. γ_P is profit ratio defined by $\frac{\sum_{j=1}^{m\leq n}\beta_{kj}}{\sum_{i=1}^{n}C_{ki}}$ in which $C_{kj}$is adopted from Table 1 and β_{kj} is ranking of parameters with positive effect on power generation for locations $1,2\ldots,k$. Similarly, γ_L is loss ratio defined by $1 - \frac{\sum_{j=1}^{m\leq n}\beta_{kj}}{\sum_{i=1}^{n}C_{ki}}$.

3.4 Decision model for optimal site selection

Most previous approaches to renewable energy site selection (Baysal et al., 2011; Defne et al., 2011) usedAnalytical Hierarchy Process (AHP) or Fuzzy Logic for the decision making process. Increasing the number of influencing factors can result in a highly intractable MCDM (Multi Criteria Decion Making) process. The BN and ID employed in this study, however, is capable of integrating techno-economic factors in wave energy exploitation such as wave energy dissipation and the level of energy flux based on the concepts explained in section 3.1 3.1 and 3.2 . Moreover, socio-economic aspects including operation and maintenance costs can also be incorportated into the BN. The probabilistic model considers the conditional dependency of sea state parameters H_S and T_z to analyze the maximum wave heights probability. The effect of sea state joint distribution on the influence parameters is then assessed. Consequently, the decision making process which specifies whether the WEC equipment can be installed at that location is carried out by extending the BN to an influence diagram illustrated in Figure 4. The decision node in Figure 4 contains two decision alternatives as “Install” and “No Install”. The utility node is conditional on the influencing parameters and the states of decision node and holds a utility table based on each configuration of its parents’ nodes. A comparison amongst the estimated expected utilities enables the decision maker to select the WEC site location with optimum power generation efficiency.

Figure 4

4. Application of the developed methodology: A case study of Tasmania

4.1 Scenario development

To demonstrate the application of developed methodology, a case study is adopted to select the sites for WEC installation in Tasmanian waters. As illustrated in Figure 5, three sites in the south coast of Tasmania are proposed as the studied locations, since the amount of wave energy potential that exist in Tasmania Coastal regions is reported to be one of the greatest in the world (Harries et al., 2006). The locations were all considered in the south coast of Tasmania in a close proximity to illustrate the strength of the developed methodology in determining the optimum location. In order to analyze the potential power generation in each location, six different sea state thresholds are studied. According to Gadonneix et al. (2010) southern Australia has world-class potentials for marine energy extraction. This capacity is due to the wave generation by global westerly wind belt with an almost infinite fetch. In this region, waves with more than 5.5m of height can consistently propagate without shoaling which results in a significantly less wave energy dissipation (Mueller et al., 2010).

Figure 5

4.2 Sea State Modeling

Actual field data from CSIRO (2016) incorporating a joint distribution of significant wave height (H_S) and zero-crossing wave period (T_z) for each location is adopted. The joint distribution of (H_S ,T_z) in location 1 is depicted in Figure 6 along with calculated energy flux illustrated as contours. In this figure, the highlighted grids represent the more probable occurrence of significant wave heights 1m to 6m, conditional on wave periods 7s to 11s. A detailed calculation of maximum wave height probability distribution is discussed in Section 3.1.

Figure 6

4.3 Wave breaking and shipping traffic Modeling

Wave breaking occurrence probability is estimated using Equations 4, 5 and 7 considering stochastic variables H_m, T_z and m. The bathymetry slope m is normally distributed as

$m \sim N(\mu = 0.5\%, \sigma = 0.025\%)$ (Navionics, 2015) while shipping traffic in the analysis area is assumed to be exponentially distributed with $D_{tr} \sim Exp(\mu = 1\text{km})$.

4.4 Cost Analysis

Decision making parameters, energy flux, wave breaking and shipping traffic are ranked based on expert judgment using integer values $C_{ki} \in [1,10]$ for each location alternative, as shown in Table 2.

Table 2

Using the specified utility functions in Equation 9, a utility table used for two decision alternatives (install or do not install WEC equipment) and each configuration of influencing factors is presented and developed in Table 3. The positive utility values for "No Installation" corresponds to the case that the capitals are invested in other profitable fields.

Table 3

The constructed influence diagram is presented in Figure 7 that incorporates the acquired sea environment data from location 2 as well as the predefined utility values presented in the previous section.

Figure 7

Previously, researchers (Baysal et al., 2011; Defne et al., 2011; Zhang et al., 2014) adopted expert judgment based methods such as AHP and Fuzzy Logic to integrate various influence factors considering their level of effectiveness on the decision (Baysal et al., 2011; Defne et al., 2011; Zhang et al., 2014). However, physical aspects such as hydrodynamic features of sea environment and the interdependency between the influencing factors are not precisely considered to optimize energy extraction efficiency. Moreover, in this study, the expert judgment is not used to incorporate the effect of each criteria on decision making and instead relative mathematical concepts are adopted.

An area with larger wave heights is expected to have higher potentials for wave energy generation. However, due to the associated costs with the design and operation of the equipment, it is necessary to determine the maximum expected utility for each decision alternative. Figure 8 present the estimated utility values for installing and not installing WEC equipment in location 1-3 with respect to six sea state thresholds, $H_S = 1,3,5,7,9,11\text{m}$. The expected utility for the installation of the equipment in each location and the difference of the expected utility between installing and not installing the equipment is optimised at wave heights of 5m ($H_S = 5$m). That means the wave heights of 5m can be adopted for power generation with acceptable economic risks. In the figures, the estimation of negative expected utilities for large wave heights is due to the excessive cost associated with the installation and maintenance of equipment in such sea states. The extensive investments required does not justify to aim for energy exploitation from waves with larger wave heights (i.e. $H_S > 5$m). The expected utility of installing the WEC devices is compared amongst all the locations. As shown in Figure 8, location 2 has the maximum expected utility $EU_{Max}(Loc2) = 1.19E + 05$, highlighting the optimum site location for WEC equipment implementations. That is, considering the adopted sea state data and local shipping congestion from southern Tasmania WEC devices can efficiently extract more energy at the location 2. Installation and operation of WEC devices in other locations (i.e. 1 and 3) will be less costly due to closer proximity to shore, however, the significant wave energy potentials in location 2 should not be disregarded. In fact, the advantage of this methodology is finding the balance between potential energy extraction and associated costs to find the optimum decision.

Figure 8

5. Conclusion

This paper presents a novel methodology for decision making in marine renewable energy applications. The developed methodology has the general applicability in MCDM for selecting the most suitable sites for implementation of WEC devices. This methodology is able to conduct a sound decision making process that incorporates the uncertainty associated with the influencing parameters in the marine environment including energy flux, wave breaking and shipping traffic. For this purpose, a Bayesian network-based model is developed to determine the probabilities of the influencing parameters.

The BN is then extended to an influence diagram for estimating the expected utility for each decision alternatives whether to install the WEC in a given location or not. As a case study, three sites in south coast of Tasmania are considered. Based on actual sea state data, the optimum location (location 2) is determined with maximized expected utility $EU_{Max}(Loc2) = 1.19E + 05$ compared to locations 1 and 3. The economic risk associated with energy extraction is also minimized by suggesting a maximum significant wave height ($H_S = 5\text{m}$) for equipment installation in this location. The priority of this model is to select the optimum location for deployment of WEC equipment, however, the developed methodology can be readily integrated with other reliability models to enable the effect of structural failures in decision making.

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Figure Captions:

Figure 1 A schematic Bayesian network

Figure 2 A schematic of influence diagram (Decision and Utility nodes are added to BN)

Figure 3 Developed methodology for decision making process in installation of wave energy converters

Figure 4 Developed influence diagram for WEC site selection

Figure 5 Three site locations considered for WEC installation in south coast of Tasmania

Figure 6 Sea state joint distribution with respect to calculated energy flux contour

Figure 7 WEC site selection in southern Tasmania using influence diagram (ID)

Figure 8 Expected utility of installing and not installing WEC equipment in Location 1 (a), Location 2 (b) and Location 3 (c). Estimations are made for six different sea state thresholds

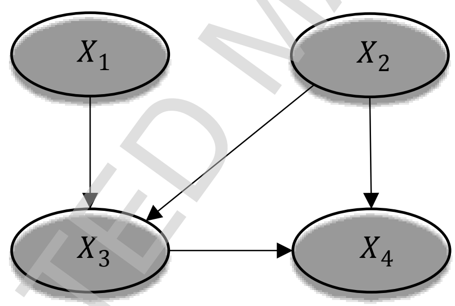

Figure 1

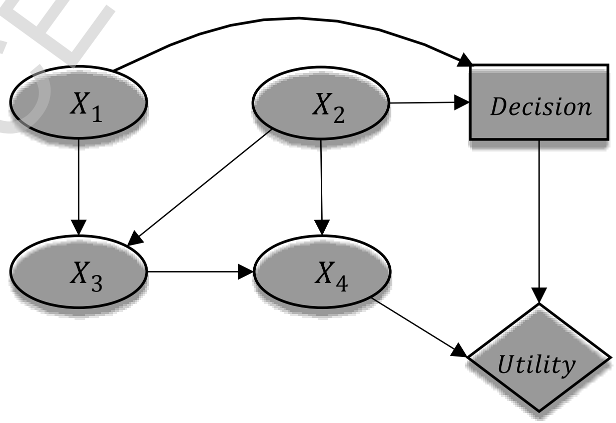

Figure 2

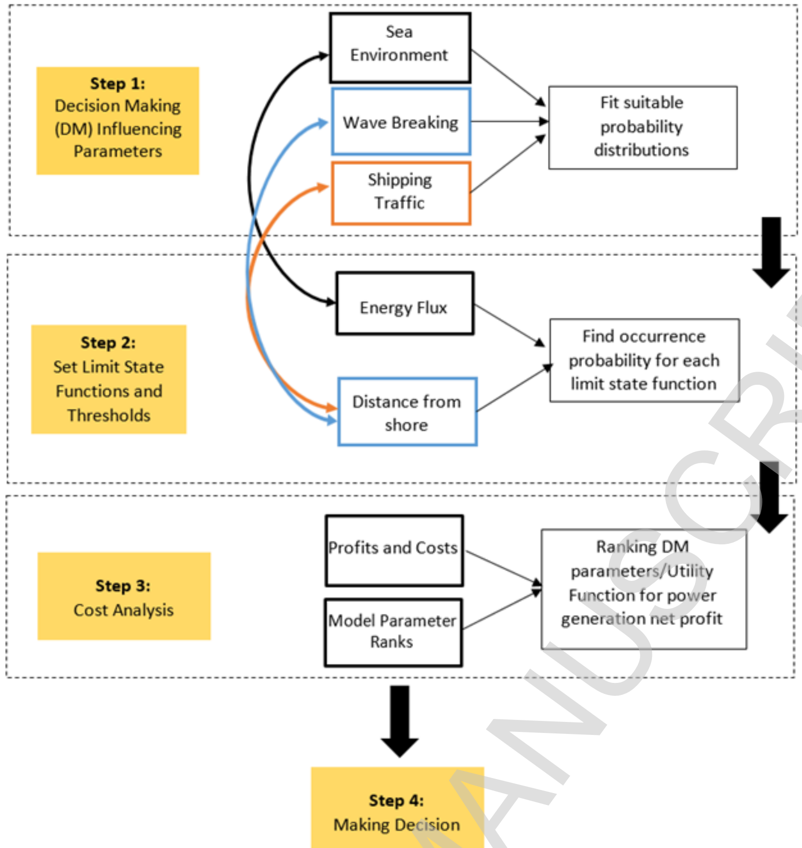

Figure 3

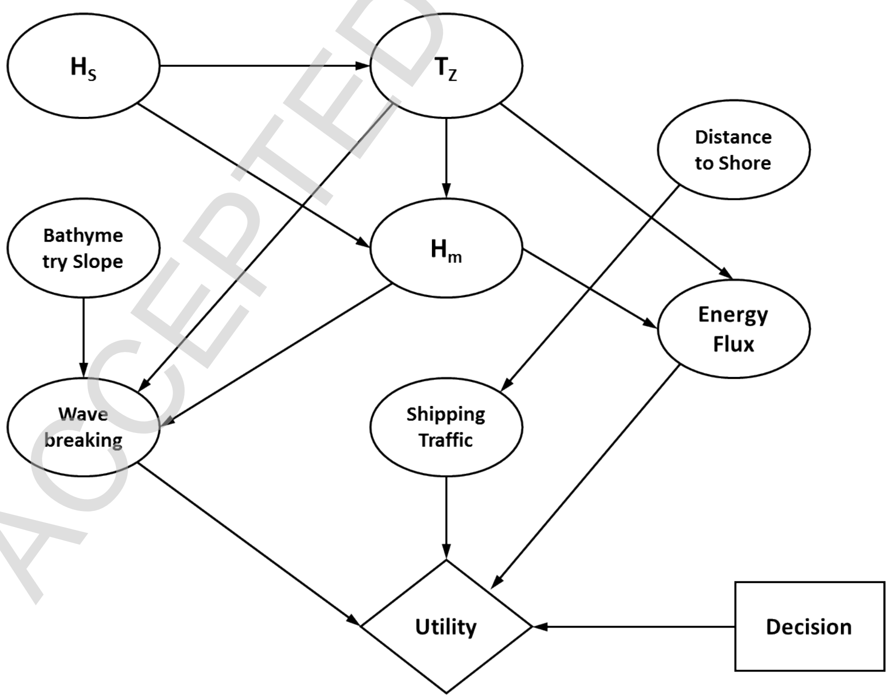

Figure 4

Figure 5

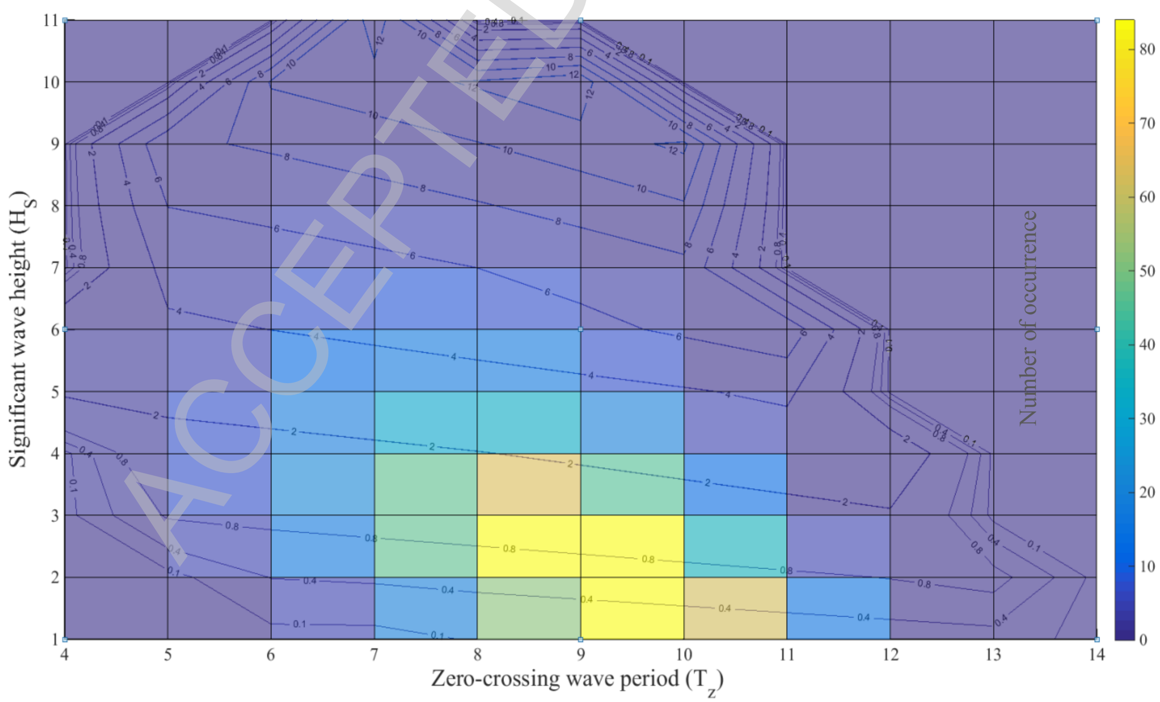

Figure 6

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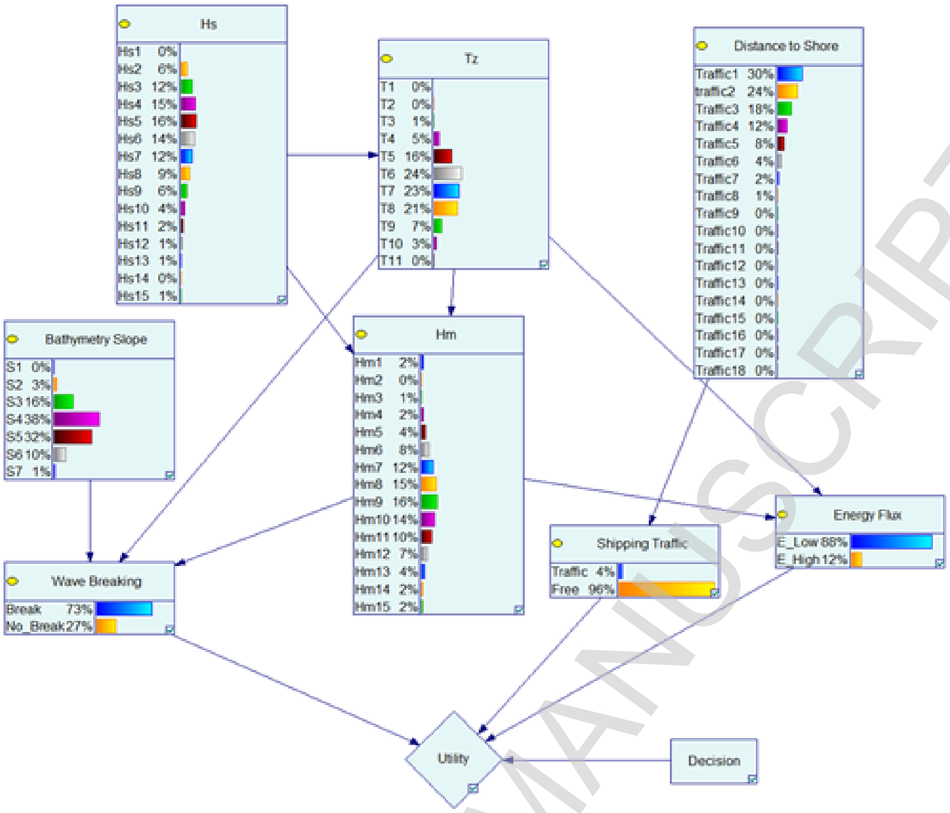

Hs
Hs1 0%
Hs2 6%
Hs3 12%
Hs4 15%
Hs5 16%
Hs6 14%
Hs7 12%
Hs8 9%
Hs9 6%
Hs10 4%
Hs11 2%
Hs12 1%
Hs13 1%
Hs14 0%
Hs15 1%
Tz
T1 0%
T2 0%
T3 1%
T4 5%
T5 16%
T6 24%
T7 23%
T8 21%
T9 7%
T10 3%
T11 0%
Distance to Shore
Traffic1 30%
traffic2 24%
Traffic3 18%
Traffic4 12%
Traffic5 8%
Traffic6 4%
Traffic7 2%
Traffic8 1%
Traffic9 0%
Traffic10 0%
Traffic11 0%
Traffic12 0%
Traffic13 0%
Traffic14 0%
Traffic15 0%
Traffic16 0%
Traffic17 0%
Traffic18 0%
Bathymetry Slope
S1 0%
S2 3%
S3 16%
S4 38%
S5 32%
S6 10%
S7 1%
Hm
Hm1 2%
Hm2 0%
Hm3 1%
Hm4 2%
Hm5 4%
Hm6 8%
Hm7 12%
Hm8 15%
Hm9 16%
Hm10 14%
Hm11 10%
Hm12 7%
Hm13 4%
Hm14 2%
Hm15 2%
Energy Flux
E_Low 88%
E_High 12%
Shipping Traffic
Traffic 4%
Free 96%
Wave Breaking
Break 73%
No_Break 27%
Utility
Decision

Figure 7

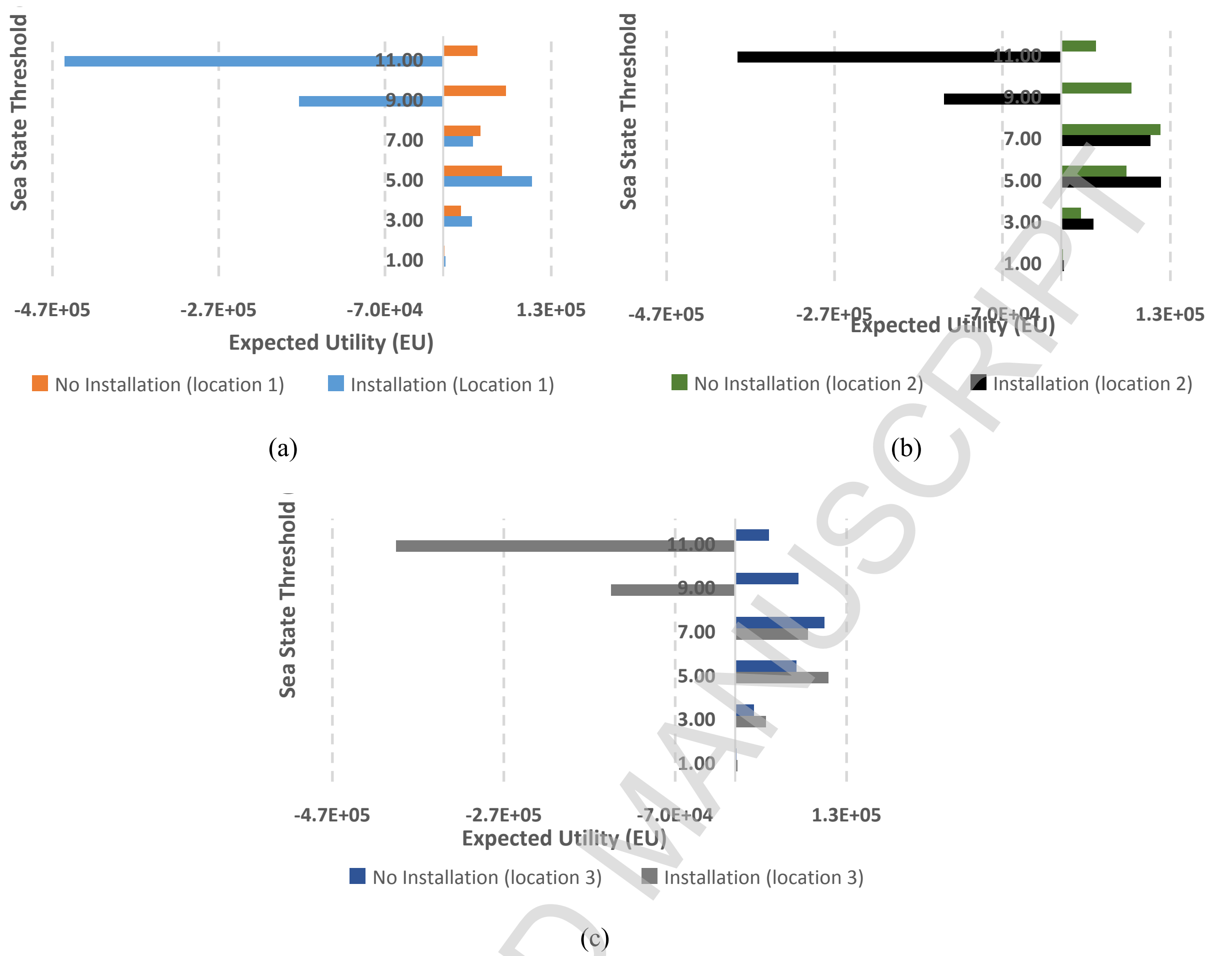
Sea State Threshold
11.00
9.00
7.00
5.00
3.00
1.00
-4.7E+05
-2.7E+05
-7.0E+04
1.3E+05
Expected Utility (EU)
No Installation (location 1)
Installation (Location 1)
(a)
Sea State Threshold
11.00
9.00
7.00
5.00
3.00
1.00
-4.7E+05
-2.7E+05
-7.0E+04
1.3E+05
Expected Utility (EU)
No Installation (location 2)
Installation (location 2)
(b)
Sea State Threshold
11.00
9.00
7.00
5.00
3.00
1.00
-4.7E+05
-2.7E+05
-7.0E+04
1.3E+05
Expected Utility (EU)
No Installation (location 3)
Installation (location 3)
(c)

Figure 8

Table 1. Ranking decision making influence parameters for different locations

Influencing parameter \ Location	Loc_1	…	Loc_k
α_1	C_{11}	…	C_{k1}
⋮	⋮		⋮
α_n	C_{1n}	…	C_{kn}
	$\sum_{i=1}^{n} C_{1i}$	…	$\sum_{i=1}^{n} C_{ki}$

.

Table 2. Rankings of decision making influence parameters for locations 1,2 and 3

Influencing parameter \ Location	Loc 1	Loc 2	Loc 3
Energy Flux	8	10	8
Wave Breaking	4	2	4
Shipping Traffic	1	1	3
Total	13	13	15

Table 3. Utility values for different configurations and decision alternatives

Sea State	Low Energy Flux							
	Wave Break				No Wave Break			
	Traffic		Free		Traffic		Free	
	Install	No Install	Install	No Install	Install	No Install	Install	No Install
$H_S = 1$m	-2.2E+03	4.3E+01	-2.0E+03	4.3E+01	-1.5E+03	4.3E+01	-1.3E+03	4.3E+01

Sea State	High Energy Flux							
	Wave Break				No Wave Break			
	Traffic		Free		Traffic		Free	
	Install	No Install	Install	No Install	Install	No Install	Install	No Install
$H_S = 1$m	2.2E+03	1.3E+03	2.5E+03	1.5E+03	3.3E+03	2.0E+03	3.6E+03	2.2E+03