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RESEARCH ARTICLE

Application of CRITIC–EDAS-Based Approach in Structural Health Monitoring and Maintenance of Offshore Wind Turbine Systems

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Abstract

Performing structural health monitoring (SHM) and maintaining an offshore wind turbine system (OWTS) involve periodic observations, analysis, and repairs of the malfunctioning part(s) of the system. In this study, criteria importance through inter criteria correlation–evaluation based on distance from average solution methodology is employed to analyze SHM and maintenance technologies for OWTS. Their various applications are highlighted, and the technologies are prioritized using six indicators, namely, compatibility, potential cost reduction, needed investment, technology maturity, ease of application and potential reliability, and availability and maintainability of the considered technology. The study also aimed to improve the reliability of OWTS and minimize its maintenance cost. The results indicate that the technology's ease of application, with a weight of 0.201 8, is the most important criterion. Furthermore, mathematical models as an SHM, along with maintenance technology, is ranked as the best alternative with an appraisal score of 0.770 6 and is considered more advantageous than other alternatives. This study provides a new research direction toward improving OWTS reliability. The findings will also aid the decision making of practitioners and researchers in the field of marine and offshore industry in relation to the optimal operations of OWTS.

Keywords Offshore wind turbine systems; Maintenance; CRITIC–EDAS; Reliability; Criteria

1 Introduction

Offshore wind turbines (OWTs) are devices that transform wind aerodynamic power into electrical power. The turbine produces electrical energy and transfers it to an offshore substation using cables. The voltage of the generated electric power is stabilized and maximized in the offshore substation and later exported to the shore (Nikitas et al., 2020). The maintenance of OWT components involves the combination of all technical and corresponding administrative actions with the aim of retaining its state or restoring it to a state in which OWTs can perform their desired function.

Article Highlights

- Ensuring the safety of an OWT in harsh offshore environments is crucial for its viability as an energy option.
- The study focuses on the application of a CRITIC-EDAS-based approach in the structural health monitoring and maintenance of offshore wind turbine systems (OWTS).
- The research investigates and analyzes SHM and maintenance technologies for OWTS.
- Eight alternatives are presented and compared with each other and were assessed.
- The study finds mathematical model(s) to be the best alternative.

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OWTS consists of various components, including a foundation, turbine tower, rotor, gearbox, hub, nacelle, and generator. The OWT foundation is the basic part that supports the OWT structure against environmental loads. It is situated underwater and requires adequate mass to support the weight of the turbine. OWT foundations can be grouped into two major types: floating and fixed. The fixed types are effective in water depths of less than 60 m, while the floating types are mainly for water depths greater than 60 m (Ömer and Mutungi, 2016). Passon and Kühn (2005) classified OWT structures into the first, second, and third generations. The first generation consists of fixed foundations, such as gravity-base and monopile foundations, which are effective for water depths less than 30 m. The second-generation foundations include a more sophisticated range, such as asymmetric tripod caisson, tripod caisson, tetrapod caisson, tripod pile foundations, and tetrapod caisson foundations, and are suitable for water depths not exceeding 60 m. The third generation is the floating type, which is the most cost-effective solution for deep and ultradeep waters (Ömer and Mutungi, 2016).

The turbine tower is part of the OWT support structure that is above the foundation (Jonkman et al., 2009). The tower in current turbines is usually a round tubular steel tower with a diameter of ~3–4 m. The height is typically about 75–110 m based on the size of the OWT and its location. The recommended practice for a turbine tower is that it should have a similar height as the diameter of the circle made by its blades during rotation. The rotor is the rotating part of the OWT and is made up of three blades and a hub. A hub is the central part to which the turbine blades are fixed. The turbine blades are mostly made of lightweight but strong composite materials and come in the form of an airfoil to give them an aerodynamic property. They usually do not have a flat shape and have a twist between their tip and their root. The gearbox, which is an important component that resides in the nacelle, increases the speed of the main shaft to the required speed of its generator. The shaft on the generator side is usually called the "high speed shaft". The nacelle accommodates all the components situated on top of the turbine, and the major components housed by the nacelle are the turbine shaft and generator. The hub performs the function of holding the turbine blades, making it possible for the blades to rotate. Meanwhile, the generator is part of the OWT that converts wind energy into the mechanical energy of the motor, thus producing useful electrical energy. The power from the wind is transferred to the generator by the turbine shaft with the aid of a gearbox, and induction generators are mostly used for this purpose.

Loads on OWT structures can be classified into dynamic and static loads. The static loads are based on the actual weights of the OWT components, while dynamic loads depend on the environment. Dynamic loads come in the form of wind or water interaction and are respectively grouped as aerodynamic and hydrodynamic loads. The most challenging of these types of loads are the dynamic loads, including the wave loads, currents, seismic, and wind loads (Bhattacharya, 2014).

The distributed wind velocity varies in terms of direction, space, and time (Tempel et al., 2011). Given that it is complicated to consider the effect of wind velocity variation in more than one direction, only the wind in the frontal direction is considered. At the same time, sea waves are a major component of environmental loads affecting OWTS. As the waves act on the OWT structure, they may result in actions whose magnitude depends on the period and height of the waves.

As offshore maintenance experiences a shift toward digitalization and automation, this study aims to review the approaches to SHM and OWTS maintenance found in the literature. The applications and prioritization of SHM and maintenance approaches in improving the reliability of the OWTS components (the foundation, turbine tower, nacelle and the blades) are also demonstrated, along with the minimization of the operational and maintenance cost of the OWTS.

2 Literature review

2.1 Trends in OWTS maintenance

Many studies have been conducted on the maintenance techniques for OWT systems, as evidenced in Lu et al. (2018), in which an artificial neural network (ANN) was employed in the degradation evaluation of OWT components, from which the relationships among the age, condition monitoring data, and life percentages of the components were modeled. Gorjian et al. (2010) reviewed degradation models for component maintenance, while Kadlec et al. (2009) demonstrated the characteristics of industrial processes in which soft sensors can fit. They also conducted a review of their applications in different industries.

An efficient data-driven predictive model capable of predicting the faults of OWTs was presented in Papatzimos et al. (2019). The Romeo project on Iberdrola Renewables (2017) aimed to implement a cloud and Internet of Things platform to provide real-time prognosis and diagnosis for the basic structural components of OWTs. The Home Offshore project (Project, 2020) aimed to hybridize drones for the inspection of OWTs using artificial intelligence (AI) for fault pattern analysis. In Rinaldi et al. (2019), the applications of AI in the offshore wind sector are highlighted. A compilation of various studies on the applications of soft sensors in various industries for maintenance purposes has been provided in Science Direct (2020). The iWindCr, a wireless sensor network (WSN) for detecting and monitoring corrosion OWT components, was developed and successfully applied to detect the state of corrosion and the outcomes of the field trial were reported (Simandjuntak et al., 2021).

2.2 Condition monitoring and maintenance approaches

A great deal of condition monitoring and maintenance approaches was employed in different areas (Kimera and Nangoo, 2019), wherein the reliability and degradation analysis of deck machinery for aging fishing vessels using Weibull and Gamma distributions was presented. Tchertchian and Millet (2022) investigated the optimal maintenance strategy for different offshore wind farms, demonstrating how different maintenance strategies can influence the environmental performance of a wind farm. Another study proposed a semiqualitative model integrating AHP and PROMETHEE to select appropriate maintenance strategies for different critical machines found in the engine room of ships (Animah and Shafiee, 2019). Asuquo et al. (2019) proposed condition monitoring of offshore machinery with the aid of evidential reasoning techniques. Meanwhile, Vanem and Anreas (2019) presented the anomaly detection and condition monitoring of ship machinery systems based on sensor data. A nonlinear analysis method was proposed by Yang et al. (2019) to extract distinct failure indicators from the oil parameters of marine turbine generators in order to facilitate the condition monitoring of marine turbine generators. In Helton et al. (2021), a machine learning (ML) algorithm was developed to predict propulsion motor overheating using data obtained from identical vessels. Bejger et al. (2020) described the use of acoustic emission elastic waves to diagnose insulated-gated bipolar transistors for the monitoring of early-stage damages.

2.3 Review of the applications of the criteria importance through intercriteria correlation – evaluation based on distance from average solution (CRITIC–EDAS) methodology

The use of the CRITIC–EDAS methodology for prioritizing SHM and maintenance technologies for OWTS was not found in the available literature. Rather, the available literature shows how the CRITIC–EDAS methodology has been used to solve problems in different areas. For example, Gorcun and Kucukonder (2021) employed it to evaluate the Ro-Ro marine port selection process. Kiraci and Durumuscelebi (2022) conducted a performance analysis of airports using CRITIC-based EDAS methodology. Li and Wang (2020) evaluated algorithms for the service quality of WSNs based on internal-valued intuitionistic fuzzy EDAS and CRITIC methods. In addition, Ghorabaee et al. (2018) incorporated the CRITIC and EDAS methods in the evaluation of construction equipment with sustainability considerations, while Zavadskas et al. (2019) applied the CRITIC and EDAS-based MCDM model for the evaluation of autonomous vehicles.

3 Research methodology

In this study, the CRITIC method is integrated with the EDAS method to prioritize maintenance technologies toward improving OWTS reliability while also minimizing the operational and maintenance cost of the system. A CRITIC method was employed to determine the weights of the criteria for the considered maintenance alternatives, while the EDAS method was used to evaluate and optimize the different maintenance alternatives.

3.1 CRITIC method

The CRITIC method is a tool for obtaining the objective weights of criteria. The tool induces conflict in the structure and the intensity of the contrast of the subject under investigation (Diakoulaki et al., 1995). The contrasts between different criteria were obtained using correlation analysis (Yilmaz and Harmancioglu, 2010). At the same time, the decision matrix was evaluated, and the criteria contrasts were determined using the standard deviation of the normalized criteria values, as well as the correlation coefficients of all pairs of columns of the normalized criteria values (Madić and Radovanović, 2015). The steps involved in the CRITIC method are described as follows:

Step 1: Perform decision matrix normalization using

$$S_{jk} = \frac{s_{jk} - s_j^{\text{worst}}}{s_j^{\text{best}} - s_j^{\text{worst}}} \tag{1}$$

where s_{jk} represents the performance rating of the considered alternative k on criterion j.

Step 2: Determine the standard deviation (∂_j) for each criterion.

Step 3: Determine the symmetric matrix with element y_{jk} (representing the linear correlation coefficient of paired criteria).

Step 4: Determine the measure of conflict created by criterion j using Equation (2):

$$\sum_{k=1}^{n}(1 - \gamma_{jk}) \tag{2}$$

Step 5: Obtain the quantity of the information based on each criterion using Equation (3):

$$C_j = \partial_j \sum_{k=1}^{n}(1 - \gamma_{jk}) \tag{3}$$

where C_j represents criteria contrast.

Step 6: Determine the objective weights of the criteria using Equation (4):

$$W_j = \frac{C_j}{\sum_{k=1}^{n} C_j} \tag{4}$$

where w_j represents the weight of the criterion.

3.2 EDAS method

Ghorabaee et al. (2015) developed the EDAS method, which is very practical when used on problems with conflicting attributes. The prioritization of alternatives is made based on their distance from the average solution. The positive distance from average (PDA) solution and the negative distance from average (NDA) solution are the two distance measures used to evaluate the alternatives. The alternative with the highest PDA value and a lower NDA value is seen as the best alternative. The steps for EDAS method computation are defined as follows (Ghorabaee et al., 2015):

Step 1: Select the criteria and the alternatives. A decision matrix $\boldsymbol{X}$ is made:

$$\boldsymbol{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{12} & x_{22} & \cdots & x_{2n} \\ x_{1n} & x_{2n} & \cdots & x_{mn} \end{bmatrix} \tag{5}$$

where $\boldsymbol{X}$ represents the performance rating of the considered alternative i on the criterion j. It is assumed that all x_{ij} are positive real numbers.

Step 2: Obtain the average solution based on all criteria with the aid of Equation (6):

$$x_j^* = \frac{\sum_{k=1}^{m} x_{ij}}{m} \tag{6}$$

where m represents the number of alternatives.

Step 3: Determine the NDA d_{ij}^- and the PDA d_{ij}^+ based on beneficial and nonbeneficial criteria using Equations (7) and (8), respectively:

$$d_{ij}^- = \frac{\max\left(0, \left(x_j^* - x_{ij}\right)\right)}{x_j^*}, \ j \in \bigcap_{\max} \tag{7}$$

$$d_{ij}^+ = \frac{\max\left(0, \left(x_{ij} - x_j^*\right)\right)}{x_j^*}, \ j \in \bigcap_{\max} \tag{8}$$

$$\frac{\max\left(0, \left(x_j^* - x_{ij}\right)\right)}{x_j^*}, \ j \in \bigcap_{\max}$$

where $\bigcap_{\max}$ and $\bigcap_{\min}$ respectively represent the sets of beneficial and nonbeneficial criteria, and x_j^* indicates a positive number.

Step 4: Obtain the weighted sum of PDA, Q_i^+ and the weighted sum of NDA Q_i^-, for all alternatives if a vector $(w_1, w_2, \cdots, w_n)$ of non-negative weights is to be employed:

$$Q_i^+ = \sum_{j=1}^{n} w_j d_{ij}^+ \tag{9}$$

$$Q_i^- = \sum_{j=1}^{n} w_j d_{ij}^- \tag{10}$$

where w_j represents the weight of the criteria.

Step 5: Obtain the normalized values of the weighted sum of the NDA and the weighted sum of the PDA for the alternatives considered using the following:

$$S_i^- = 1 - \frac{Q_i^-}{\max_i Q_i^-} \tag{11}$$

$$S_i^+ = 1 - \frac{Q_i^+}{\max_i Q_i^+} \tag{12}$$

where S_i^- and S_i^+ represent the normalized weighted sum of the NDA and the weighted sum of the PDA, respectively.

Step 6: Determine the appraisal score S_i for all alternatives considered using Equation (13):

$$S_i = \frac{1}{2}\left(S_i^+ + S_i^-\right) \tag{13}$$

Step 7: Rank the alternatives, in which the one with the highest S_i value is considered the best.

4 Case study on the application of CRITIC – EDAS-based approach in structural health monitoring and maintenance of offshore wind turbine systems

In this section, the SHM and OWTS maintenance are considered in demonstrating the suitability of the integrated CRITIC–EDAS methodology. The mechanism of the integrated approach is used to optimize technologies for OWTS maintenance.

4.1 Alternatives descriptions

Eight maintenance technologies were considered in this study: the use of autonomous vessels, AI, soft sensors, mathematical models, inspection and repair robots, drones, ML, and big data.

Autonomous vessels are more suitable for the inspection of the underwater parts of the OWT. They were applied in the water eye project (CEIT Watereye Project, 2020), which aimed to deploy a network of drones with ultrasound sensors to effectively monitor OWT devices.

AI: This is regarded as the present and future of OWT maintenance (Chatterjee and Dethlefs, 2021). It enables computers and machines to solve problems in the same manner as intellectual human ability (Ertel, 2017). AI-equipped systems can analyze data and learn from them to improve their capabilities. AI consists of different techniques that support the development of intelligent behavior in machines and computers. Techniques associated with AI include optimization algorithms, ANNs, search functions, and fuzzy-logic systems.

Soft sensors: Soft sensors have already been applied in other industries, and this concept may provide a significant contribution to the monitoring and maintenance of OWT systems. These are evaluation models that are capable of replicating measurement signals that are not from the existing instrumentation and using them as a data source to monitor the instruments and detect their imminent faults. Soft sensors use system knowledge and hardware-generated signals in the stimulation and monitoring of parameters that are expensive or extremely difficult to monitor directly using real sensors. The guidelines for an effective soft sensor application are provided in Fortuna et al. (2007).

Mathematical models: The Wiener process (Van Noortwijk, 2009; Grall et al., 2002), the inverse Gaussian process (Wang and Xu, 2010), renewal theory (Grall et al., 2002), and the Gamma process (Van Noortwijk, 2009) are typical mathematical models employed for continuous deterioration. The proportional hazard model is mostly employed if the degradation depends on environmental conditions (Si et al., 2011; Singpurwalla, 1995). In Gorjian (2010), a comprehensive review of degradation models is made.

Inspect and repair robots: The use of inspect and repair robots is an emerging development used for maintenance purposes, and BladeBUG is an example of such a robot (BladeBUG, 2020). It is a crawler robot capable of climbing and walking on blades of OWT systems and can be operated beyond the line of sight. The BladeBUG is capable of scanning the surface of the blade to detect signs of deterioration and carry out repairs when necessary. This approach prevents blade inspections and maintenance by technicians.

Drones: Drones are currently used for OWT inspection and maintenance activities. They can be used in monitoring different parts of the nacelle and tower, including the blades. The use of drones prevents the need to shut down the OWT, especially while the maintenance is being carried out.

ML: This approach is centered on the implementation of algorithms and models whose predictive performances can be improved automatically due to the availability of more data. To achieve this, the training of the models using the initial data set is important in learning how the outcome can be predicted. The three basic classes of ML methods are the unsupervised, supervised, and reinforcement methods (Soraghan, 2020). A supervised method is normally preferable in SHM applications due to the fact that it gives room for the quantification and classification of the damage, while the unsupervised model only gives room for its identification (Martinez-Luengo et al., 2016).

Big data: As a result of the increasing volume of performance monitoring and component health indicators, as well as the addition of vessel parameters during offshore wind field operations, significant advantages can be provided by big data systems in the process of collecting, scaling, and predicting data compared with other traditional databases, such as spreadsheets.

4.2 Criteria descriptions

The criteria employed in this study are compatibility; potential reliability, availability, and maintainability (RAM); technology maturity, ease of application; potential cost reduction; and the investment needed. Compatibility refers to the suitability of the technology for OWT maintenance, while technology maturity refers to the level at which a technology has been applied for maintenance purposes. Ease of application refers to the ease of applying the technology for OWT maintenance, while potential cost reduction refers to the prospect of the technology saving future operational costs. Finally, the investment needed criterion refers to the total cost needed to carry out the maintenance activity using the technology.

4.3 Application of the CRITIC method in the weight estimation of the maintenance method optimization criteria

During the weight determination exercise, three experts with equal experience in OWT maintenance were consulted in the rating of the basic criteria using a 5-point Likert scale. The experts' ratings are presented in Table 1. As shown in Table 2, the mean of the rating made by the three experts was taken as the actual rating as they have equal experience with the subject being investigated. The CRITIC method was employed in the determination of the weights of the maintenance method selection criteria.

The normalization of the decision matrix in Table 2 was performed using Equation (1), and the obtained results can be found in Table 3. The standard deviation of the normalized values for each criterion was calculated, and the results can be found in Table 3.

Table 4 presents a symmetric matrix constructed using the correlation coefficients of all pairs of columns.

The measure of the conflict created by each criterion due to the decision situation defined by the other criteria was obtained and presented in Table 5.

The criteria contrasts were obtained with the aid of Equation (3). The results are presented in Table 6.

The weights of the criteria were obtained with the aid of Equation (4). The results are presented in Table 7.

4.4 Application of the EDAS method in the estimation of appraisal score for prioritizing maintenance technologies

The EDAS method was applied in maintenance technology optimization. The average solution of criteria was obtained using Equation (6). The obtained results are presented in Table 8.

The NDA solution was obtained for each alternative using Equation (7). The results are compiled in Table 9.

The weighted sum of the NDA was obtained for each alternative using Equation (10). The results are presented in Table 10.

The PDA solution for each alternative was obtained using Equation (8). The results are presented in Table 11.

The weighted sum of the PDA was determined for each

Table 1 Expert ratings

Expert	Alterna tives	Autonomous vessels	Artificia intelligence	Soft sensors	Mathematical models	Inspect and repair robots	Drones	Machine learning	Big data
Expert 1	Compatibility	3	5	4	3	5	5	2	3
	Potential RAM	3	4	4	2	3	2	4	3
	Technology maturity	1	2	2	5	1	3	3	1
	Ease of application	3	2	2	2	3	3	4	2
	Potential cost reduction	2	5	2	3	4	2	3	3
	Investment needed	3	3	2	1	4	2	2	4
Expert 2	Compatibility	4	4	3	4	5	4	3	4
	Potential RAM	2	3	3	2	3	1	4	2
	Technology maturity	3	4	2	5	3	5	5	1
	Ease of application	2	2	3	3	3	3	3	2
	Potential cost reduction	4	5	4	3	4	4	3	5
	Investment needed	3	3	3	1	4	2	3	5
Expert 3	Compatibility	5	3	2	5	5	3	4	5
	Potential RAM	4	5	5	2	3	3	4	4
	Technology maturity	2	3	2	5	2	4	4	1
	Ease of Application	1	2	4	4	3	3	2	2
	Potential cost reduction	3	5	3	3	4	3	3	4
	Investment needed	3	3	1	1	4	2	1	3

Table 2 Alternative mean ratings

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Autonomous vessels	4.00	3.00	2.00	2.00	3.00	3.00
Artificial intelligence	4.00	4.00	3.00	2.00	5.00	3.00
Soft sensors	3.00	4.00	2.00	3.00	3.00	2.00
Mathematical models	4.00	2.00	5.00	3.00	3.00	1.00
Inspect and repair robots	5.00	3.00	2.00	3.00	4.00	4.00
Drones	4.00	2.00	4.00	3.00	3.00	2.00
Machine learning	3.00	4.00	4.00	3.00	3.00	2.00
Big data	4.00	3.00	1.00	2.00	4.00	4.00
Best value	5.00	4.00	5.00	3.00	5.00	1.00
Worst value	3.00	2.00	1.00	2.00	3.00	4.00

alternative using Equation (9). The determined results as shown in Table 12.

The values of the weighted sum of the NDA and the PDA were normalized using Equations (11) and (12), respectively. The appraisal scores for all the technology types considered were determined using Equation (13). The maintenance technology alternatives were ranked based on their appraisal scores, as shown in Table 13.

4.5 Discussion of results

In this study, the CRITIC–EDAS method was employed to prioritize SHM and maintenance technologies for OWTS. The CRITIC method was first applied to determine the weights of the suitable criteria for maintenance technology optimization. The results showed that the technology's ease of application, with a weight of 0.201 8, and the technolo-

Table 3 Rating values of normalized alternatives

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Autonomous vessels	0.50	0.50	0.25	0	0	0.33
Artificial intelligence	0.50	1.00	0.50	0	1.00	0.33
Soft sensor	0	1.00	0.25	1.00	0	0.67
Mathematical models	0.50	0	1.00	1.00	0	1.00
Inspect and repair robots	1.00	0.50	0.25	1.00	0.50	0
Drones	0.50	0	0.75	1.00	0	0.67
Machine learning	0	1.00	0.75	1.00	0	0.67
Big data	0.50	0.50	0	0	0.50	0
Standard deviation ∂_j	0.320 4	0.417 3	0.339 1	0.517 5	0.378 0	0.354 7

Table 4 Symmetric matrix

Criteria	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Compatibility	1.000 0	−0.500 8	−0.184 9	−0.161 5	0.442 3	−0.553 8
Potential RAM	−0.500 8	1.000 0	−0.362 9	−0.206 7	0.339 7	−0.221 4
Technology maturity	−0.184 9	−0.362 9	1.000 0	0.534 3	−0.348 4	0.831 1
Ease of application	−0.161 5	−0.206 7	0.534 3	1.000 0	−0.547 7	0.557 3
Potential cost reduction	0.442 3	0.339 7	−0.348 4	−0.547 7	1.000 0	−0.626 0
Investment needed	−0.553 8	−0.221 4	0.831 1	0.557 3	−0.626 0	1.000 0

Table 5 Alternative measure of conflict

Criteria	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed	$\sum(1-r)$
Compatibility	0	1.500 8	1.184 9	1.161 5	0.557 7	1.553 8	5.958 7
Potential RAM	1.500 8	0	1.362 9	1.206 7	0.660 3	1.221 4	5.952 1
Technology maturity	1.184 9	1.362 9	0	0.465 7	1.348 4	0.168 9	4.530 8
Ease of application	1.161 5	1.206 7	0.465 7	0	1.547 7	0.442 7	4.824 3
Potential cost reduction	0.557 7	0.660 3	1.348 4	1.547 7	0	1.626 0	5.740 1
Investment needed	1.553 8	1.221 4	0.168 9	0.442 7	1.626 0	0	5.012 8

Table 6 Criteria contrasts

Criteria	∂	$\sum(1-r)$	C_j
Compatibility	0.320 4	5.958 7	1.909 2
Potential RAM	0.417 3	5.952 1	2.483 8
Technology maturity	0.339 1	4.530 8	1.536 4
Ease of application	0.517 5	4.824 3	2.496 6
Potential cost reduction	0.378 0	5.740 1	2.169 8
Investment needed	0.354 7	5.012 8	1.778 0
$\sum_{j=1}^{n} C_j$			12.373 8

Table 7 Objective weights of criteria

Criteria	W_j
Compatibility	0.154 3
Potential RAM	0.200 7
Technology maturity	0.124 2
Ease of application	0.201 8
Potential cost reduction	0.175 4
Investment needed	0.143 7

Table 8 Average Solution of Criteria

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Autonomous vessels	4	3	2	2	3	3
Artificial intelligence	4	4	3	2	5	3
Soft sensors	3	4	2	3	3	2
Mathematical models	4	2	5	3	3	1
Inspect and repairs robots	5	3	2	3	4	4
Drones	4	2	4	3	3	2
Machine learning	3	4	4	3	3	2
Big data	4	3	1	2	4	4
Av.	3.875	3.125	2.875	2.625	3.500	2.625

Table 9 Negative distance from average (NDA)

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Weights of criteria	0.154 3	0.200 7	0.124 2	0.201 8	0.175 4	0.143 7
Autonomous vessels	0	0.040 0	0.304 3	0.238 1	0.142 9	0.142 9
Artificial intelligence	0	0	0	0.238 1	0	0.142 9
Soft sensors	0.225 8	0	0.304 3	0	0.142 9	0
Mathematical models	0	0.360 0	0	0	0.142 9	0
Inspect and repair robots	0	0.040 0	0.304 3	0	0	0.523 8
Drones	0	0.360 0	0	0	0.142 9	0
Machine learning	0.225 8	0	0	0	0.142 9	0
Big data	0	0.040 0	0.652 2	0.238 1	0	0.523 8

Table 10 Weighted sum of the NDA

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed	Q_i^-
Autonomous vessels	0	0.008 0	0.037 8	0.048 0	0.025 1	0.020 5	0.139 4
Artificial intelligence	0	0	0	0.048 0	0	0.020 5	0.068 5
Soft sensors	0.034 8	0	0.037 8	0	0.025 1	0	0.097 7
Mathematical models	0	0.072 3	0	0	0.025 1	0	0.097 4
Inspect and repair robots	0	0.008 0	0.037 8	0	0	0.075 3	0.121 1
Drones	0	0.072 3	0	0	0.025 1	0	0.097 4
Machine learning	0.034 8	0	0	0	0.025 1	0	0.059 9
Big data	0	0.008 0	0.081 0	0.048 0	0	0.075 3	0.212 3

gy's potential RAM criterion, with a weight of 0.200 7, were the two most important criteria. The criteria weights were used to facilitate the application of the EDAS method in the evaluation of the technologies. The results in Table 13 revealed that the use of mathematical models for OWTS maintenance was ranked as the best alternative with an appraisal score of 0.770 6, followed by the use of ML technology and AI with appraisal scores of 0.749 9 and 0.669 1, respectively.

Table 11 Positive distance from average (PDA)

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed
Weights of criteria	0.154 3	0.200 7	0.124 2	0.201 8	0.175 4	0.143 7
Autonomous vessels	0.032 3	0	0	0	0	0
Artificial intelligence	0.032 3	0.280 0	0.043 5	0	0.428 6	0
Soft sensors	0	0.280 0	0	0.142 9	0	0.238 1
Mathematical models	0.032 3	0	0.739 1	0.142 9	0	0.619 0
Inspect and repair robots	0.290 3	0	0	0.142 9	0.142 9	0
Drones	0.032 3	0	0.391 3	0.142 9	0	0.238 1
Machine learning	0	0.280 0	0.391 3	0.142 9	0	0.238 1
Big data	0.032 3	0	0	0	0.142 9	0

Table 12 Weighted sum PDA

Alternatives	Compatibility	Potential RAM	Technology maturity	Ease of application	Potential cost reduction	Investment needed	Q_i^+
Autonomous vessels	0.005 0	0	0	0	0	0	0.005 0
Artificial intelligence	0.005 0	0.056 2	0.005 4	0	0.075 2	0	0.141 8
Soft sensors	0	0.056 2	0	0.028 8	0	0.034 2	0.119 2
Mathematical models	0.005 0	0	0.091 8	0.028 8	0	0.089 0	0.214 6
Inspect and repair robots	0.044 8	0	0	0.028 8	0.025 1	0	0.098 7
Drones	0.005 0	0	0.048 6	0.028 8	0	0.034 2	0.116 6
Machine learning	0	0.056 2	0.048 6	0.028 8	0	0.034 2	0.167 8
Big data	0.005 0	0	0	0.000 0	0.025 1	0	0.030 1

Table 13 Appraised scores of alternatives

Alternatives	Q_i^+	Q_i^-	S_i^+	S_i^-	S_i	Rank
Autonomous vessels	0.005 0	0.139 4	0.023 3	0.343 4	0.183 4	7
Artificial intelligence	0.141 8	0.068 5	0.660 8	0.677 3	0.669 1	3
Soft sensors	0.119 2	0.097 7	0.555 5	0.539 8	0.547 7	4
Mathematical models	0.214 6	0.097 4	1.000 0	0.541 2	0.770 6	1
Inspect and repair robots	0.098 7	0.121 1	0.459 9	0.429 6	0.444 8	6
Drones	0.116 6	0.097 4	0.543 3	0.541 2	0.542 3	5
Machine learning	0.167 8	0.059 9	0.781 9	0.717 9	0.749 9	2
Big data	0.030 1	0.212 3	0.140 3	0.000 0	0.070 2	8

5 Conclusion

The review and prioritization of SHM and maintenance technologies for OWTS were conducted using the CRITIC–EDAS methodology. The results reveal that using mathematical models as a maintenance tool is the most feasible choice, as the models are easy to apply and are compatible with OWTS maintenance. Furthermore, mathematical models require little or no operational cost and are technologically mature, as they have been successfully applied for maintenance purposes in other industries. These results have significant implications for the optimal operation of OWTS. Furthermore, they provide useful insights into SHM and OWTS maintenance and are capable of driving innovation in the offshore renewable energy sector. This study provides a new research direction toward improving OWTS reliability and can be utilized by marine and offshore industrial experts in decision making on how to ensure optimal OWTS operations.

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