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Maintenance Strategy Selection for Multi-Component Systems using a combined Analytic Network Process and Cost-Risk Criticality Model

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Abstract

Selection of an appropriate maintenance strategy for multi component systems is a very complex task due to diversity of components and their different failure modes, existence of various dependencies among components, and a large number of competing criteria that need to be taken into consideration. In this study, we propose a combined analytic network process (ANP) and cost risk criticality analysis model to select a *cost-effective*, *low-risk* maintenance strategy for different sets of components associated with the system. The proposed model consists of four maintenance alternatives (i.e., failure based, time based, risk based, and condition based) among which the most appropriate strategy, on the basis of two criteria of maintenance implementation costs and failure criticality, is to be chosen. The former criterion includes the annual maintenance expenditure required for hardware, software, and personnel training, while the latter focuses on the capability of maintenance in mitigating the failure vulnerability and enhancing the reliability and resilience. The possible dependencies among selection criteria as well as the failure interactions between components are taken into account in evaluating the maintenance alternatives. Finally, the model is applied to determine a suitable maintenance strategy at the design stage for a new wind turbine configuration consisting of several mechanical, electrical and auxiliary components. The results are then compared to the operational practices of maintenance and to the results obtained using an analytic hierarchy process (AHP) model.

Keywords

Maintenance strategy selection; Multi component system; Analytic Network Process (ANP); Cost risk criticality; Analytic Hierarchy Process (AHP); Wind turbine.

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Introduction

For many engineering organizations, such as nuclear power plants, aircraft, power generators, submarine, medical equipment and high tech products, it is extremely important to prevent the occurrence of random failures during actual operation. Such organizations are called 'high reliability organizations (HROs)' because they sustain high levels of reliability and safety despite operating in a hazardous environment (for more see Labib[1]). In these organizations, a catastrophic failure may have substantial consequences to health, safety, security, and the economic efficiency. For this purpose, there is a critical need to select a suitable maintenance strategy for different components/parts of the system.

An appropriate maintenance strategy not only reduces the risk of catastrophic damages but also results in substantial savings through reduced maintenance costs and/or improved product quality and customer satisfaction. On the other hand, improper selection of maintenance may adversely affect the system's reliability, availability, and safety. It has been reported in some studies that a significant portion of annual maintenance budget is wasted due to insufficient or inefficient maintenance activities. [2]

Selection of an appropriate maintenance strategy for multi component systems is a very complex task due to diversity of components and their different failure modes, existence of various dependencies among components, and a large number of competing criteria that need to be taken into consideration. The decision maker (i.e., system owner or service agent) must decide on the most appropriate maintenance strategy for each piece of equipment among a set of possible alternatives such as failure based, time based, risk based, and condition based. Moreover, many different goals or comparing criteria (e.g. safety aspects, environmental issues, failure costs, reliability of equipment, and the investment required for implementation) must be taken into account for evaluation of the alternatives. Therefore, maintenance strategy selection is considered as a complex multiple criteria decision making (MCDM) problem.

From the latter half of the 20th century, the MCDM approach has been quite extensively used to select the most appropriate maintenance strategy for single component systems. [3] In this analysis approach, each alternative is evaluated with respect to all criteria and their associated sub criteria using a suitable measure. Then, the evaluation ratings are aggregated to obtain a global evaluation for each alternative. Finally, the alternatives are prioritized. In order to find out the optimum solution, several techniques, e.g. Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR) could be utilized. In what follows, some recent publications on the topic and the methods employed are briefly reviewed:

Labib *et al.* [4] developed an AHP model for maintenance strategy selection regarding four criteria: frequency of maintenance calls, downtime, spare parts cost, and bottle necks. Bevilacqua and Braglia [5] presented an AHP model to select the best maintenance strategy in

the oil refinery industry according to four criteria of cost, damages, applicability, and added value. A conceptual model of using fuzzy logic and multiple criteria to select cost effective maintenance approaches was proposed by Al Najjar and Alsyouf [6]. Labib *et al.* [7] proposed a decision model based on the AHP and fuzzy logic to select a suitable strategy among four maintenance alternatives: operate to failure, fixed time, condition based, and design out maintenance. Bertolini and Bevilacqua [8] presented a combined AHP and goal programming (GP) approach to select the best strategy for maintenance of critical centrifugal pumps in the oil refinery industry. Wang *et al.* [9] developed a fuzzy AHP model in which four criteria of cost, safety, feasibility and added value were considered for selection of a maintenance alternative. Shyjith *et al.* [10] utilized the AHP method to select an optimum maintenance strategy for a textile spinning mill ring frame unit. Ahmadi *et al.* [11] proposed an MCDM methodology based on the AHP, TOPSIS, VIKOR and benefit cost analysis to select a suitable maintenance strategy for aircraft systems. Arunraj and Maiti [12] extended the methodology in [8] by taking both the risk and cost as criteria in maintenance strategy selection of chemical plants. Cheng and Tsao [13] presented an ANP model to determine a suitable maintenance strategy for railway rolling stock. Tan *et al.* [14] applied the AHP method to select the most practicable maintenance strategy for the oil refinery industry according to four criteria of cost, safety, feasibility and added value. Kumar and Maiti [15] developed a fuzzy ANP methodology to decide on the best maintenance alternative for chemical plants. Chan and Prakash [16] proposed a distance-based fuzzy MCDM method to select an appropriate maintenance strategy for manufacturing firms. Shahin *et al.* [17] applied the ANP method to determine a suitable maintenance strategy in mining industry on the basis of four criteria: reliability, availability, maintainability and cost. Zaim *et al.* [18] used the AHP and ANP methods for determining the most appropriate maintenance strategy in a local newspaper printing facility. Nezami and Yildirim [19] presented a fuzzy VIKOR model to select an appropriate maintenance strategy for a manufacturing company based on a number of social, environmental and economic criteria. Goossens and Basten [20] suggested the use of the AHP approach for maintenance strategy selection of naval ships. Azadeh and Abdolhossein-Zadeh [21] developed a model based on the AHP and a distance-based fuzzy MCDM approach to prioritize different maintenance policies. Kirubakaran and Ilangkumaran [22] proposed a hybrid model comprising fuzzy AHP, grey relational analysis (GRA) and TOPSIS technique for the selection of optimum maintenance strategy for pumps used in the paper industry. Tajadod *et al.* [23] compared the performance of different MCDM approaches (including AHP and ANP) in ranking the maintenance strategies for a dairy manufacturing factory.

Even though the above studies have reported many benefits (in terms of reduced operating costs and/or enhanced reliability and safety levels) to asset management of single-component systems, the MCDM analysis has received very limited attention in maintenance strategy selection of multi-component systems. A multi-component system can consist of hundreds of different items which are often “interacting” with one another, either in one way

(unidirectional) or two ways (bidirectional). A single component failure in these systems may affect the reliability of other components which are structurally dependent and it can cause a multiple component replacement. This implies that failure of a component in multi component systems can negatively impact the overall reliability performance, system's operating expenditure (OPEX), and the quality of system's output. Beside components' failure interactions, the criteria taken into account in the selection process of maintenance alternatives may be dependent on one another or vary together. For instance, the larger the investment on maintenance technology in terms of hardware or software the better the detectability of unexpected failures and the less the risk of potential damages.

Neglecting the above mentioned dependencies leads to inaccurate evaluation of the maintenance efficiency, and thereby, an inappropriate selection of the maintenance strategies to protect system. For this reason, a *system-wide* maintenance strategy selection framework must be developed so that the best "balance" between whole maintenance costs and the risks associated with system failures is achieved. In the current paper, an MCDM approach is developed to select a suitable maintenance strategy that achieves a trade off between implementation cost of maintenance and criticality level of failures within the system. The main contributions of this study lie in the following three aspects:

- A combined ANP and "cost-risk criticality analysis" model is proposed aiming to select a cost-effective, low-risk maintenance strategy for different sets of components associated with a system. The possible dependencies among selection criteria as well as the interactions between component failures (cascade effects) are taken into account in evaluating the maintenance alternatives.
- The proposed model consists of two sets of criteria, namely, cost of maintenance and criticality of failure. The former criterion includes the annual maintenance expenditure required for hardware, software, and personnel training, while the latter focuses on the capability of maintenance in mitigating the failure vulnerability and increasing the reliability and resilience. In this regard, the criticality measures considered in the literature are extended.
- The model is applied to determine a suitable maintenance strategy at the design stage for a new wind turbine configuration consisting of several mechanical, electrical and auxiliary components. To the best of the authors' knowledge, this paper is the first academic paper dealing with maintenance strategy selection of wind power systems using the MCDM techniques.

The remainder of this paper is structured as follows. Section "Research background" presents an overview of the background information on which our methodology is built. In Section "Proposed methodology", the proposed maintenance strategy selection model is described. In Section "Application and results", an application of the model is presented and the results are discussed. Finally, the paper is concluded in Section "Conclusions and future work".

Research Background

MCDM analysis in the marine renewable energy sector

The use of marine renewable energy sources (i.e., wind, wave and tidal) for the production of electricity brings significant economic and environmental benefits to all the stakeholders involved. Marine renewable energy planning is recognized to be a more complicated decision making problem than fossil fuels and onshore renewable sources. In most situations, there are many points of view and differing perspectives amongst investors, asset owners, asset operators, and service agents that need to be taken into account. The traditional single criteria decision making approaches normally aim at identifying a solution based on only one criterion (e.g. the lowest cost) and hence cannot merge and analyze all perspectives concerned with the decision making process. To overcome this gap, the MCDM approach (as a flexible tool that can take into consideration several conflicting aspects) was developed in the 1960s.

In the MCDM approach, options are first evaluated and then ranked to determine the most desirable alternative(s) by considering all aspects. This approach has so far been applied to solve various decision making problems within the marine renewable energy sector [24], including energy resource planning, site selection, material selection, design improvement, and risk management. Table 1 lists a number of application areas of the MCDM methodology in marine renewable energy and then presents the techniques used in each study to obtain the optimal solution.

"Table (No. 1)"

Among various MCDM methods, the AHP and ANP are mostly used to find out the optimum solution. In AHP technique, the decision problem is constructed as a hierarchical structure in which the goal of decision is located at the top level, criteria and sub criteria are represented at the intermediate levels, and the alternatives are at the bottom [32], whereas in the ANP technique, the goal, criteria and alternatives are in the form of clusters. ANP differs from AHP in that it allows interdependence within a cluster as well as feedback between clusters [33] (see Fig. 1). For this reason, the ANP technique is chosen for the analysis of maintenance strategies for interacting multi component systems.

"Fig. (No. 1)"

Risk criticality analysis

Criticality analysis is a fundamental part of effective asset management. Analogously to risk, criticality is defined as the combined effect of the probability of occurrence of an event and the severity of harm resulting from that event. In general, the criticality analysis is executed according to a criticality measure which is defined on the basis of probability of failure and

its likely cost consequences. However, some analytical techniques like Failure Mode and Effects Analysis (FMEA) uses three criteria to assess the risk: i) how frequently a failure is likely to occur; ii) the severity of the effect, and 3) how easily the failure can be detected.

FMEA is an engineering tool which is extensively used by a broad range of industries to identify, evaluate, and eliminate all potential failures or risks to a system. It is over five decades since FMEA was first used in NASA's reliability improvement projects. Since then, this technique has been applied to risk assessment studies within the oil and gas, automotive, construction, transport, and the marine renewable energy industry. This technique determines the risk priorities of failure modes by using a rating called Risk Priority Number (RPN), which is the product of the occurrence (O), severity (S) and detection (D) of a failure, i.e.,

$$\mathrm{RPN} = \mathrm{O}\times\mathrm{S}\times\mathrm{D}, \tag{1}$$

where O is the probability of the failure occurrence, S is the severity of the failure, and D is the probability of not detecting the failure. The three risk factors are evaluated using a ten-point scale, as described in the literature (see, e.g. [34]).

Even though the FMEA has been proven to be one of the most efficient tools for prioritization of the failure modes, several drawbacks are associated with this technique. One major drawback is that the RPN is not expressed in financial terms and hence, it cannot be informative enough for decision-makers from the perspective of criticality. Another drawback is that the three factors O, S and D are considered to be "independent" and their relative importance is not taken into account (i.e., the risk factors are assumed to have the same importance). To overcome the traditional FMEA shortcomings, a number of criticality analysis approaches (e.g. the multi-attribute FMEA as in [35]) have been suggested. These approaches typically involve the steps as outlined below:

(1) define the system;
(2) list the components/parts of the system (functional analysis);
(3) identify all failure modes of the components/parts under consideration;
(4) perform a *criticality analysis* to evaluate the risk level of each failure;
(5) rank the failures with respect to the criticality measure (level);
(6) take actions on the high-risk failures;
(7) check the effectiveness of corrective actions and revise risk analysis.

The criticality analysis may be quantitative or qualitative, depending on the availability of data. In general, the criticality analysis is executed according to a *criticality measure* which is defined on the basis of some factors such as the probability of failure and its likely cost consequences. In this study, the criticality of a failure is expressed in terms of a quantitative index, called "Cost-Priority-Number (CPN)". The CPN is evaluated based on three interrelated criteria, namely, the *probability* of failure (P), the incurred *costs* (C), and *not-detection* possibility (N) (for more, see [36]). The main advantage of using CPN approach

compared to RPN is its capability to take into account the effects of failure interactions among components when evaluating the system's criticality.

Proposed methodology

ANP/CPN methodology (design stage)

In this Section, we present a methodology for selecting the most appropriate maintenance strategy at the "design" stage of a multi component system. The ten steps of the methodology are listed below:

1. Select a system and list all components under consideration

In order to analyse the suitability of different maintenance strategies for each piece of equipment, a multi-component system is chosen and all technical and non-technical information relating to the maintenance of components will be gathered.

2. Determine alternative maintenance strategies for each component

Several alternative strategies can be taken into consideration for maintenance of the engineering systems. In this paper, four maintenance strategies are more appropriate for our system studied in Section "Application and results". These alternatives are introduced briefly as following:

- Failure-based maintenance (FBM): Under this maintenance strategy, a repair action is carried out after an equipment failure or upon a severe decline in production.
- Time-based maintenance (TBM): Under this maintenance strategy, repair actions are undertaken at specific dates over the operational year. [37]
- Risk-based maintenance (RBM): This strategy aims to reduce the overall risk of system failure. The inspection and maintenance schedule is optimized on the basis of quantified risks caused by failure of individual components and/or *cascading* outages. The high-risk components are maintained usually with greater frequency, whereas for low-risk components the effort is minimized to reduce the total scope of work and cost of the maintenance program. [38]
- Condition-based maintenance (CBM): In this maintenance strategy, continuous monitoring and inspection techniques are employed for the early detection of faults/failures and determining necessary maintenance and repair tasks ahead of failure.[39]

3. Identify and classify the selection criteria

In order to evaluate and prioritize the maintenance strategies, the asset owner must specify a set of criteria. The criteria considered in this study can be divided into two groups:

- Cost of maintenance

The implementation cost of a maintenance strategy is often considered as an important criterion in evaluating the maintenance alternatives. Different maintenance strategies require different expenditure on *hardware*, *software*, and *personnel training*. For each maintenance strategy, there might be needed to purchase/lease a number of support facilities, maintenance tools, monitoring and prognostic sensors, and some computers. Some software are also required for analyzing the data collected from sensors, and lastly, it is vital to train technicians and professionals to schedule and perform repair services.

- Criticality of failure

The criticality level of a failure is measured on the basis of three measures of P, C, and N. 'P' is a value between zero and one which represents the likelihood that a component fails and can be derived from the historical data. 'C' is a positive value representing the costs associated with a failure, including renewal and replacement, lost production, maintenance labour, logistics, transport as well as cascading effects. 'N' is a value between zero and one which represents the proportion of time that maintenance actions are not able to detect and avoid vulnerabilities. This value can be estimated by dividing the expected number of actual failures to the total number of failure vulnerabilities.

4. Identify criteria/alternatives/components' (inter)dependencies

Dependence among components is a key factor influencing the criticality of a failure in multi component systems. Generally, three types of *structural*, *stochastic*, and *economic* dependence are considered between components.[40] Structural dependence means that maintenance of a failed component implies maintenance of multiple other components in the system. Stochastic dependence implies that failure of a component can affect the states of other components. Economic dependence implies that performing maintenance on a certain group of components costs less money and/or time than on each component separately. A dependency analysis may focus on the type of (inter)dependence (i.e., structural, stochastic, and economic), order of (inter)dependence (i.e., first order, second order or higher), level of (inter)dependence (i.e., partial or maximal), etc. The (inter)dependencies can be identified by asking some questions, like, "which components may be affected when a particular component fails?". To answer the questions, constructing a dependency graph could be very useful. The dependence graph is a diagram representing an overview of all (inter)dependencies among components within the system. A typical example of a dependency graph is shown in Fig. 2. The one way arrows in the diagram show the dependencies, whereas the two way arrows represent the interdependencies between components.

"Fig. (No. 2)"

In real world decision making problems, there may also exist two way relationships among criteria and alternatives as well as intra relationships between criteria. For instance, the correlation between two criteria of "not detection possibility" and "software cost" is such that a maintenance strategy with high confidence in fault detection may require more investment in software.

5. Construct a network model

In this step, a network model is constructed with a goal, criteria, sub criteria, and alternatives. Fig. 3 illustrates a network structure of the ANP/CPN decision model applied to maintenance strategy selection of marine renewable energy systems. As shown, the proposed network model includes three clusters. The first cluster is the main goal of problem (i.e., selection of a cost efficient and low risk maintenance strategy). The second cluster in the network consists of two main criteria, which are namely, cost and criticality. Each criterion is then broken down into three sub criteria as discussed in step 3. Finally, the third cluster represents the alternative strategies. The relationships among the decision elements are also determined and reflected in the network model.

"Fig. (No. 3)"

6. Perform pairwise comparisons of the decision elements

Pairwise comparison is a useful technique for assigning weights (priorities) to a number of different decision making elements. Instead of considering all elements and attempting to prioritize them all, the pairwise comparison breaks down the problem to comparing two elements at a time. The result of each comparison is recorded as a value and then all values are combined to calculate relative weights for each element. In order to prioritize the maintenance alternatives, a series of pairwise comparisons between decision criteria and alternatives have to be performed by system owners (operators). In addition, the interdependencies among the decision elements must be examined pairwise. The relative importance values are expressed with Saaty's 1–9 scale in [32], where a score of 1 represents equal importance between the two elements and a score of 9 indicates the extreme importance of one element compared to the other one. A reciprocal value is assigned to the inverse comparison, that is, $a_{ji}=1/a_{ij}$, where a_{ij} denotes the comparative importance of the element i over element j.

To build the pairwise comparison matrices, four sets of questions (A, B, C, and D) are asked from the decision makers. The questions are listed below:

Question A: This question gives comparison data for the two criteria, namely, implementation costs of a maintenance strategy and the criticality of a component failure. Which of these two criteria is more important for the selection of a maintenance strategy and by how much?

Question"'set'"B: This question set gives comparison data for the sub criteria considered in each criterion. For example, for the cost criterion, three sub criteria were taken into account, these are: (i) hardware, (ii) software and (iii) training cost. Which of these three sub criteria is more important with regard to implementation costs of a maintenance strategy and by how much? Moreover, the importance of sub criteria to each other is measured by asking questions like "how much software cost is affected by improving detectability?".

Question"'set'"C: This question set compares each alternative against the others based on the sub criteria described in step 3. For example, for the probability of failure, which one of maintenance strategies reduces more the likelihood of failure and by how much?

Question"'set'"D: This question set compares the six sub criteria with respect to each maintenance strategy. For example, taking into account the software cost for CBM strategy, how is its capability in fault detection? Or in other words 'does the detection confidence improved worth the software cost incurred by CBM implementation?'

7. Calculate priority vector for all the comparison matrices and test the consistency

Once the pairwise comparisons are done, the local priority vector w is derived using the following equation:

$$A \times w = \lambda_{max} \times w, \tag{2}$$

where A represents the pairwise comparison matrix, w is the eigenvector, and λ_{max} is the largest eigenvalue of A. The consistency property of the pairwise comparison matrix also needs to be examined. The consistency ratio (CR) is used to identify possible errors in judgments. The CR value is defined as follows [33]:

$$CR = \frac{\lambda_{max} - n}{(n-1) \times RI}, \tag{3}$$

where n is the number of elements and RI represents the average consistency index for numerous random entries of same order reciprocal matrices. The values of RI for n=3 to n=11 are computed and given in Table 2. If the value of CR is smaller or equal to 10%, the inconsistency is acceptable, otherwise, the decision makers are asked to revise their judgments in order to improve the consistency level.

"Table (No. 2)"

8. Conduct ANP analysis

The impact of the decision elements on each other in a network can be presented by a matrix, called the *super-matrix*. The super-matrix is a partitioned matrix where each sub-matrix is composed of the priority vectors obtained from the pair-wise comparisons. The

columns of the super matrix represent the relationships between two clusters and the corresponding values in the columns reflect the influence that the elements of the clusters on the left hand side of the matrix exert on those in the header of the matrix. If there exists no relationship between two clusters, the corresponding entry in the super matrix is zero.

Since there usually exist some interdependencies among clusters in a network, the columns of the super matrix may sum more than one. In this case, the super matrix will be an unweighted one which needs to be normalized to make a weighted super matrix. Then, to achieve a convergence on the obtained weights, the weighted super matrix is raised to the power of $2p + 1$, where p is an arbitrarily large number, and this new matrix is called the limit super matrix. All the columns of the limit super matrix are the same, so the final priorities of the elements (alternatives, criteria, and sub criteria) can be derived from any column in the matrix.

9. Select the most appropriate maintenance strategy

In this step, an index called "desirability index" is calculated for the selection of the best maintenance alternative. The desirability index for alternative i, D_i is defined as the following Equation: [29]

$$D_i = \sum_{j=1}^{J} \sum_{k=1}^{K_j} C_j M_{kj} A_{ikj}, \tag{4}$$

where J is the index set for criterion j, K_j is the index set of sub-criteria for criterion j, C_j represents the relative importance of criterion j, M_{kj} is the relative importance of sub-criterion k of criterion j, and A_{ikj} is the rating of alternative i on sub-criterion k of criterion j. The alternative with the largest desirability index is selected as the best maintenance strategy. In the proposed ANP model, the best alternative is the alternative with the highest value in its row of the limiting super-matrix.

10. Feed results back into design, review and update the maintenance decisions regularly.

Maintenance decision-making process in the high reliability organizations is often *dynamic* and needs to be continually improved. So, the maintenance strategies must be updated according to the failure criticalities experienced during the operation stage. Upgrading the maintenance decisions often require using more accurate sensors, applying advanced technologies to analyze measured parameters, and improving technicians' skills in identifying potential failures.

In what follows, we present a methodology for selecting/upgrading the maintenance strategies at operational stage.

Cost-risk-benefit analysis (operational stage)

The process for carrying out the cost-risk-benefit analysis includes ten steps as shown in Fig. 4.

1. Define the set of system components: $X = \{1,2,...,S\}$, where S denotes the total number of components under consideration.
2. Define the set of maintenance alternatives: $M = \{1,2,3,4\}$ and denote by i the index for maintenance alternatives, where $i \in M$ and i:='1' , '2' ,'3' , '4' represent the index for FBM, TBM, RBM and CBM, respectively.
3. Select a component $x \in X$ for upgrading decision, and set i_c as the index for its design-stage (or current) maintenance strategy.
4. Estimate the cost-priority-number (CPN) for component x under maintenance strategy i, which is the product of the probability (P), cost consequence (C) and not-detection possibility (D) of a failure. The CPN value is continuous and is expressed in monetary unit, and hence, it can be easily used for comparison purposes. Furthermore, the cascading effects of a failure or error can be taken into account in calculating cost consequences (C) and, thereby, in the CPN value.
5. Estimate the annual CPN for component x under maintenance alternative i, which is defined as:

$$\mathrm{ACPN}(xi) = \mathrm{V}(xi) \times \mathrm{CPN}(xi), \quad x=1, 2, \ldots, S \ ; \ i=1, 2, 3, 4 \tag{5}$$

   where $\mathrm{V}(xi)$ is the expected annual number of component x's failures under maintenance strategy i.
6. Calculate the potential reduction in annual CPN that may be achieved by upgrading the maintenance strategy from alternative i_c (current) to alternative i_t (target). That is,

$$\mathrm{ACPN}(i_c \rightarrow i_t) = \mathrm{ACPN}(xi_c) - \mathrm{ACPN}(xi_t), \text{ for any } i_c, i_t \in M, \ i_c \neq i_t, \tag{6}$$

7. If $\mathrm{ACPN}(i_c i_t) < 0$, the upgrade decision is ignored and another component must be selected (go to step 3). Otherwise, estimate the annual extra cost required to upgrade the maintenance alternative from i_c to i_t. That is,

$$\mathrm{C}(i_c \rightarrow i_t) = \mathrm{HC}(i_c \rightarrow i_t) + \mathrm{SC}(i_c \rightarrow i_t) + \mathrm{TC}(i_c \rightarrow i_t), \text{ for any } i_c, i_t \in M, \ i_c \neq i_t, \tag{7}$$

   where HC(.), SC(.) and TC(.) represent, respectively, the hardware, software, and the training cost.
8. Calculate the 'cost-risk-benefit ratio' for upgrading the maintenance strategy from alternative i_c to j. That is,

$$\mathrm{CRB}(i_c \rightarrow i_t) = \frac{\mathrm{ACPN}(i_c \rightarrow i_t)}{\mathrm{C}(i_c \rightarrow i_t)} \quad \text{for any } i_c, i_t \in M, \ i_c \neq i_t, \tag{8}$$

where ACPN($i_c \rightarrow i_t$) and C($i_c \rightarrow i_t$) are given by Eqs. (6) and (7), respectively.

9. If CRB($i_c \rightarrow i_t$) $\leq$ 1, then stop the upgrading process and select another component (go to step 3). Otherwise go to step 10.
10. Select the target maintenance alternative with largest cost-risk-benefit ratio, and upgrade the design-stage (current) maintenance strategy accordingly.

"Fig. (No. 4)"

As can be seen, the proposed methodology achieves a sensible trade-off between the extra costs required for upgrading the maintenance strategy and the reduction of the expected annual CPN due to this upgrade.

Application and results

In this Section, a case study illustrates our findings. The proposed ANP/CNP decision model is applied to select a cost-effective and low-risk maintenance strategy for a new wind turbine configuration at its design stage. Then, according to the collected field data from wind farm over the first year of operation, the cost-risk-benefit analysis is used to decide whether upgrading the maintenance strategies is economically viable or not. Finally, the ANP/CNP results are compared with the practices of maintenance based on operational data as well as with the results obtained using an AHP model.

Nowadays, many different types of wind turbines are available in the market. Li and Chen [41] categorized the wind turbines into several classes according to type of their generator, gearbox, and power converters. This paper considers a new wind turbine design that features a non-integrated drive train with a rotor shaft supported by two bearings, a combined planetary/spur wheel gearbox, and a double-fed asynchronous generator. The three-bladed rotor system is also equipped with an electrical blade angle adjustment and a cast iron rotor hub.

A wind power generation system, as a complex system, consists of hundreds of different sets of components. In this study, as shown in Fig. 5, ten components with higher failure likelihood and/or severe consequences are considered.

"Fig. (No. 5)"

A dependency diagram representing the dependencies and interdependencies among these components is drawn in Fig. 6. As an example, the component "generator" is dependent on the component "brake" which means that the state of "generator" is dependent on the state of "brake" but not vice versa. On the other side, two components of "blade" and "low-speed shaft" are interdependent which implies that the state of "blade" is dependent on the state of "low-speed shaft" and vice versa. Furthermore, the state of one component may

impact the state of other components in the second or higher order of dependency. For example, the second-order dependence between two components of “gearbox” and “generator” can be described as follows:

> The state of “low-speed shaft” depends on the state of “gearbox” and the state of “generator” is dependent on the state of “low-speed shaft”. Hence, the state of “generator” depends on the state of “gearbox”.

“Fig. (No. 6)”

In this paper, only the first-order dependencies among the components are taken into account and the second or higher order of dependency will be investigated in our future work. When a wind turbine component fails, the failed component as well as all the components, which are structurally dependent upon, stop operating and will undergo a maintenance action. In this action, the failed component is replaced by a new one, and meanwhile the other components are preventively repaired to such degrees that their ages are reduced by small percentages. Such executing the maintenance activities for a group of components will result in lower costs compared to the case when maintenance tasks are conducted individually. This implies that our model takes into account the “economic” dependence among components in evaluating the efficiency of maintenance alternatives and measuring the criticality of a system failure.

4.1. Design stage

On the basis of collected information from four experts, the ANP/CPN decision model was first applied. The ANP software package “Super Decisions” (http://www.superdecisions.com) was utilized for this purpose. First of all, the local priorities of two criteria with respect to the main goal are obtained using a pairwise comparison matrix as given in Table 3. In evaluation of the maintenance strategies for a wind turbine system, a greater weight was given to failure criticality criterion rather than maintenance cost, because a wind turbine failure may have a substantial negative influence on power grid safety.

“Table (No. 3)”

Now, all the interconnected sub-criteria are compared together at the second level in terms of main criteria, and then, the related pairwise comparison matrices are constructed. For the criticality criterion, not-detection is regarded as the most important sub-criteria and is evaluated as being 2 times more important than likelihood, and 2.5 times more important than consequence [42, 43]. For the cost criterion, software cost is regarded as the most important sub-criteria and is evaluated as being 1.5 times more important than hardware cost, and 2.5 times more important than training cost. The priority weights for sub-criteria with respect to the criterion are shown in Table 4.

“Table“(No.“4)”

From the answers to questionnaire B in step 6, the amount of interdependency among sub criteria is measured. The priority weights of sub criteria against each other are given in Table 5.

“Table“(No.“5)”

Afterwards, the priority weights for alternative maintenance strategies (i.e., FBM, TBM, RBM, and CBM) with respect to the sub criteria are obtained. The estimated priority weights for the component ‘gearbox’ are reported in Table 6. Likewise, the priority weights of maintenance strategies against sub criteria for all other components are computed.

“Table“(No.“6)”

Finally, the priority weights for the sub criteria with respect to the maintenance alternatives are calculated. Table 7 presents the priority weights of each sub criterion against four maintenance strategies for component ‘gearbox’. The priority weights for all other components are computed similarly.

“Table“(No.“7)”

The priority vectors obtained from previous steps are placed in the appropriate columns to build the unweighted super matrix. Table 8, for example, represents the unweighted super matrix for component ‘gearbox’. As can be seen, four out of five sections of unweighted super matrix were completed using the priority weights of criteria, sub criteria and alternatives presented in Tables (4)–(7). The zero elements in the unweighted super matrix show the independency among the clusters in the rows and columns. The global weights of sub criteria against the main goal (i.e., determining a cost effective, low risk maintenance strategy) were obtained by multiplying the weight of criterion by the local weight of sub criteria and are entered into ‘goal’ column.

“Table“(No.“8)”

Later, the unweighted super matrix is transformed into a weighted matrix. The transformation process involves multiplying the unweighted super matrix by the priority weights of the clusters. Finally, the weighted super matrix is transformed into the limit super matrix by raising it to powers. The limit super matrix for component ‘gearbox’ is shown in Table 9.

“Take“in“Table“(No.“9)”

The final priority of the four maintenance alternatives for component ‘gearbox’ is represented in Table 10.

“Take“in“Table“(No.“10)”

As shown, CBM is chosen to be the most appropriate maintenance alternative for component ‘gearbox’ from both perspectives of failure criticality and maintenance implementation costs. This maintenance alternative follows closely by RBM strategy. Similarly, the final priorities of the maintenance strategies were obtained for all other components and are shown in Table 11. The preferred maintenance strategy (i.e., the alternative with highest priority) for each component has been also highlighted.

“Table“(No.“11)”

From Table 11, it can be concluded that CBM is superior to other maintenance strategies for most of the wind turbine components, followed by RBM for a few others (i.e., ‘low speed shaft’, ‘tower’, and ‘yaw driver’). It also shows that the CBM score for the critical component ‘blade’ is the highest among all components. Although ‘mechanical brake’ and ‘controller’ are not very risky components from criticality point of view, CBM strategy was chosen for their maintenance since the associated implementation cost for these components is not that much large.

4.2. Operational stage

Now, according to the collected field data, the cost risk benefit analysis is applied to upgrade the maintenance strategies if required. For this purpose, three components including ‘low speed shaft’, ‘tower’, and ‘yaw driver’ with RBM strategy are selected. Using annual CPN calculations for wind turbine components reported in our earlier study [36], the cost risk benefit ratios for upgrading the decision of maintenance strategies from RBM to CBM are estimated 0.94, 1.02, and 0.95, respectively. So, upgrading the maintenance strategy from alternative RBM to CBM could be beneficial (even in small amounts) only for the ‘tower’. The reason for this result might be that the wind turbine was installed in an offshore area and the tower was stressed in a harsh maritime environment and suffered from multiple types of deterioration and external damages [44]. Hence, CBM alternative could be more cost effective and less risk maintenance strategy than RBM over the rest of the tower’s life cycle.

4.3. Comparisons

Some comparisons are made between the ANP/CPN results, operational practices of maintenance, and the results obtained using an AHP model. The results of comparisons are given in Table 12.

“Table“(No.“12)”

The findings are discussed below to establish some relationships that might be useful for future designs of wind turbines.

i. Criticality perspective

Based on the local scores obtained with regard to failure criticality criterion, it can be inferred that CBM is the preferred maintenance strategy for all components as it has the most capability for reducing the cost-priority-number (CPN). The same is, to a lesser extent true for RBM and TBM, but FBM has the least potential to reduce the CPN value since this is a reactive strategy.

ii. Cost perspective

The local score based on maintenance cost criterion prefers FBM alternative for all components. So, FBM incurs the lowest cost for implementing the maintenance in wind turbine systems. Similar to results obtained based on criticality criterion, the next appropriate strategy from the perspective of maintenance implementation cost is TBM. However, our proposed model provides a mix result as it aggregates the local scores of the maintenance strategies with due regard to the weights of both selection criteria.

iii. AHP technique

The AHP technique has been implemented in 'Expert Choice' software (http://Expertchoice.com). While comparing the AHP results with the practices of maintenance based on operational data, it is found out that for some components (such as 'gearbox' and 'generator') the AHP-based maintenance alternative matches with operational decision. However, the strategies for three components of 'wind vane', 'yaw motor', and 'tower' must be upgraded from RBM alternative to CBM. This implies that the ANP/CPN decisions need less upgrade than the decisions made based on the AHP method. So, taking into account the interdependencies among selection criteria as well as between alternatives and selection criteria provides more realistic results compared to the AHP method which ignores such interdependencies. In addition, the AHP technique recommends using CBM strategy for component 'yaw driver'. However, RBM was chosen as the most appropriate strategy according to the ANP/CPN methodology.

2. Conclusions and future work

The selection of a suitable maintenance strategy for multi-component systems is a complicated multiple-criteria decision making (MCDM) problem. In this paper, a combined analytic network process (ANP) and cost-risk criticality analysis model is proposed to select a cost-effective and low-risk maintenance strategy for different sets of components associated with a system. The proposed model consists of two sets of criteria, these are, annual cost of maintenance and criticality of failure. The cost criterion involves investment costs for hardware, software, and personnel training, while the criticality criterion focuses on the capability of maintenance strategy in reducing the cost-priority-number (CPN)

associated with an unexpected failure. The main benefit of using ANP/CPN in our analysis is that it allows taking into account various types of structural, stochastic and economic dependencies among components as well as the possible correlations between decision making criteria.

The proposed model was finally applied to determine an appropriate maintenance strategy at the design stage for a new wind turbine configuration, consisting of ten mechanical, electrical and auxiliary components. Our analysis results revealed that the condition based and risk based maintenance strategies are two preferred strategies for wind turbine power systems. While comparing the ANP/CPN results with practices of maintenance over the first year of operation, it was found out that an upgrading in maintenance strategy of some components is necessary. This implies that the proposed ANP/CPN decision model is suitable to be used during the "design" stage of wind turbines, but at the "operational" stage a more quantified analysis of failure criticality is required to evaluate ultimate effects on the system performance. Hence, the proposed cost risk benefit analysis would be suitable for use in operational stage.

There is substantial scope for future research in the area of maintenance strategy selection for multi component systems. The following are some possible extensions:

(a) We confined our analysis to only one type of interactions between components of a system, i.e., the direct physical dependencies. The indirect environment-mediated interactions (i.e., component–to-the environment–to component) will be considered in our future study.
(b) In addition to the proposed methodology, some other hybrid MCDM models (such as ANP-TOPSIS) can be developed to find out the solution.
(c) The proposed methodology will be extended in the nearest future to apply to systems with larger scale, e.g. a wind farm which typically consists of several interacting wind turbines with different configuration.

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Notation

A	pairwise comparison matrix
A_{ikj}	rating of alternative i on sub-criterion k of criterion j
ACPN	Annual CPN
C	cost consequences of a failure
C_j	relative importance of criterion j
CPN	Cost-Priority-Number
CR	consistency ratio
CRB	cost-risk-benefit ratio
D	no-detection rating of a failure $\in \{1,2,\ldots,10\}$
D_i	desirability index for alternative i

HC	hardware cost
i	index for maintenance alternatives, i=1, 2, 3, 4.
J	index set for criteria
K_j	index set of sub-criteria for criterion j
λ_{max}	largest eigenvalue of a pairwise comparison matrix
M	set of maintenance alternatives
M_{kj}	relative importance of sub-criterion k of criterion j
n	number of elements
N	not-detection possibility of a failure
O	occurrence rating of a failure $\in$ {1,2,…,10}
P	probability of a failure occurrence
RI	consistency index
RPN	Risk-Priority-Number
S	severity rating of a failure $\in$ {1,2,…,10}
SC	software cost
TC	training cost
V(xi)	annual number of component x's failures under maintenance strategy i
w	eigenvector
X	set of system components

Table 1– MCDM applications in the marine renewable energy sector.

Application area	References	Technique(s)
Selection of energy sources	Stein [25]	AHP
Energy planning	Maslov et al. [26]	Electre III
Material selection	Maity and Chakraborty [27]	ANP
Layout design	Lee *et al.* [28]	AHP
	Yeh and Huang [29]	DEMATEL and ANP
Structural design	Meng et al. [30]	TOPSIS
Risk management	Shafiee [31]	ANP

Table 2– Random Index (*RI*). [32]

N	1	2	3	4	5	6	7	8	9	10	11
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Table 3– Comparison matrix for maintenance strategy selection criteria.

Maintenance selection criteria	Criticality	Cost	Priority weights (normalized)
Criticality	1.00	5.00	0.8333
Cost	0.20	1.00	0.1667

Table 4– Importance weights of sub-criteria with respect to main criteria.

Criteria	Sub-criteria	Priority weights (normalized)
Criticality		
	Probability	0.2632
	Cost consequence	0.2105
	Not-detection	0.5263
Cost		
	Hardware	0.4839
	Software	0.3226
	Training	0.1935

Table 5– Importance weights of sub-criteria against each other.

Sub-criteria	P	C	N	HC	SC	TC
P	0.0000	0.0000	0.0000	0.3602	0.2098	0.2989
C	0.0000	0.0000	0.0000	0.4823	0.2402	0.4330
N	0.0000	0.0000	0.0000	0.1575	0.5500	0.2681
HC	0.4466	0.4637	0.1634	0.0000	0.0000	0.0000
SC	0.2528	0.2123	0.5396	0.0000	0.0000	0.0000
TC	0.3006	0.3240	0.2970	0.0000	0.0000	0.0000

Table 6– Importance weights of maintenance strategies with respect to sub-criteria for ‘gearbox’.

	Sub-criteria					
Maintenance strategies	P	C	N	HC	SC	TC
FBM	0.2097	0.1988	0.1611	0.3014	0.1183	0.2352
TBM	0.2249	0.2346	0.2446	0.2887	0.2168	0.1603
RBM	0.2725	0.2858	0.2800	0.2124	0.2990	0.2990
CBM	0.2930	0.2808	0.3143	0.1975	0.3660	0.3055

Table 7– Importance weights of sub-criteria with respect to maintenance alternatives for ‘gearbox’.

	Maintenance strategies			
Sub-criteria	FBM	TBM	RBM	CBM
P	0.4236	0.4633	0.1958	0.1320
C	0.3542	0.3387	0.3108	0.2105
N	0.2222	0.1981	0.4934	0.6575
HC	0.4145	0.3661	0.2438	0.1948
SC	0.2225	0.3378	0.3620	0.4948
TC	0.3630	0.2961	0.3942	0.3104

Table 8– Unweighted super-matrix for maintenance strategy selection for ‘gearbox’.

Cluster node level			Alternatives				Criteria						Goal
							Cost			Criticality			
			FBM	TBM	RBM	CBM	P	C	N	HC	SC	TC	
Alternatives	FBM		0.0000	0.0000	0.0000	0.0000	0.2097	0.1988	0.1611	0.3014	0.1183	0.2352	0.0000
	TBM		0.0000	0.0000	0.0000	0.0000	0.2249	0.2346	0.2446	0.2887	0.2168	0.1603	0.0000
	RBM		0.0000	0.0000	0.0000	0.0000	0.2725	0.2858	0.2800	0.2124	0.2990	0.2990	0.0000
	CBM		0.0000	0.0000	0.0000	0.0000	0.2930	0.2808	0.3143	0.1975	0.3660	0.3055	0.0000
Criteria	Criticality												0.8333
		P	0.4236	0.4633	0.1958	0.1320	0.0000	0.0000	0.0000	0.3602	0.2098	0.2989	0.2193
		C	0.3542	0.3387	0.3108	0.2105	0.0000	0.0000	0.0000	0.4823	0.2402	0.4330	0.1754
		N	0.2222	0.1981	0.4934	0.6575	0.0000	0.0000	0.0000	0.1575	0.5500	0.2681	0.4386
	Cost												0.1667
		HC	0.4145	0.3661	0.2438	0.1948	0.4466	0.4637	0.1634	0.0000	0.0000	0.0000	0.0807
		SC	0.2225	0.3378	0.3620	0.4948	0.2528	0.2123	0.5396	0.0000	0.0000	0.0000	0.0538
		TC	0.3630	0.2961	0.3942	0.3104	0.3006	0.3240	0.2970	0.0000	0.0000	0.0000	0.0322
Goal			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 9– Limit super-matrix for maintenance strategy selection for ‘gearbox’.

Cluster node level			Alternatives				Criteria						Goal
							Cost			Criticality			
			FBM	TBM	RBM	CBM	P	C	N	HC	SC	TC	
Alternatives	FBM		0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661
	TBM		0.7766	0.0777	0.0777	0.0777	0.0777	0.0777	0.0777	0.0777	0.0777	0.0777	0.0777
	RBM		0.0911	0.0911	0.0911	0.0911	0.0911	0.0911	0.0911	0.0911	0.0911	0.0911	0.0911
	CBM		0.0985	0.0985	0.0985	0.0985	0.0985	0.0985	0.0985	0.0985	0.0985	0.0985	0.0985
Criteria	Criticality												0.4075
		P	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163	0.1163
		C	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317	0.1317
		N	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595	0.1595
	Cost												0.2592
		HC	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857	0.0857
		SC	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921	0.0921
		TC	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814	0.0814
Goal			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 10– Priority scores of maintenance strategies for ‘gearbox’.

Maintenance strategy	Limiting value	Priority (limiting values normalized by clusters)
FBM	0.0661	0.1983
TBM	0.0777	0.2331
RBM	0.0911	0.2732
CBM	0.0985	0.2954

Table 11–The priority scores of the four maintenance strategies for ten wind turbine components.

ID (Fig. 5)	Assembly	FBM	TBM	RBM	CBM
a	Low speed shaft	0.1848	0.2505	0.2932	0.2715
b	Gearbox	0.1983	0.2331	0.2732	0.2954
c	Generator	0.1880	0.2441	0.2790	0.2889
d	Wind vane	0.2289	0.2470	0.2575	0.2666
e	Controller	0.1983	0.2331	0.2732	0.2954
f	Yaw motor	0.1927	0.2555	0.2732	0.2786
g	Tower	0.1902	0.2208	0.3012	0.2878
h	Yaw driver	0.2087	0.2420	0.2789	0.2704
i	Blade	0.1690	0.2249	0.2855	0.3206
j	Brake	0.2198	0.2353	0.2695	0.2754

Table 12– The results of comparisons.

ID (Fig. 5)	Assembly	Criticality perspective	Cost perspective	AHP	ANP/CPN	Upgrade?
a	Low speed shaft	CBM	FBM	TBM	RBM	No
b	Gearbox	CBM	FBM	CBM	CBM	No
c	Generator	CBM	FBM	CBM	CBM	No
d	Wind vane	CBM	FBM	RBM	CBM	No
e	Controller	CBM	FBM	CBM	CBM	No
f	Yaw motor	CBM	FBM	RBM	CBM	No
g	Tower	CBM	FBM	RBM	RBM→	CBM
h	Yaw driver	CBM	FBM	CBM	RBM	No
i	Blade	CBM	FBM	CBM	CBM	No
j	Brake	CBM	FBM	CBM	CBM	No

Figure 1. An ANP model structure.

Figure 2. Dependencies (→) and interdependencies (←→) among two multi-component systems.

Figure 3. A network model for maintenance strategy selection of marine renewable energy systems.

Figure 4. Cost-risk-benefit analysis for maintenance strategy selection/updating.

Figure 5. The wind turbine system considered in this study.

Figure 6. A dependency diagram for wind turbine components (→: dependence ; ←→ : interdependence).

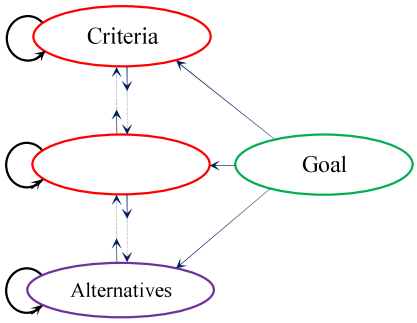


Figure 1– An ANP model structure.

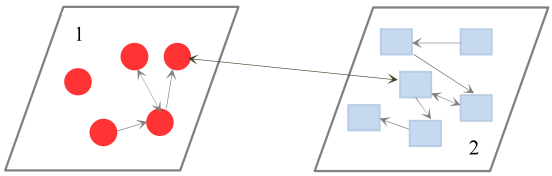


Figure 2–Dependencies (→) and interdependencies (←→) among two multi-component systems.

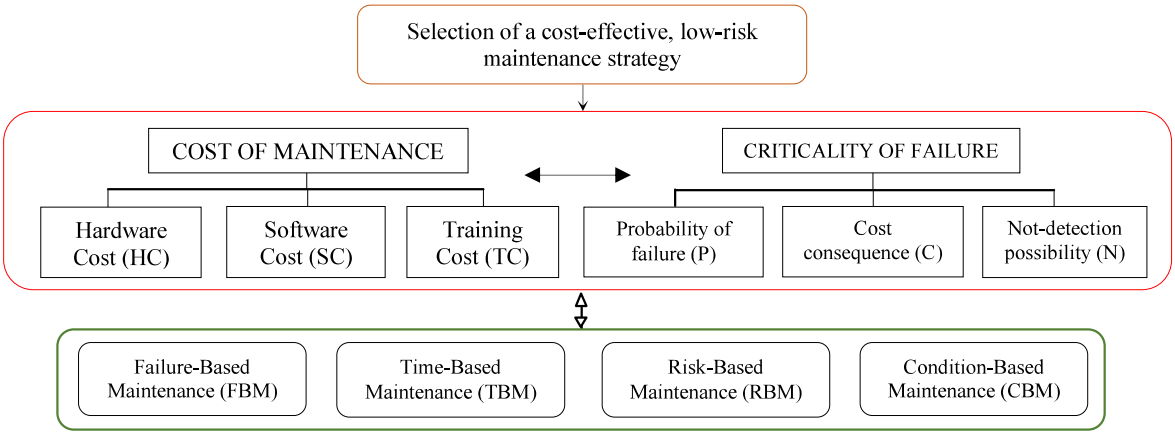


Figure 3– A network model for maintenance strategy selection of marine renewable energy systems.

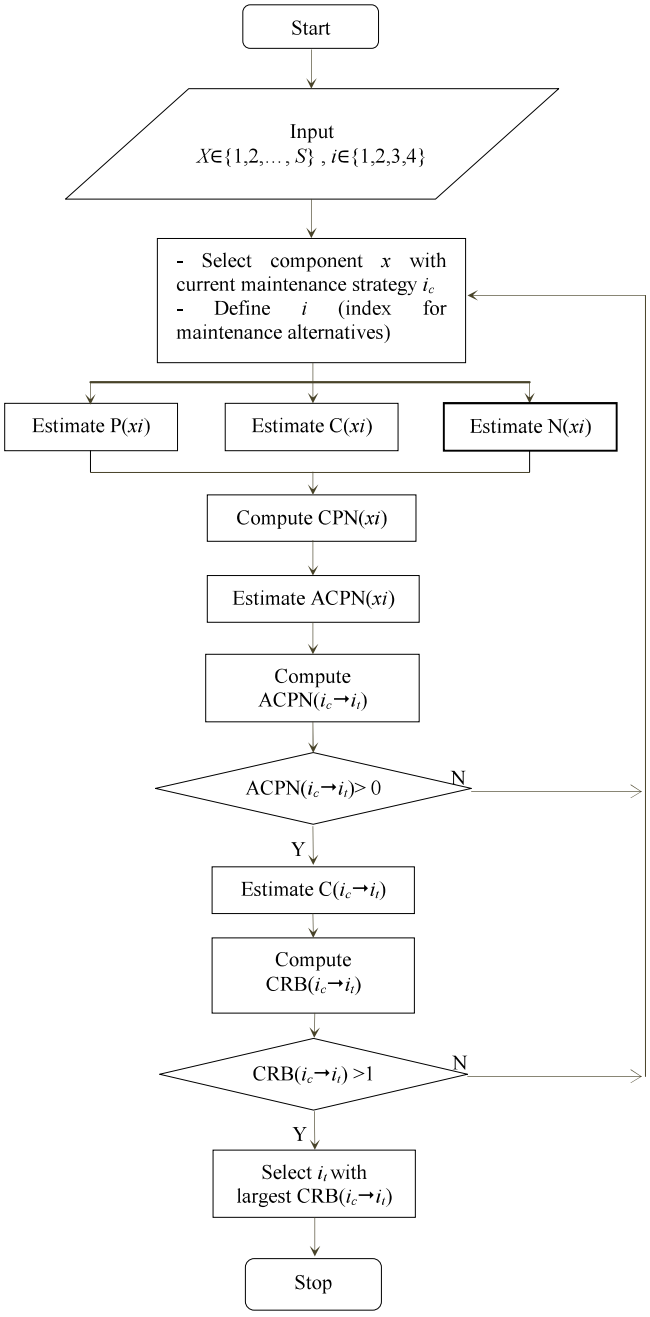


Figure 4– Cost-risk-benefit analysis for maintenance strategy selection/updating.

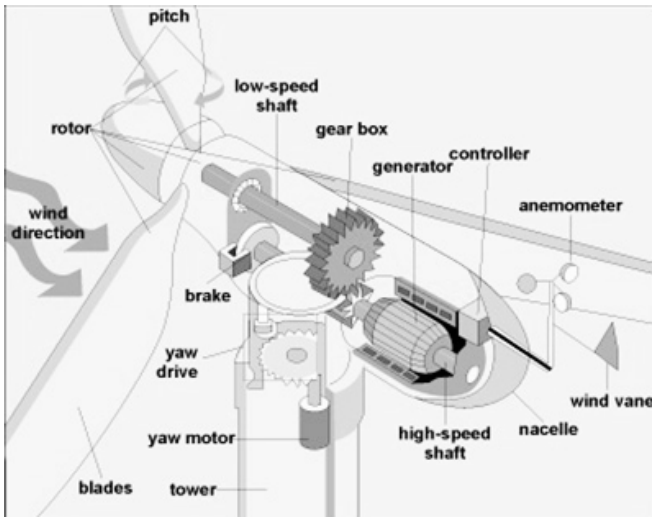


Figure 5– Wind turbine components (source: NREL).

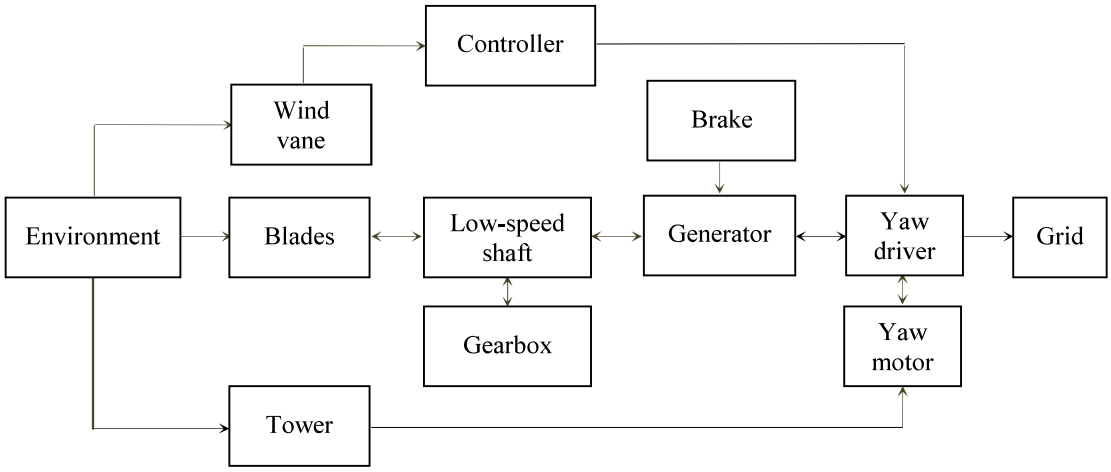
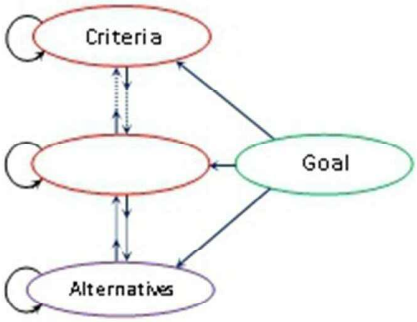
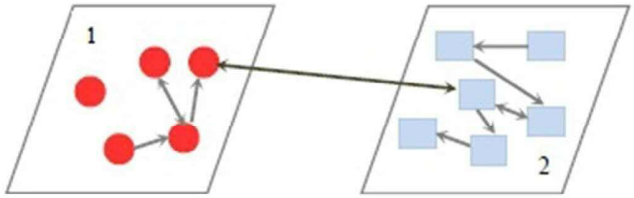


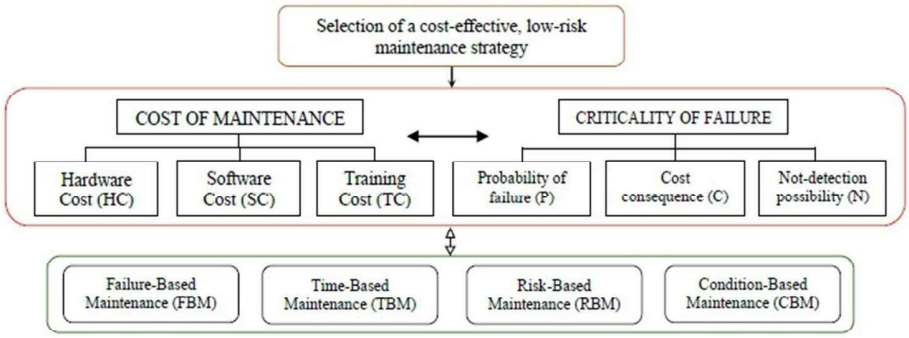
Figure 6– A dependency diagram for wind turbine components (→: dependence ; ↔ : interdependence).



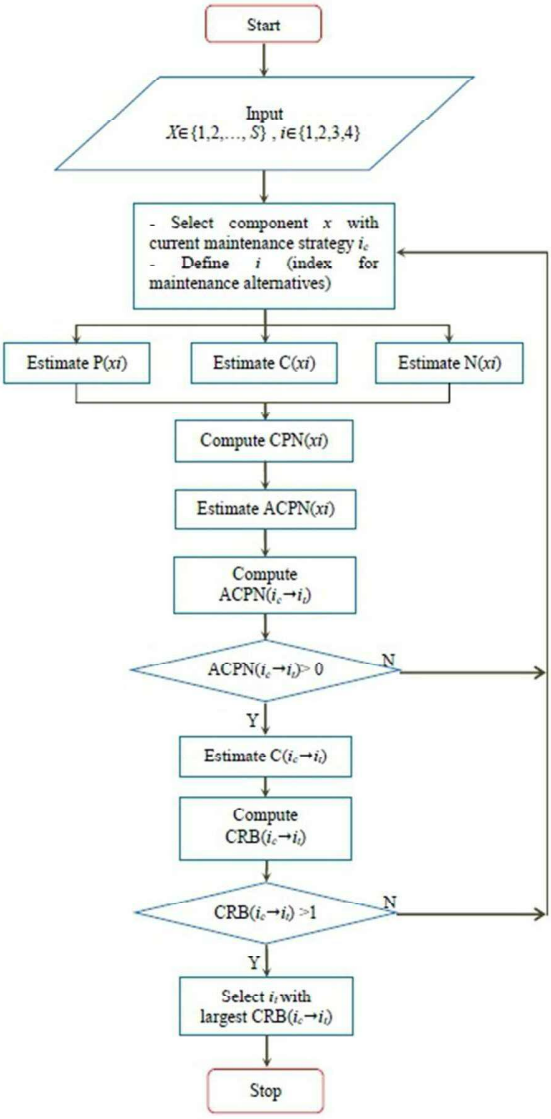
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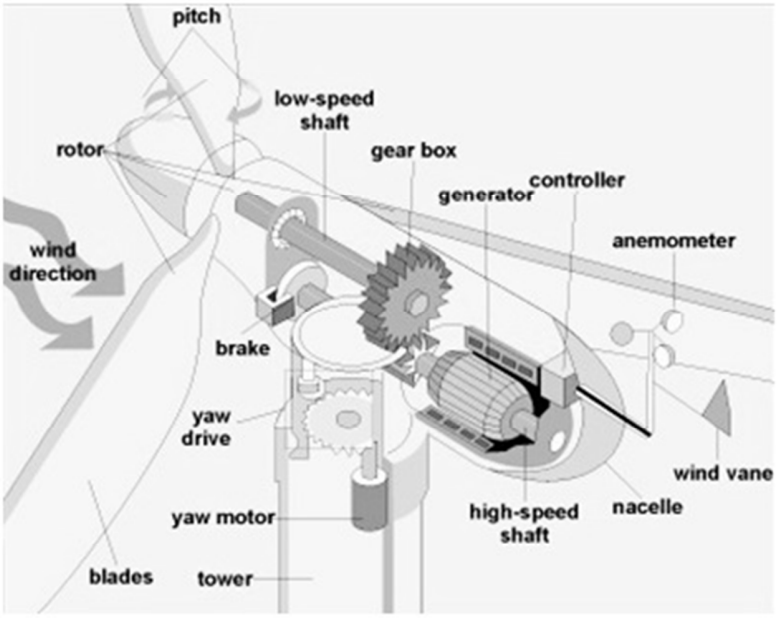
102x45mm (96 x 96 DPI)



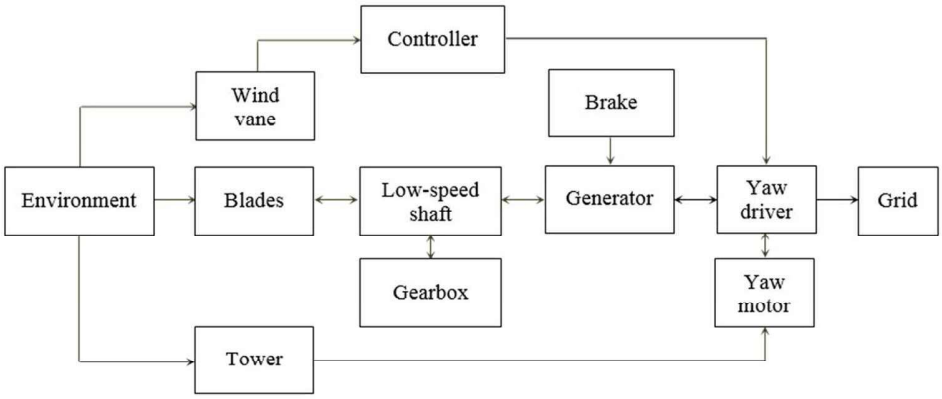
197x81mm (96 x 96 DPI)



115x214mm (96 x 96 DPI)



93x75mm (120 x 120 DPI)



181x85mm (120 x 120 DPI)



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Maintenance strategy selection for multi-component systems using a combined analytic network process and cost-risk criticality model

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