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OPTIMIZATION ALGORITHMS APPLIED TO MAINTENANCE STRATEGIES FOR WIND TURBINES AND STUDY OF A MULTI-CRITERIA METHOD FOR THE IMPROVEMENT OF PREVENTIVE MAINTENANCE

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ABSTRACT

Nowadays, many research teams are more focusing on optimizing the use of renewable energy sources such as wind and solar energy which turned-out to be the solution of the energy crisis and the increasing of fossil power price all over the globe.
In Our country, the policy adopted by the government is to encourage the use and the development of solar energy and wind power. Morocco, land which enjoys an illuminating sun and a speed of winds of the most considerable, put wind force in the middle of its strategy of development of renewable energy sources, as bottomless deposit in perpetual evolution.
The aim of this work is to present a literature review of different kind of maintenance strategies applied in the wind power industry. It will cover the use of optimization techniques and algorithms in order to boost performance, help in monitoring and reduce the cost of energy and maximize the profitability of a wind farm. The choice between adopting classical techniques or use new methods based on artificial intelligence and machine learning or even combination of multiple algorithms is a decisive factor for the success or failure of wind farm projects.
Thereafter we will develop a multi-criteria study in order to determine the essential equipment of the wind turbines in order to improve the maintenance programs. The multi-criteria method captures all the information deemed necessary for the comparison between the equipment.

1. Introduction

The Moroccan wind energy project is part of the energy strategy which aims to put in place by 2020 a capacity of 2,000 megawatts, allowing an annual production of 6600 GWh. It means 26 % of our current electricity production. It saves 1.5 million TEPs annually, or 750 million US dollars a year, and avoids the emission of 5.6 million tons of CO_2 per year.
Some renewable energy is generated from wind [1] and might be cheap in terms of cost comparing to fossil fuels if the price of it (cost per kilowatt) is minimized. The cost could be significantly high due to manufacturing and installation details. Moreover, operation and maintenance cost[2] shall increase the bill. In the following, we focus on three maintenance strategies which are: Reactive, Preventive and Predictive [3].

2. Maintenance process and the defining parameters

Each organization is performing the type of maintenance strategy that is adapted with its budget and its perspective. There are three types of maintenance strategy[4]:

2.1. Reactive (corrective) strategy

A reactive strategy[2] means to run a component until it is damaged and causes the wind turbine (or a machine in general) to shut down. Then, the fix is performed, and all the process continue to run until the next incident occur. This strategy is the most expensive because when a component [5]is broken suddenly, replacement could cost much more than planned maintenance[6], and also the bug of a component in the system could deteriorate other components, which leads to an additional cost. Using reactive strategy, the general expenses is not easy to control or monitor since the failure of a component is unpredictable, and third-party contractors might not be available immediately. Now, many organizations are still performing corrective maintenance on their assets. This type of maintenance takes place only in the event of an incident, always unforeseen, unexpected and especially expensive. Indeed, when a device or asset is unavailable and needs to be repaired or replaced. To avoid corrective maintenance (and high maintenance costs), maintenance departments establish preventive maintenance plans[7], usually based on time.

2.2. Preventive strategy

A preventive maintenance [4] is a planned maintenance strategy (time-based) which is triggered and scheduled based on events. It is mostly based on operator experience, age of the machine, and manufacturer recommendations [2]. The main idea is that an operating component has to repaired at specific time frames and then be replaced after certain life. The common issue with preventive maintenance is that the intervals between inspections in most cases are too long to detect a defect at its early stage. The other issue with the preventive maintenance strategy[2] is that the scheduled inspection intervals are based on the average operation conditions [8], whereas each wind turbine and wind farm has its own site and operating condition. The manufacturer recommended inspection schedule for a same component may not be suitable for a wind farm in different location, and most likely the 20-year operation life might not be met.

2.3. Predictive (proactive) strategy

A predictive maintenance [9], which is also called condition-based strategy, is the cost-optimal strategy[10]. It is performed by monitoring the status of the machine, based on several sets of data (such as vibration, oil, temperature, etc.). By analyzing the online data [11], the operator can potentially detect the issues as early as possible and schedule applicable economical remedies[10]. Through this strategy, wind farm operators can also repair and replace a group of parts at the same

time, as one of the major costs of wind turbine repair is the daily cost of crane rental. Instead of renting a crane for a few days to change only one part, they can replace a group of damaged components on several wind turbines in the farm.

The production industry relies heavily on proactive maintenance. The data provided by sensors [12]helps to plan the appropriate maintenance times, so as to reduce unwanted downtime. This evolution[13] is extended throughout the field of maintenance. As sensors are becoming more affordable and accessible, they are integrated by default in (new) installations and the technique for data analysis is available, it is possible to switch to proactive maintenance "just in time ". This allows better control of asset performance and more efficient use of available maintenance resources. Maintenance can be done at times when it does not immediately cause serious problems in business processes. The advantage of sensors is that they collect data permanently. In combination with the analysis of big data, models can be identified and can predict unavailability.

3. Fault Diagnosis Techniques

Fault diagnosis is the main part of the predictive maintenance approach[11], which is done before root causes analysis and prognosis[14]. The wind power industry mainly uses three main techniques to detect drive-train faults:

3.1. Oil Analysis

Oil analysis is used extensively in the wind energy industry as a useful method [14]to monitor bearings and gearboxes [6]. Lubricant samples are collected in order to assess whether the lubricant is still healthy[15]. Also, contaminants in the lubricant can indicate if any environmental debris/dirt or wear particles are present in the lubricant which significantly could reduce the service life by causing machine wear. The procedure includes oil sampling, analytical tests and data analysis [7], which provides information on form, quantity, and size of the derbies. If there are wear particles in the oil samples, as a result of a defect in the component, the defect is potentially severe and immediate action needs to be taken. While this technique has proven to be useful, oil analysis cannot be used to detect the location of the defect in the component, as they are usually manufactured from a same material [8].

3.2. Temperature Analysis

Thermocouples or similar devices (for example Resistance Temperature Detector- RTD) are attached to the component to collect temperatures [7] to analyze the gradient. However, while this method is useful, thermal analysis is also not a robust analysis to detect the location and size of the faults, especially in bearings. Non-destructive infrared thermography method, on the other hand, is capable of detecting faults at their early stages providing their locations, yet this method is not currently cost efficient and easy to implement for wind turbines [16].

3.3. Vibration Analysis

Vibration analysis[17] is perhaps the most efficient type of drive-train defect detection method. For example, an undamaged bearing generates a steady state vibration, but a fault in any elements of it can change the condition and produce noticeable vibration impulses. In other words, fault(s) on bearing element amplify the vibration. Therefore, vibration analysis is a great tool to detect these types of changes. Vibration analysis (including time domain, frequency domain and combination of time and frequency domains) of mechanical components has been used for a long time in both academia and industry and has been significantly improved during almost the last two decades. In terms of wind turbine application, the very old turbines did not benefit from online vibration monitoring, but today’s installed turbines are typically fully equipped with vibration sensors on different parts of the drive train including main bearing, gearbox, gearbox bearings, and

generator bearings, and an operation center monitors the status of the drive-train. For a typical 1.5 MW wind turbine, eight to eleven vibration sensors are installed on the drive-train [13]. For these wind turbines there is one sensor on the main bearing, six on the gear case, and four on the generator bearings (two on drive-end and two on non-drive-end bearings). Vibrations from the wind turbine drive-train, unlike oil samples, can be monitored remotely from the diagnosis center. There are several communication configurations, for instance, a group of wind turbines are connected locally to a small server, which itself is connected to wind farm server via wireless connection. The wind farm server is then connected to the diagnosis server via a local-area network (LAN) and can be controlled and monitored remotely.

4. Optimization algorithms

With the development of CMS[18] (Condition monitoring system), intelligence techniques[19] have been increasingly employed to fault diagnostic and prediction[20]. The intelligent algorithms[21] such as machine learning (ML),genetic algorithm (GA), artificial neural network (ANN), artificial intelligence (AI), etc. show advantages in data processing and optimizing calculation[22], which is significant to the information generated by the Supervisory Control and Data Acquisition (SCADA) system[23]. In practice, the information collected by sensors[24] is not all relevant and useful. The intelligent-based data mining techniques are able to select the meaningful data and find out how the changes of variables can reflect the system conditions.

4.1. SCADA

Supervisory Control and Data Acquisition (SCADA) [25] is a system for control and remote supervision of wind turbines. Data gathered for each turbine include temperature, electrical parameters, rotor speed and others are used for root cause analysis after fault had been occurred. However, SCADA data mining combined to artificial intelligence techniques are capable of condition monitoring on a large scale.

4.2. Artificial intelligence

Using improvements of technology[26]in industrial sectors such as renewable energy is a strong approach that leads immediately to promising results in terms of predicting, monitoring and controlling wind power manufactures. In fact, artificial intelligence methods are giving the possibilities of automated data acquisition and data processing for all life cycle phases which result in reducing breakdowns and costs and thereby help for optimization of operation and maintenance strategies.

4.2.1. Intelligent agent

Using One of the implementations of artificial intelligent [27] is placing intelligent agent like drones or remotely controlled components. These tools have the potential to improve the controlling and monitoring capabilities of wind turbines. For example: Using infrared scans or microphones for rotor blades in order to detect and locate the presence of defects or damages in the inspection and testing stage of life cycle.

4.2.2. Grid support

Power generators are also evolving by taking over the responsibility of grid-supporting [28] and even grid controlling tasks. Their new job is now the control of voltage and frequency in order to increase penetration of electrical energy supply[29]. This implies building appropriate hardware for power setting and grid connection. For better use, the wind turbine relies on predicted wind and weather conditions to employ and settle upon its operation to the external conditions. Studies have been done lately to meet or exceed requirements for regulating the power output of wind

turbines. Algorithms using artificial intelligent are taken into consideration and have been developed to deal with the rise demands of grid support.

4.3. Big Data and Machine learning

In addition to SCADA data mentioned before, remote and condition monitoring systems needs a way to analyze and identify pattern in large amounts of information in order to initiate improvements in the process of maintenance of wind turbines. Artificial Intelligence [30] and Machine Learning algorithms were already being used in the wind power industry. for instance, artificial neural networks have been used to calculate the link and the connection between the actual meteorological input variables from the weather forecast model and the expected power production of the wind farms. Studies have been done for SCADA data to identify defects in components of wind turbine using machine learning algorithms such as artificial neural networks, self-organizing maps or support vector machines. Big Data driven approaches might be a great option for operators to decide whether to apply lifetime extension, repowering or decommissioning different pieces of wind turbine. More than that, this could also give a big help to reduce the cost of operation and maintenance processes.

5. Optimization Techniques

Maintenance optimization[24] can be developed considering three purposes: minimum cost, maximum power generation, and maximum availability or reliability. Once the optimization purposes are determined and all required data are collected, appropriate methods should be employed to achieve the target. Qualitative and quantitative are the main two categories of optimization techniques. This session will focus on the latter.

5.1. Markov Models

Conventional binary reliability modeling is insufficient for complex wind turbine system since it considers the system to be either in a working state or in a failed one. Markov approach is an efficient solution to model multi-states degradation system, and it has been widely applied. A Markov model consists of system state, degradation process, and repair process. The system [26]state is usually graded into three types, namely, perfect functioning, degradation, and failure. The degradation state can be minor or major. There are three kinds of repair activities in Markov models. Perfect repair brings the system back to the perfect functioning condition; while minimal repair keeps the system remain in the last functioning state before failure. If the imperfect repair is performed, the system will transit into a less degraded condition. In conventional discrete and continuous Markov models, transition rates only depend on the current state, which is sometimes inadequate in practice. Semi-Markov model, which has been widely studied recently, considers that the transition probability is time-varying, and the state variables are not subjected to exponential distribution. The proposed method enables the WT practitioner to make maintenance decisions after inspection and minimize long-term cost. In non-homogeneous Markov models, the state transition rates are time-dependent, namely, the degradation rates increase with the time. In terms of the analysis of complex systems, it is difficult to establish and solve the Markov model. Simulation model is a flexible technique to solve this issue. The principle of simulation models is to generate various scenarios based upon uncertainties. Studies proposed an approach for verifying and partly validating operation and maintenance (O&M) simulation models for offshore wind farms, considering the limitation of maintenance resources. The weather conditions are also studied in this research.

5.2. Bayesian Networks

A Bayesian network[32] is a directed acyclic graphical model that describes causal relationships between failure modes and causes. In general, nodes represent stochastic variables and directed links represent relationships in the networks. The Bayesian method is widely applied in fault diagnosis and maintenance planning. This work also studied the influence of failure probability, inspection interval, reliability of inspections, and maintenance decision logic.

6. Classification of critical wind turbine equipment

Wind turbines are made up of a large number of nerve centers, which perform multiple different functions from one station to another.

6.1. Main components of a wind turbine

A "classic" wind turbine generally consists [33] of :

6.1.1. The tower

Generally made of metal, supports all the equipment used to produce electricity (nacelle + rotor). It is fixed on a foundation implanted in the ground, a heavy concrete base which ensures the anchoring and the stability of the wind turbine. The wind turbines mast today reaches 80m high for the most powerful (exceptionally up to 100 m). The wind turbines are so high,it is because the wind blows stronger at a few tens of meters high, where it is not disturbed by the effect of obstacles: relief, trees, houses ... And the power supplied by a wind turbine is proportional to the cube of the wind speed. The tower must be strong enough to support not only the nacelle and the rotor, but also the powerful loads caused by the wind: on the one hand the power exerted by the wind directly on the tower, on the other hand the power transmitted by the rotor.

6.1.2. A rotor

Composed of several blades (generally 3) and the nose of the wind turbine. The blades are today made of composite materials that are both light and provide sufficient rigidity and resistance: polyester reinforced with fiberglass and / or fiber of carbon. Their length currently reaches between 30 and 55 meters, or a diameter of the rotor between 60 and 110 meters. The power of a wind turbine is proportional to the area swept by its blades (a circle), therefore to the square of its rotor diameter. A rotor scans a circular disc during a rotation and can therefore collect the energy of the air molecules passing through this disc. The rotor is connected to the nacelle by the hub, It transforms the kinetic energy of the wind into mechanical energy.

6.1.3. A nacelle

Mounted at the top of the tower and housing the mechanical and pneumatic components and certain electrical and electronic components necessary for the operation of the machine. The electricity produced in the nacelle is transported to the ground by electric cables running down inside the wind turbine tower. The different components of a nacelle:

- The speed multiplier: it is used to increase the speed of rotation between the primary shaft and the secondary shaft which drives the electric generator.
- The secondary shaft generally includes a mechanical brake which makes it possible to immobilize the rotor during maintenance operations and to avoid runaway of the machine.
- The generator: it is the one that converts mechanical energy into electrical energy.
- An electronic controller responsible for monitoring the operation of the wind turbine. It is actually a computer that can manage the start of the machine when the wind speed is sufficient (of the order of 5 m /s), manage the pitch of the blades, braking of the machine,

the orientation of the "rotor plus nacelle" assembly facing the wind so as to maximize energy recovery. To carry out these various tasks, the controller uses the data provided by an anemometer (wind speed) and a wind vane (wind direction), usually located at the rear of the nacelle. Finally, the controller also manages the various possible failures that may occur.

Various cooling devices (generator, multiplier) by fans, water or oil radiators. Thanks to a supervision and control system, a wind turbine can be stopped automatically and very quickly if necessary. The operational safety of wind turbines is thus ensured continuously. In the case of wind turbines producing electricity, a delivery station located near the wind farm makes it possible to connect this park to the electrical network to inject all of the energy produced there.

6.2. The multi-criteria method

In our study, we will limit ourselves to the analysis of critical equipment. For the classification of critical equipment, we are faced with a difficult choice given the multitude of criteria to be taken into account.

We used a recently developed method which is “The multi-criteria method”.

The multi-criteria method captures all the information deemed necessary for the comparison between the equipment.

In our case, the criteria chosen for the classification of critical equipment are:{Citation}

Criterion 1: The safety impact of the equipment failure.

Criterion 2: The impact of equipment failure on the production chain (yield, availability).

Criterion 3: The human and material resources necessary for the repair of the equipment.

Criterion 4: The intervention time on the equipment.

Criterion 5: Maintainability of the equipment.

- Complexity of the kinematic chain,
- Access difficulties,
- Lack of material handling equipment,
- Composition of the equipment of several sub-assemblies…

The multi-criteria matrix is constructed on the basis of the above criteria.

The multi-criteria matrix is presented as follows:

Rotating equipment (j) / Criteria (i)	Weighting coefficient C_i of criterion (i)	Equipment 1	Equipment 2	Equipment j
1. The impact of the failure on security	C_1	N_{11}	N_{12}	N_{1j}

2. The impact of the failure on production	C_2	N_{21}	N_{22}	N_{2j}
3. The necessary human and material resources	C_3	N_{31}	N_{32}	N_{3j}
4. The intervention time on the equipment	C_4	N_{41}	N_{42}	N_{4j}
5. Maintainability of equipment	C_5	N_{51}	N_{52}	N_{5j}
Total = Tj =		$\sum (C_i \times N_{ij})$	$\sum (C_i \times N_{ij})$	$\sum (C_i \times N_{ij})$

Table 1: The multi-criteria matrix

With:
$0 \leq Ci \leq 10$: Ci represents the weighting coefficient of each criterion and translates the relative importance of this one compared to the other criteria.
$0 \leq Nij \leq 10$: Nij represents the score given to equipment j for criterion i.
The coefficient Ci and the score Nij are given by a group of employees following a vote and will be taken in the meantime [0, 10].
For each piece of equipment j the sum will be determined by the total:
$Tj = \sum (Ci \times Nij)$
Finally, the rotating equipment is classified in descending order according to the total Tj obtained by each of them.

The application of the multi-criteria method consists, first of all, in evaluating the weighting coefficient relating to the above-mentioned criteria.
Table I below represents this coefficient Ci corresponding to each criterion.

Criteria (i)	**Weighting coefficient Ci of criterion (i)**
1. **Criteria 1 :** The impact of the failure on security	$C_1 = 10$
2. **Criteria 2 :** The impact of failure on production	$C_2 = 10$
3. **Criteria 3 :** The necessary human and material resources	$C_3 = 8$
4. **Criteria 4 :** The intervention time on the equipment	$C_4 = 8$
5. **Criteria 5 :** Maintainability of equipment	$C_5 = 5$

Table 2: Evaluation of the weighting coefficient

We establish a rating scale corresponding to each criterion
Table II illustrates the grading scale adopted for the application of the method.

Criteria (i)	**Mark (Nij)**
Criteria 1 : The impact of the failure on safety	
- Significant risk to human safety. - Significant risk on neighboring equipment. - Significant risk on the other components of the equipment. - Without impact.	10 [5 – 9] [1 – 4] 0
Criteria 2 : The impact of failure on production	

- Immediate production stop. - Production stopped after a few hours of operation (after failure). - Reduction of the production rate. - Impact on product quality. - Environmental impact. - Without impact.	10 [8 – 9] [4 – 7] [1 – 10] 10 0
Criteria 3 : The necessary human and material resources	
- More than 12 agents + Crane + Clark + Hoists. - [9 to 12 agents] + Crane + Clark + Hoists. - [7 to 9 agents] + Clark + Hoists. - [4 to 7 agents] + Clark + Hoists. - [3 to 4 agents] + Clark + Hoists. - [2 to 3 agents] + Hoists.	10 9 8 7 [2 – 6] [1 – 3]
Criteria 4 : The intervention time on the equipment	
- Greater than one day - [8hours to 16hours]. - [4hours to 8hours]. - [0h to 4hours].	[8 – 10] [6 – 7] [4 – 5] [0 – 3]
Criteria 5 : Maintainability of equipment	
- Very difficult to repair (kinematic complexity, difficult to access…..) - Difficult to repair. - Easy to repair.	[7 – 10] [4 – 6] [0 – 3]

Table 3: Grading scale adopted

Based on the multi-criteria method, the components of the wind turbine would be scale-rated by maintenance personnel taking into account their background and experience in the field. They would rate each criterion and develop preventive maintenance schedules in order to reduce maintenance costs and downtime suffered by the crush of the wind turbine.

Conclusion

This paper presents different types of maintenance strategy in wind farm projects. Predictive strategy helps to react just in the right time and seems to be the most efficient in the production industry. The next chapter covers fault diagnosis techniques and put in light that vibration analysis is a great tool to detect changes in wind turbine devices. After that, different techniques and methods for monitoring and controlling wind turbines have been introduced. As we see, old techniques are now combined with new ones involving intelligent artificial and data mining in order to maximize power generation, minimize cost and optimize availability and reliability. The multi-criteria method gives us the possibility of classifying wind turbine equipment by degree of criticality in terms of impact on safety, productivity and installation while exploiting the background and experience of the maintenance service personnel.

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