International Journal of Production Management and Engineering

http://dx.doi.org/10.4995/ijpme.2015.3318

Received 2014-10-16 Accepted: 2015-02-28

Fuzzy maintenance costs of a wind turbine pitch control device

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Abstract: This paper deals with the problem of estimation maintenance costs for the case of the pitch controls system of wind farms turbines. Previous investigations have estimated these costs as (traditional) "crisp" values, simply ignoring the uncertainty nature of data and information available. This paper purposes an extended version of the estimation model by making use of the Fuzzy Set Theory. The results alert decision-makers to consequent uncertainty of the estimations along with their overall level, thus improving the information given to the maintenance support system.

Key words: Wind turbine, Pitch Control, Maintenance cost, Fuzzy sets.

1. Introduction

Wind power technology is one of the major growing areas in the energy sector. In a few years' time wind power has gone from a minor energy source to a large-scale industry. Proper and well-planned service and maintenance strategies are very important to ensure an efficient energy production and required to effectively reduce the costs associated with Wind Turbine (WT) support.

Maintenance management approaches aim to find a sound balance between costs and benefits of performing maintenance. Some experiments and studies show that there is a large potential to reduce overall costs in the maintenance of WTs (e.g. Bertling *et al.*, 2006).

According to Morthorst (2003), Operation and Maintenance (O&M) costs constitute a sizeable share of the total annual costs of a WT. For a new machine, O&M costs might easily have an average share over the lifetime of the WT of approximately 20% to 25% of the total cost per kWh produced. In an attempt to shed some light on this problem, other works (e.g. Carvalho *et al.*, 2013a) has been focused on studying the active power control system or pitch control system of WTs.

This system assumes primordial importance in the wind turbine, because: i) it is crucial in the optimization of the turbine efficiency; ii) it is very important with regard to the safety of the turbine (Naranjo *et al.*, 2011); and iii) reveals frequent failures and large residence time in failure state compared to other systems of the machine (Nilsson & Bertling, 2007; Carvalho *et al.*, 2013b). Consequently, to guarantee a normal operation, they are usually needs maintenance actions, which are only provided by the manufacturer (Teresa, 2007). Moreover, information related to failure modes, (un) availability and maintenance costs of these systems remain confidential and only the manufacturer has knowledge about them. This situation does not facilitate, for example, the work of company managers who search for better warranty and maintenance contracts.

In complex systems, such as pitch control systems, the maintenance management function is commonly supported by analyses of collected data as well as on the quality and experience of maintenance engineers and others experts in this field. In this context, this function is often very difficult, and unrealistic decisions come out from the process with undesirable frequency. So, it is expected that the Fuzzy Set Theory, applied in the maintenance management, will lead to more realistic decisions.

The study presented in this paper is based on an analysis of two years data collected from 21 identical WTs installed in a wind farm in Portugal. The data were provided confidentially by the company that manages the wind farm. For this reason, the name of the company and the WT brand are not revealed. Each WT under analysis has a nominal power of 2 MW, three rotor blades and an active power control (pitch).

The main objective of the study consists on reporting the gathering process of information about WT functioning and its failures and costs, and conducting some reliability analyses, providing an estimate of the associated maintenance costs of the pitch system.

The remainder part of the paper is organized as follows. Section 2 introduces the fundamentals of the Fuzzy Set Theory. Section 3 describes the system under study, the pitch control of the WTs, and its fault and error states. In Section 4, it is proposed a model for the fuzzy maintenance costs of the pitch control system. Section 5 reports the results of the application of the proposed model and discusses its practical relevance. Finally, the main conclusions of this study are discussed in Section 6.

2. Fuzzy Set Theory

2.1. Introduction

The Fuzzy Set Theory has been extensively studied in the past 30 years, largely motivated by the need for a more expressive mathematical structure to deal with human factors. This theory has a major impact on industrial engineering and maintenance management systems. During the last decade, several models for maintenance management problems have been incorporating uncertainty of their parameters by using fuzzy sets (e.g. Yuniarto and Labib, 2006; Khanlari *et al.*, 2008; Sharma *et al.*, 2008; Shen *et al.*, 2009). Nevertheless, most of the current literature on maintenance simply omits the uncertainty that is inherent to real processes. Fuzzy sets are adequate, for instance, to estimate the lifetime or the failure rate of a given equipment that operates in different environments. In most cases, statements in plain language may be the best form to express the knowledge about a system. However, this information is naturally very inaccurate and any realistic estimate inferred from that is always an approximation.

2.2. Basic Concepts

A fuzzy set A, in the universe of discourse X, is defined by a membership function, $\mu_A(x)$: $X \rightarrow [0,1]$, which assigns, for each element of X, a membership degree to A.

Definition 1: Given a fuzzy set A defined on X and any number $\alpha \in (0, 1]$, the α-cut set, A^α, is the crisp set expressed by Eq. (1).

$$A^\alpha = \{x: A(x) \geq \alpha\} \tag{1}$$

The α-cut set concept allows us to manipulate fuzzy sets by using the interval arithmetic. Alternatively, such manipulation can be performed by the extension principle introduced by Zadeh (1975). This is an important tool by which classical mathematical theories can be fuzzified. On the other side, defuzzification is the conversion of a fuzzy quantity to a crisp quantity. Despite the fact that the bulk of the information emerging every day is fuzzy, most of the actions or decisions implemented by humans or machines are crisp or binary. A detailed application of defuzzification methods can be found in Klir and Yuan (1995).

Among the innumerous types of fuzzy sets, those that are defined in the set of the real numbers assume a particular importance. These sets have a quantitative meaning and under certain conditions they can be treated as fuzzy numbers, e.g. when intuitively and linguistically they represent approximate numbers, such as “the preventive maintenance duration is around τ hours” (Ross 1995).

In reliability and maintenance studies, the triangular and trapezoidal numbers are the most used number patterns because their simplicity and adequacy on representing uncertainty, vagueness and subjectivity of data and human judgment. Without loss of generality, this paper only deals with triangular fuzzy numbers. A triangular fuzzy number, A, can be defined by a triplet (a_1, a_2, a_3), where $\mu_A(a_1) = \mu_A(a_3) = 0$ and $\mu_A(a_2) = 1$. Each α-cut, A^α, is a closed interval represented as $A^\alpha = [a_1^\alpha, a_3^\alpha]$, where:

$$\begin{aligned} a_1^\alpha &= (a_2 - a_1)\,\alpha + a_1 \\ a_3^\alpha &= a_3 - (a_3 - a_2)\,\alpha \end{aligned} \tag{2}$$

The family of cut sets $\{A^\alpha: \alpha \in (0, 1]\}$ is a representation of the fuzzy number A. An illustrative graphic representation of A is shown in Figure 1.

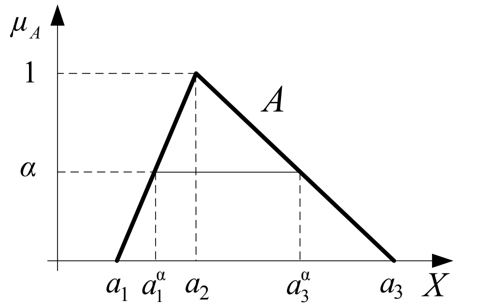

Figure 1. Representation of a triangular fuzzy number.

Like functions, f, are important in mathematical modeling, fuzzy functions, $\tilde{F}$, are important in fuzzy modeling. The usual way of obtaining a fuzzy function is to extend a function to map fuzzy sets to fuzzy sets. There are two common methods to accomplish this extension: the extension principle procedure; and the α-cut and interval arithmetic procedure. This paper uses the extension principle (Zadeh 1975). The extension principle may be generalized to functions of many independent variables $X_1, X_2,\ldots, X_n$ (Buckley & Eslami, 2002).

Let $A_1, A_2,\ldots, A_n$ be triangular fuzzy numbers of X_1, $X_2,\ldots, X_n$ respectively, represented by the α-cuts: $A_1^\alpha=[a_{11}^\alpha, a_{13}^\alpha]$, $A_2^\alpha=[a_{21}^\alpha, a_{23}^\alpha],\ldots, A_n^\alpha=[a_{n1}^\alpha, a_{n3}^\alpha]$. Using the extension principle, it is possible to extend f to $\tilde{F}$, where $B=F(A_1, \ldots, A_n)$. If $B^\alpha=[b_1^\alpha, b_3^\alpha]$, then

$$b_1^\alpha=min\{f(x_1, \ldots, x_n): x_1\in A_1^\alpha, \ldots, x_n\in A_n^\alpha\}$$

$$b_3^\alpha=max\{f(x_1, \ldots, x_n): x_1\in A_1^\alpha, \ldots, x_n\in A_n^\alpha\}$$

Note that *min* and *max* can be used in these equations, for the reason that a continuous function in a closed interval takes its maximum and minimum. Therefore, if there are two triangular fuzzy numbers, A_1 and A_2, and supposing that:

$$\partial f/\partial x_1>0 \text{ and } \partial f/\partial x_2<0$$

that is, f is an increasing (decreasing) function in $x_1(x_2)$, hence, for all α:

$$b_1^\alpha=f(a_{11}^\alpha, a_{21}^\alpha) \text{ and } b_3^\alpha=f(a_{13}^\alpha, a_{23}^\alpha) \quad (3)$$

3. Pitch control device

The main purpose of a pitch system is to prevent the power of the electric generator from being exceeded in the case of high wind speeds, as well as preventing relieve strain on the structure and components of the wind turbine. This system acts on the aerodynamic forces by controlling the loads and power.

In the active control, blades may undergo rotation about its longitudinal axis, which makes it changes the angle of attack of the blades with respect to the relative wind speed. This process takes place through hydraulic or electric systems, which respond to an electronic control which checks the power output. Whenever the power is too high, the control triggers the mechanism. The main advantages of this system are related to its capability to limit the power for high wind speeds, facilitating the start-up operation, to diminish the efforts and to optimize power when the turbine is operating at partial load. The pitch system also assumes primordial importance with regard to the safety of the turbine. A flaw in this system, combined with adverse climatic situation (e.g. a storm) may lead to an uncontrolled rotation speed of the blades and catastrophic consequences, including, in the limit, a total destruction of the turbine. The states that actively influence the reliability of the active control power are:

Fault blade load control (State S1): the control effort in the turbine is constantly monitored. This state means that an undue effort has been exercised in the blade. The wind turbine is still operating, but it is under reduced power. The maintenance service has to rectify stress effects. This state actively influences the state S2.

Pitch control error (State S2): The angles of the three blades are continuously monitored. When there is a difference in the angles of the blades (can be erroneously due to a measurement error), state S2 arises, which leads to a shutdown of the turbine and the engine restarts automatically. If the problem persists for a predefined number of times, the maintenance service will have to repair the fault.

4. Fuzzy maintenance costs of the pitch control device

Recent studies have been emphasizing the importance of the pitch system for the functioning, cost optimization and security of the wind turbine (Carvalho *et al.*, 2013a). In this study it was very difficult to estimate the maintenance costs related to these two states, S1 and S2. The wind farm company only knows the information that can be observed from the data made available to this study. From that, with relevance to the analysis of maintenance costs, one can highlight the record of the exact time of occurrence of each state in each turbine and the wind speed at the time of occurrence. Such information allows estimating the downtime cost, for states S1 and S2, as well as the number of preventive and corrective maintenances carried out in two years. However, the costs of corrective and preventive maintenance, and the number of replacements made, were not revealed by the WT manufacturer (who performs maintenances as well). One can only know approximate values from the experience of managing experts from this and from others wind farms who were consulted in the context of this work. Therefore, part of the information collected does not follow statistical analysis, but rather statements of experts, based on their knowledge and experience and, consequently, they are subject to an increased level of uncertainty.

4.1. Maintenance costs

Knowing the costs of maintenance, albeit mere approximations, allows the wind farm company to make better decisions, particularly with regard to contracts for the maintenance established with the manufacturer. However, this information either does not exist or is not public.

In the context of this study, the contract that the wind farm company has with the manufacturer assumes the execution of four interventions per year in each turbine, conducted at quarterly intervals. Specifically, the manufacturer performs an electrical preventive maintenance, a mechanical preventive maintenance, a visual inspection and a lubrication operation. The manufacturer is also responsible for any corrective maintenance that is necessary, as well as some improvement maintenance he may consider as fundamental. This maintenance provided by the manufacturer is a necessary condition to offer warranty to the wind farm company. Associated costs are 38000€ per year per turbine by 15 years. In reality, it is not possible to know the exact cost for each preventive and corrective maintenance, since the maintenance contract does not explicit these costs.

4.1.1. Costs of unavailability

Table 1 summarizes the frequency, duration and cost of the resulting unavailability of states S1 and S2, for the 21 turbines, in the two years.

Table 1. Resume of the effects of states S1 and S2 for the 21 machines in two years.

	State	
	S1	S2
N.º of occurrences	196	431
Unavailable time (hh:mm:ss)	949:55:08	1609:32:52
Unavailable cost (€)	108276.40	129733.20
Average unavailable time (h)	5	4
Average unavailable Cost (€)	552	301

The cost of downtime shown in the last row of Table 1 was estimated as a function of wind speed records and the ratio of power with wind speed, displayed in Figure 2.

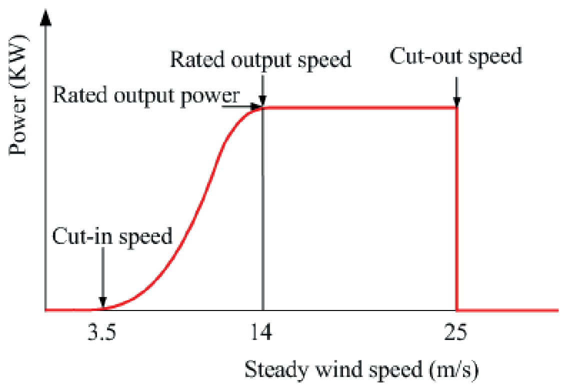

Figure 2. Power curve as a function of wind speed.

The data of average wind speed and the respective wasted power by the turbine, and other details, resulting from the appearance of these two states can be found in Qiu *et al.* (2012).

The energy wasted by the occurrence of each state is given by:

Energy [MWh]= (Power[kW]×MDT[h])/1000

where the mean downtime (MDT) is the average time that a system is non-operational for being either in state S1 or state S2. The cost of down-time was estimated supposing that the energy produced is sold at 90€ per MWh. More details about this estimation can be found in Carvalho *et al.* (2013b).

4.1.2. Preventive maintenance costs

For the preventive maintenance of the pitch system, experts mentioned that a preventive maintenance of the active power control system costs at least 580€ and requires about 4 hours, which additionally represents an approximate unavailability cost of 293€ due to preventive maintenance, assuming an average wind speed of 8 m/sec.

4.1.3. Corrective maintenance costs

Analyzing data from the 431 recorded instances of state S2, it resulted in 53 repairs, i.e. 12.3% of cases requiring maintenance. The maintenance usually consists in replacing the engine of blades. To ensure machine availability, repairs are never made on site. The engine is replaced and thereafter is repaired in the manufacturer. The experts indicate that the cost of each engine is around 2000€. Among the 196 occurrences of state S1, 46 triggered a corrective maintenance, which corresponds to 23.5% of all cases. When the maintenance team makes an intervention in the failure load control (S1), usually they replace the sensors that somehow quantify the load exerted on the blade. A new sensor costs around 50€.

4.2. Total maintenance costs

The total maintenance cost of the active power control system for the 21 machines in the two years can be given by Eq. (4).

$$C=C_{CMS1}\times N_{CMS1}+C_{CMS2}\times N_{CMS2}+2\times 4\times 21\times \times(C_{PM}+C_{UPM})+N_{OS1}\times C_{US1}+N_{OS2}\times C_{US2} \quad (4)$$

where:

C: total cost of maintenance of the active power control system for the 21 machines in the two years;
C_{CMS1}: corrective maintenance cost of state S1;
C_{CMS2}: corrective maintenance cost of state S2;
C_{PM}: preventive maintenance cost of pitch sytem;
C_{UPM}: unavailability cost, due to preventive maintenance;
C_{US1}: average unavailability cost, due to state S1;
C_{US2}: average unavailability cost, due to state S2;
N_{CMS1}: number of corrective maintenance of the state S1;
N_{CMS2}: number of corrective maintenance of the state S2;
N_{OS1}: number of occurrences of the state S1;
N_{OS2}: number of occurrences of the state S2.

Table 2 presents estimates for the values of these parameters. These estimates were calculated from data provided by the management of the wind farm and information obtained from interviews with managers of the park. Applying these values in Eq. (4), it was estimated the amount of 492,887€ to the cost spent on pitch system maintenance of the 21 turbines of the wind farm, in the two years under review.

Thus, on average, the annual maintenance cost of each active power control system was around 11735€. Note that the only available information for the maintenance cost is that which prevails at the contract between the company and the manufacturer, i.e. 38000€ per year per turbine.

As mentioned above, the true costs of corrective and preventive maintenance, and the number of replacements made, were not revealed by the WT manufacturer. Thus the total maintenance cost obtained by Eq. (4) contain a certain level of uncertainty which depend of their parameters uncertainty.

Some issues may arise at this point, such as: What is the confidence level for the total value of the maintenance cost obtained by Eq. (4)? How to represent non-probabilistic uncertainty present in some of the cost components? How the uncertainty in the cost components affect the uncertainty in the total cost of maintenance?

In the following section, these issues will be addressed using the theory of fuzzy sets introduced above, in Section 2.

5. Fuzzy total maintenance cost analysis

Consider the same parameters of Eq. (4), but admit now that the uncertainty inherent to the following parameters must be not neglected: preventive maintenance cost, C_{PM}, and unavailable costs due to preventive maintenance, C_{UPM}. Estimates for these costs (Table 2) have a very fragile analytical basis due to limited access to the data (these are not provided by the companies providing maintenance services to the park), so it is assumed that the uncertainty associated with these costs is high. The preventive maintenance cost, C_{PM}, for example, is exclusively known by the experts' opinion. The unavailable costs due to preventive maintenance, C_{UPM}, are also very uncertainty, because it is assumed an average wind speed of 8 m/s.

The uncertainty associated with these parameters was appraised from the great experience and indispensable collaboration of two managers of the park. By consensus, the managers presented, for each of these cost parameters, the value they considered most plausible, and the values below and above from which they consider as impossible to occur. Based on this information, is was set up the fuzzy triangular numbers for C_{PM} and C_{UPM}. Table 3 shows the parameters of the Eq. (4), assuming those as triangular fuzzy numbers.

Table 3. Crisp and fuzzy parameters estimates of the maintenance cost function.

Parameter	Estimative (€)
C_{CMS1}	50
C_{CMS2}	2000
$\tilde{C}_{PM}$	(450, 580, 800)
$\tilde{C}_{UPM}$	(180, 293, 350)
C_{US1}	552
C_{US2}	301

Eq. (4) can now be rewritten as:

$$\tilde{C} = C_{CMS1} \times N_{CMS1} + C_{CMS2} \times N_{CMS2} + 2 \times 4 \times 21 \times \times (\tilde{C}_{PM} + \tilde{C}_{UPM}) + N_{OS1} \times C_{US1} + N_{OS2} \times C_{US2} \quad (5)$$

Using the extension principle, C extends to $\tilde{C}$, where $\tilde{C}=C(\tilde{C}_{PM}, \tilde{C}_{UPM}, C_{CMS1}, \dots)$.

If $C^{\alpha} = [c_1^{\alpha}, c_3^{\alpha}]$, by Eq. (2) and Eq. (3) results:

$c_1^{\alpha} = C[(580–450)\alpha+450, (293–180)\alpha+180, 50,\dots]$

and

$c_3^{\alpha} = C[800–(800–580)\alpha, 350–(350–293)\alpha, 50,\dots]$

Then, by Eq. (5), the maintenance cost will be between 452,063€ and 539,423€.

These values determine the confidence interval of the total maintenance cost C (universe of discourse C). The higher the magnitude of this interval, the greater is the uncertainty present in the cost. Figure 3 represents this result graphically, as a triangular fuzzy number.

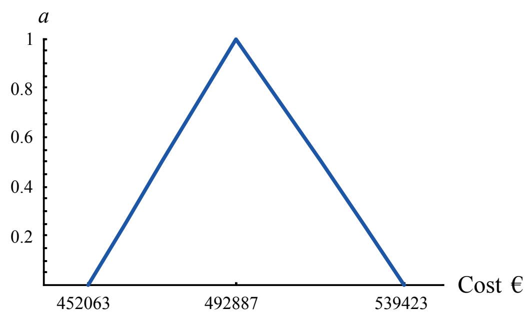

Figure 3. Fuzzy maintenance cost.

By determining the mean total cost for each turbine, $\tilde{C}_{WT}$, it is obtained the fuzzy number:

$$\tilde{C}_{WT} = \tilde{C}/21 \times 2 = (452063,\ 492\,887,\ 539423)/42 = (10763,\ 11735,\ 12843)$$

This approach seems to give rise to more realistic solutions, allowing for better decisions in decision making processes. On the other hand, the difficulty of interpreting the results increases. These difficulties are due to the large quantity of possible outcomes for C_{WT}, represented by the universe of discourse of $\tilde{C}_{WT}$. The way to reduce uncertainty in the value of C_{WT} involves obtaining more information about C_{PM} and C_{UPM}, thus reducing the universe of discourse of the fuzzy parameters $\tilde{C}_{PM}$ and $\tilde{C}_{UPM}$.

Figure 4 shows the fuzzy maintenance cost, $\tilde{C}$, when the universe of discourse of $\tilde{C}_{PM}$ and $\tilde{C}_{UPM}$ is reduced by 30%. In this case, we had set $\tilde{C}_{PM}$=(490, 580, 735) and $\tilde{C}_{UPM}$=(210, 293, 330).

It is thus noted that the uncertainty reduction of about 30% of $\tilde{C}_{PM}$ and $\tilde{C}_{UPM}$ leads to the same level of reduction in the uncertainty of $\tilde{C}$.

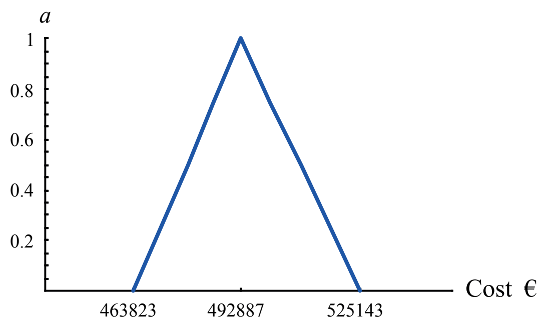

Figure 4. Fuzzy maintenance cost (reducing uncertainty).

Frequently, the membership function is defuzzificated to obtain a crisp number. However, a lot of information that can be relevant to the decision process is lost in the defuzzification operation. That is, the fuzzy result is richer than the crisp result, and the former should be preferred whenever possible.

6. Conclusions

In complex systems it is impossible to has a perfect knowledge about the involved parameters (failure rates, unavailability times, etc.) and about their interdependency relationships. Considering these results as "crisp" values is equivalent to assume that there is no uncertainty in these data. But, in fact, the uncertainty of data is intrinsic to the system and it is not probabilistic. To overcome these limitations, the application of the Fuzzy Set Theory proves to be an interesting approach for capturing the vagueness and fuzziness of the cost parameters. The application of this theory allows to propagate the uncertainty from parameters to results in the modelling process. The study reported in this paper has demonstrated the validity of these conclusions in the case of a particular maintenance cost problem. Moreover, the proposed fuzzy modelling approach will allow managers to make their decisions based on a reacher set of information than that they would have by the application of tradicional crisp valued parameters approach.

Acknowledgements

This work was financed with FEDER Funds by Programa Operacional Fatores de Competitividade – COMPETE and by National Funds by FCT – Fundação para a Ciência e Tecnologia, Project: FCOMP-01-0124-FEDER-022674.

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