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RAM factors in the operation and maintenance phase of wind turbines

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Abstract

The high complexity of technological systems and the increasing requirement and competitiveness of markets request the implementation of adequate management strategies for these systems in order to improve their availability and productivity. In this context, RAM factors constitute a strategic approach for integrating reliability, availability and maintainability, by using methods, tools and engineering techniques to identify and quantify equipment and system failures that prevent the achievement of its objectives. This paper presents the most relevant aspects and findings of a study conducted for assessing the operational performance of a wind turbine system installed in a wind farm in Portugal. The study was based on the analysis of the behavior of states defined for each individual wind turbine over a period of two years, and was aimed to identify and evaluate the effects of RAM-type factors. Given the structure and nature of the data, a Markov Chain approach was adopted for this evaluation. The main finding was that the usage of a particular technique (the frequency and duration technique) is adequate to effectively evaluate the overall performance of the wind farm and find opportunities for improvements.

Keywords: RAM factors; reliability; availability; maintainability.

1 Introduction

Currently, technological systems have a very high degree of complexity resulting from increasing requests of customers and a highly competitive market. Technological developments allow these systems meet the majority of their functional requirements that are present at the design phase, and, in some cases, exhibit other features resulting from the need to search for a differential technology. Among these functional requirements, studied and incorporated at the design phase, the Reliability, Availability and Maintainability are particularly relevant to companies that operate technological systems (operation and maintenance phase), and they are listed in the bibliography as RAM factors (Lundteigen *et al.*, 2009).

The direct implications of RAM factors in the Life Cicle Cost (LCC) of technological systems (production, transport, communications, energy, etc.) have been justifying the growing importance of this issue in the context of Industrial Engineering. Therefore, RAM is a strategic theme composed by the interconnection of factors that use methods, tools and engineering techniques to identify and quantify failures or shortcomings that prevent an equipment or system to achieve the performance goals originally proposed (NP EN 50126, 2000).

According to Komal *et al.* (2010), the application of processes for predicting the condition of the equipment along with the execution of preventive maintenance actions will lead to better performance of its operations. For this purpose, it is necessary to use reliability techniques for the knowledge of the correct functioning of the equipment that supports the implementation of best management practices.

Understandably, there are several reasons for studying the RAM factors of a technological system, such as: the need to respond to a contractual process; the optimization of maintenance policies – these are usually recommended by suppliers but established within a context that is different from the reality; the monitoring and control of operating and maintenance costs of complex systems – such costs are usually very relevant and may exceed several times the acquisition cost (Markeset and Kumar, 2003); the need to obtain performance indicators such as the Overall Equipment Effectiveness (OEE); the compliance with safety regulations, or the identification of improvement opportunities for existing or future equipments or systems. For all of this, the study of the RAM factors is an area with a high earning potential for any company that operates technology systems which include, of course, the wind power production of electricity.

The study presented in this paper is primarily focused on the analysis and evaluation of RAM factors of a modern wind turbine technology installed in a wind farm in Portugal. Wind farms are equipped with technology that capture and store (into digital databases) enormous amounts of data including output data and (fundamentally) data related to their operational behavior (McFadden, 1990). The treatment and analysis of these data may support better decisions at both operational and strategic levels. Many of the operational decisions are taken automatically by the control system of the wind turbine park. However, many other decisions, especially strategic decisions, need to be grounded on more sophisticated statistical analyses of the data provided by the system.

The study reported in this paper is exclusively based on the analysis of operational data and aims to describe the performance of the wind turbine over time. In particular, it intends to propose a model for predicting the behavior of an actual wind turbine system, by using appropriate techniques of data processing and analysis, in order to obtain performance indicators related to the RAM factors.

2 System description

The system consists on a wind turbine energy converter comprising a three-bladed rotor, an active pitch control and a variable operating speed controller. This system is part of a 108 meters tower with wind turbine blades of 82 meters in diameter, and generates a rated power of 2MW. The study focuses on data gathered from 28 wind turbines (towers) of the same type of advanced technology that are currently installed in a wind farm in Portugal. The data is from the years 2009 and 2010 and was provided by a company that manages and operates the wind farm. Each record (in the database) contains the identification of the wind turbine, the state, the date and time of the occurrence (the change for the state) and the instantaneous wind speed. Table 1 shows the structure of the data along with an example of five successive records.

Table 1. Structure of the data registered by the wind turbine system.

Date	Hour	Minute	Second	Wind turbine number	State	SubState	Speed (m/s)	Service	FaultMsg
2009.01.02	5	28	14	18	0	0	4,2	False	False
2009.01.02	5	29	18	16	0	0	2,7	False	Falso
2009.01.02	8	16	16	19	50	50	7,4	False	True
2009.01.02	9	9	31	22	25	25	6,3	False	Falso
2009.01.02	9	9	56	19	8	8	6,7	True	Falso
...									

A first analysis was conducted in order to identify the states that are related to a machine stop due to failure and therefore related with a maintenance action. At this point, it was noted that wind turbines can stop due to exogenous factors such as lack of wind and storms, or due to scheduled preventive maintenance or even lack of reading by sensors that record wind data, temperature, humidity and some other data. It was concluded that the signaling of a failure or production shutdown is not only related to technical problems but also to problems with external or natural factors. However, the information provided is limited to the data mentioned above, plus some relevant information obtained from the instruction manual of the wind turbine, so the study is performed on a statistical analysis of these data, which are specifically records of the states in each one of the wind turbines in the farm, at every second, 24 hours a day. More than two hundred states were identified as representative of the behavior of the wind turbine components over time. These states may indicate that: the wind turbine is in full operation; there is no wind minimum speed necessary to produce; the wind turbine is under maintenance activities; there is ice or moisture in the blade; etc. That is, the records are related to all that can happen to wind turbines at each moment.

3 System modeling

The study of RAM factors reported in this paper involves the application of different tools and methodologies. We start the study by performing a Pareto analysis to the available data in order to identify the key states of the turbine and reduce the state-space (and state diagram) of the turbine system for the following analyses. We then use a Markov chain framework to determine some indicators associated to RAM factors. This framework constitutes one of the most used tools for analyzing and evaluating the performance of reparable systems (Gupta *et al.*, 2009), and it is adequate for the case study of this paper due to its historical data type and structure (Table 1) and due to the nature of its underlying processes' behavior. Finally, we apply the Frequency and Duration Technique to further simplify the state diagram, in order to determine the reliability indices of the system and analyze its overall performance.

3.1 Data analysis

It was possible to identify 69 states of the turbine, but many of these states occurred very few times during each year and/or represented a very low annual residence time. Therefore, the study was focused on the 11 most visited states (Figure 1-a) and the 11 states with the highest residence annual time (Figure 1-b). Note that the majority of the states are common to the two these sets. Additionally, the administration of the wind farm identified two other states (S_{22} and S_{27}) that needed to be included in the state-space, given their reported importance for the performance analysis.

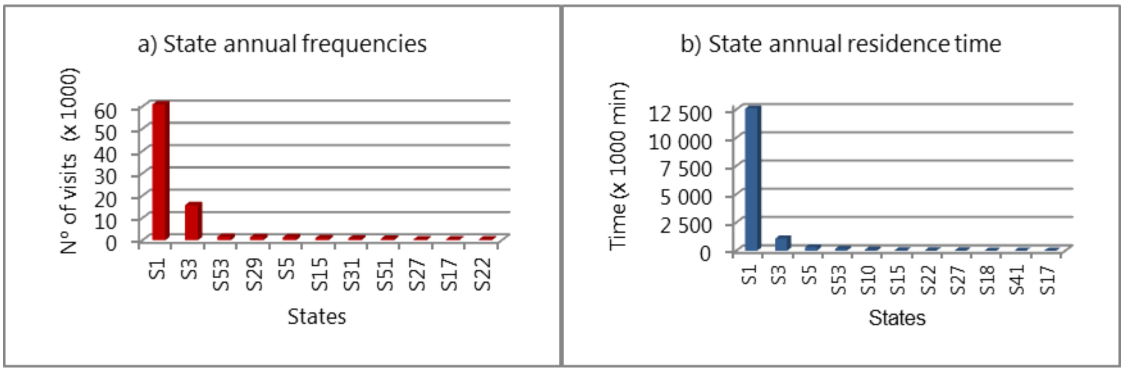

Figure 1. Pareto analysis of: (a) the 11 most visited states, and (b) the 11 states with the highest residence annual time.

3.2 State-space identification and characterization

The integrated list of the states identified in the previous sub-section resulted in a set of 14 states, eight of which are common to both lists. Table 2 lists the 14 states which therefore compose the state-space, E. The same table also classifies each state according to its operational availability. This classification was performed by taking in account the reading of the data and the relevant information from the instruction manual of the wind turbine.

According to the classification in above, any state $S_i \in \mathrm{E}$ is considered as a full operating state of availability when the wind turbine does not present any loss in its operational readiness. This means that the turbine may exhibit this state, but it can be out of production due to exogenous failures such as lack of wind or problems in the electric distribution network. Any state $S_i \in \mathrm{E}$ has a "partial" operational availability when the wind turbine is neither fully operational nor unavailable.

Table 2. List of states in the state-space.

State	Description	Classification
S_1	Turbine in operation	Full availability
S_3	Lack of wind	Full availability
S_5	Maintenance activities	Unavailability
S_{10}	Ice detection	Partial availability
S_{15}	Cable twisted	Unavailability
S_{17}	Fault yaw inverter	Unavailability
S_{18}	Anemometer interface	Partial availability
S_{22}	Pitch control error	Unavailability
S_{27}	Fault blade load control	Partial availability
S_{29}	Mains failure	Full availability
S_{31}	Feeding fault	Unavailability
S_{41}	Protection circuit breaker tripped	Unavailability
S_{51}	Turbine reset	Unavailability
S_{53}	Remote control PC	Partial availability

In these cases, it operates or can operate in degraded mode with loss of performance. Finally, any state $S_i \in E$ is considered a state of operational unavailability if the wind turbine is unavailable at the observed state S_i (out of operation, waiting for corrective maintenance, being under preventive maintenance activities, etc.).

3.3 Markov chain modelling framework

Having established the state space of the system (wind turbine), we now proceeded to analyze the data in order to characterize the average times of transitions between all states of E. Let M_k be one of the 28 wind turbines and t_{ijk} the mean residence time of the wind turbine k (k = 1, 2, 3, ..., 28) in state S_i before changing to state S_j (i, j $\in E$ and $i \neq j$). For each M_k, we calculated all residence times t_{ijk} and the average time spent in each state per wind turbine (Table 3) by using a Microsoft Excel™ macro. The blanks in the table correspond to nonexistent transitions. The transitions with null values represent transitions whose duration is less than a tenth of a minute.

Table 3. Average time of transition processes (minutes/turbine).

	S_1	S_3	S_5	S_{10}	S_{15}	S_{17}	S_{18}	S_{22}	S_{27}	S_{29}	S_{31}	S_{41}	S_{51}	S_{53}
S_1		643	889	1.040	1.009	999	475	616	517	892	721	949	1.475	1.203
S_3	66		83	0	50	2	6	3	0	68		3	43	68
S_5	167	183		2	2		208	11	91		14		19	1.198
S_{10}	362	579	902			2		27		117	24		351	15
S_{15}	26	38	3			0	0	0		3	0		2	0
S_{17}	1	1	89	0				0					19	0
S_{18}	1	0	174		0			0	0				193	
S_{22}	0	0	301	0	0	0			0	0			110	6
S_{27}	0	0	172				0			9	0		207	
S_{29}	0	0	0	0	0			0	0		0	0	7	5
S_{31}	1	0	21	0	0			0	0	0			28	75
S_{41}			261										52	1
S_{51}	0	0	0		0	0	0	0		0	0			0
S_{53}	45	29	448	0	3			512		19	56	0	634	

Table 3 shows that, in general, the average times of concurrent processes are heterogeneous, having a great diversity in their magnitude. In such conditions, and according to Nunes *et al.* (2002), adopting the Markov assumption (even if the processes are not modeled by exponential distributions) does not introduce significant errors in the values of the measures (or indicators) of performance in steady state. In this way, the adoption of the Markov hypothesis in this study is adequate and can be justified by the simplifications that it provides for the forthcoming analyses.

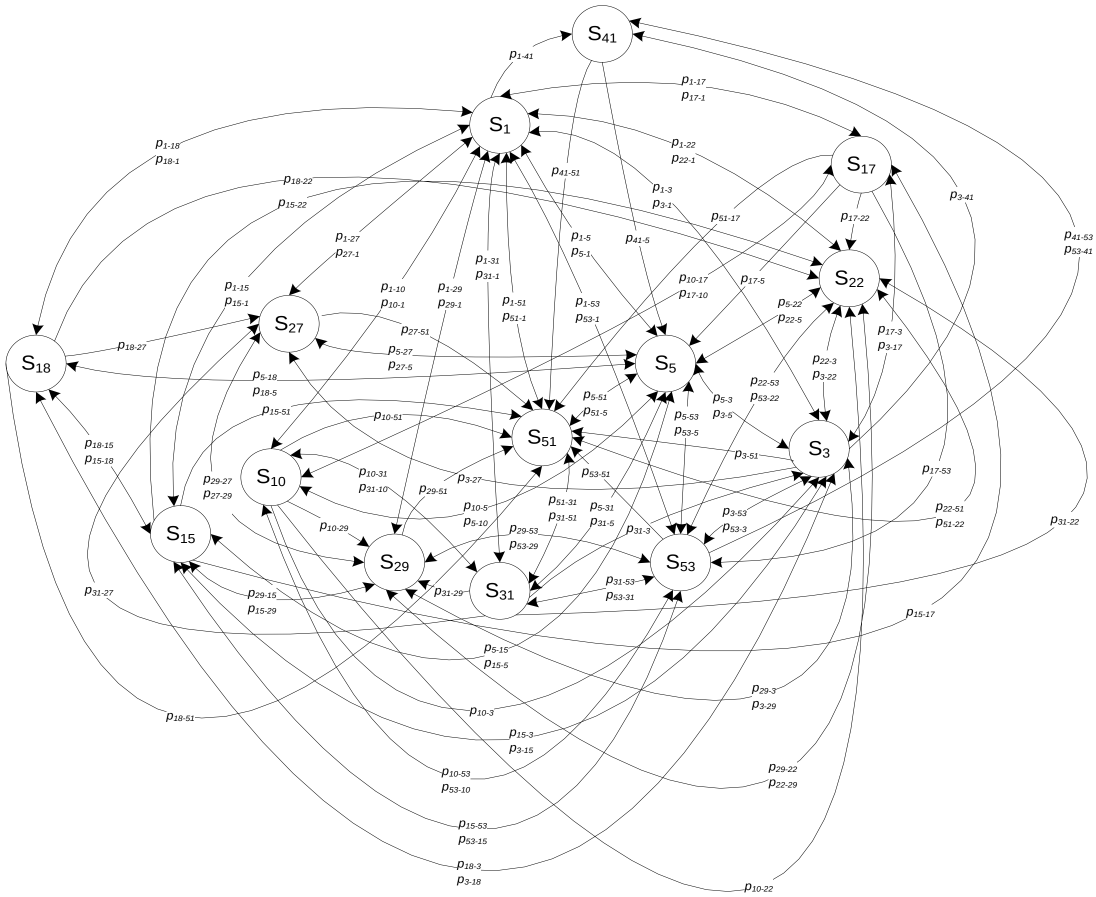

Figure 2. Diagram of transitions in the wind turbine system.

Figure 2 shows the state diagram of the wind turbine considered in this study. The transition process from state i to state j (i, j ϵ E and i≠j) is represented by $p_{i\text{-}j}$. For example, the transition from state 29 to state 0 is represented by $p_{29\text{-}0}$.

By adopting the Markov assumption, the transitions between states occur at constant rates. Table 4 shows the transition rates between states of the system (infinitesimal generator matrix Q of the Markov chain). Note that the elements of the main diagonal of Q, q_{ii}, are the rates at which the system leaves state i.

Table 4. Q matrix of transition rates between states (transitions per minute).

	S_1	S_3	S_5	S_{10}	S_{15}	S_{17}	S_{18}	S_{22}	S_{27}	S_{29}	S_{31}	S_{41}	S_{51}	S_{53}
S_1	-0,016	0,0151	0,0059	0,0027	0,0383	1,5450	1,6619	3,1013	7,1116	2,2020	1,4271	0	12,963	0,0229
S_3	0,0015	-5,270	0,0054	0,0017	0,0264	1,0473	37,333	9,6	0	2,5787	2,4585	0	0	0,0347
S_5	0,0011	0,0119	-1,343	0,0011	0,3255	0,0112	0,0057	0,0033	0,0058	0	0,0470	0,0038	56	0,0022
S_{10}	0,0009	0	0,4745	-0,811	0	33,6	0	0	0	0	14	0	0	2,3333
S_{15}	0,0009	0,0198	0,6222	0	-34,04	0	112	0	0	28	0	0	0	0,3835
S_{17}	0,0010	0,4066	0	0,6468	4	-69,85	0	0	0	0	0	0	0	0
S_{18}	0,0021	0,1675	0,0048	0	14	0	-162,6	0	0	0	0	0	0	0
S_{22}	0,0016	0,3051	0,0927	0,0376	9,3333	28	7	-19,87	0	28	4,0975	0	62,222	0,0019
S_{27}	0,0019	4	0,0109	0	0	0	4,6666	0	-7,228	6,8571	9,3333	0	0	0
S_{29}	0,0011	0,0146	0	0,0085	0,3076	0	0	7	0,1065	-67,99	2,5454	0	0	0,0525
S_{31}	0,0013	0	0,0720	0,0415	0	0	0	0	0	0	-33,95	0	48	0,0177
S_{41}	0,0010	0,2916	0	0	0	0	0	0	0	0	0	-0,871	0	2,5454
S_{51}	0,0006	0,0232	0,0538	0,0028	0,4087	0,0534	0,0051	0,0090	0,0048	0,1501	0,0353	0,0192	-179,1	0,0015
S_{53}	0,0008	0,0147	0,0008	0,0686	5,6	5,6	0	0,1573	0	0,2046	0,0132	0,8484	0	-5,396

From matrix Q, we can determine the steady-state probabilities of the system by solving the following system of equations:

$$\begin{cases} \pi^T . Q = 0^T \\ \pi^T . H = 1 \end{cases} \quad (1)$$

since $H = [1 \ \ 1 \ \dots 1]^T$

Table 5 shows those steady-state probabilities along with other performance indicators: frequency, mean residence time, and cycle time.

Table 5. Mean time of transportation processes (minutes/turbine).

State	State probability (P_i)	Frequency (min^{-1})	Mean duration (min)	Mean cycle time (min)
S_1	0,963079234	0,015765	61,0905	63,433
S_3	0,002221719	0,01171	0,189731	85,398
S_5	0,001230543	0,001653	0,744317	604,87
S_{10}	0,019051208	0,015465	1,2319	64,662
S_{15}	0,000305184	0,010389	0,029377	96,26
S_{17}	0,000220613	0,015411	0,014315	64,887
S_{18}	4,10587E-05	0,006679	0,0061473	149,72
S_{22}	0,000817087	0,016236	0,0503244	61,59
S_{27}	0,00171888	0,012425	0,138336	80,48
S_{29}	0,0001116	0,007588	0,0147074	131,79
S_{31}	7,56882E-05	0,00257	0,0294485	389,08
S_{41}	0,008770865	0,007644	1,14742	130,82
S_{51}	6,52551E-06	0,001169	0,0055808	855,23
S_{53}	0,002349795	0,01268	0,185321	78,867

Table 5 shows that there is wide discrepancy in steady state probabilities across states. As expected for a high availability system, state S_1 (which corresponds to a state of full operation) is the one with the highest probability value. There is also a set of states (S_{22}, S_1, S_{10} and S_{17}) with a same frequency of visit. Not being the most visited state, state S_1 is however by far the one with the highest probability of occurrence. This is due to the fact that S_1 is the state with the highest average occupancy (about 16 times greater than the sum of the occupancy times of all other states). Finally, the states with the highest occupation frequency are the states with the lowest cycle time.

3.4 Simplification of the state diagram

By applying of the Frequency and Duration Technique (FDT), the state diagram of a Markov system (Figure 2) can be ultimately simplified (reduced) for two states: a state of readiness and a state of failure or unavailability (Billinton and Allan, 1983). By analyzing the actual behavior of the system (wind turbine), it was initially considered, in this process of simplification, that each of the 14 states would be merged (ranked) into three aggregate states (Table 6). In this new state-space, state S_D represents the set of states of full operation of the wind turbine, state S_{DP} represents the set of states of degraded operation of the wind turbine, and state S_F represents the set of failure states of the wind turbine.

Table 6. Diagram of states (simplified model).

State	Description
S_D	Full operation of the turbine
S_{DP}	Operation in degraded
S_F	Failure of the turbine

State S_D comprises states S_1, S_3 and S_{29} of the state diagram of the wind turbine. State S_{DP} represents states S_{10}, S_{18}, S_{27} and S_{53}. Finally, state S_F adds the remaining states of the wind turbine: S_5, S_{15}, S_{17}, S_{22}, S_{31}, S_{41} and S_{51}. Figure 3 shows the state diagram of the simplified system, formed by the three states, S_D, S_{DP} and S_F.

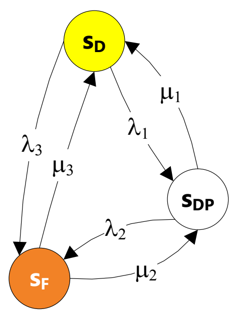

Figure 3. Simplified 3 states state-space diagram.

From the values of probability, frequency and mean residence times of individual states shown in Table 3, we can determine the cumulative values of the probabilities, frequencies and average time for states S_D, S_{DP} and S_F in steady-state phase (Figure 4).

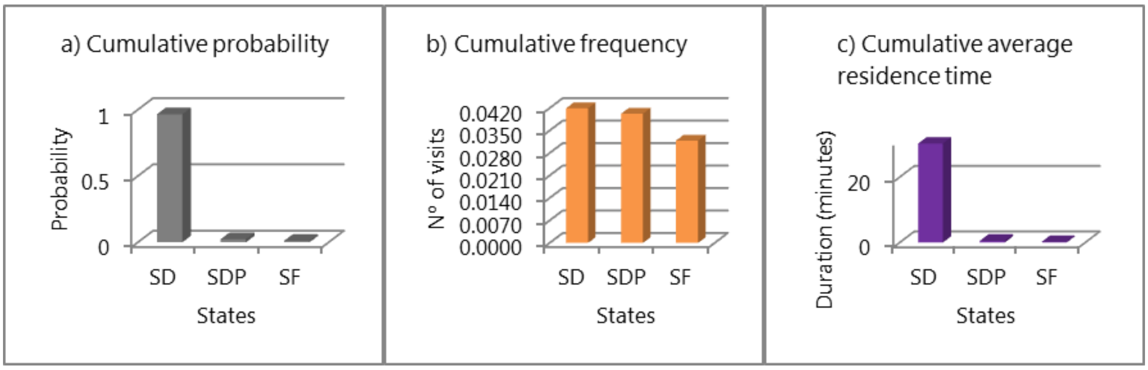

Figure 4. Cumulative values for the aggregated states S_D, S_{DP} and S_F: a) probabilities; b) frequencies; and c) average residence time (minutes).

It can be seen from the graphs in Figure 4 that the frequency of S_D, S_{DP} and S_F states are almost identical, but the S_D states have a greater residence time, which justifies their highest probability of occurrence.

In the simplification process undertaken in this study, we proceeded at first to simplify the state diagram of Figure 2 for a state diagram with three states. However, the FDT allows the reduction of any state diagram to a diagram with only two states, an operating state and a failure state.

In order to reduce the system to a set of two states, we then applied the FDT, proceeding to the abolition of the state S_{DP} by considering that all the individual states that make up this aggregate state are failure states. Thus, we came out to a state model of the system with only two states: a state of readiness, S_D, which aggregates all the states of full availability of the wind turbine and a state of unavailability, S_F, consisting of all states of partial availability and unavailability of the wind turbine (Figure 5). The resulting probabilities, frequencies and average residence times are shown in Figure 6.

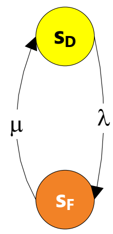

Figure 5. Simplified 2 states state-space diagram.

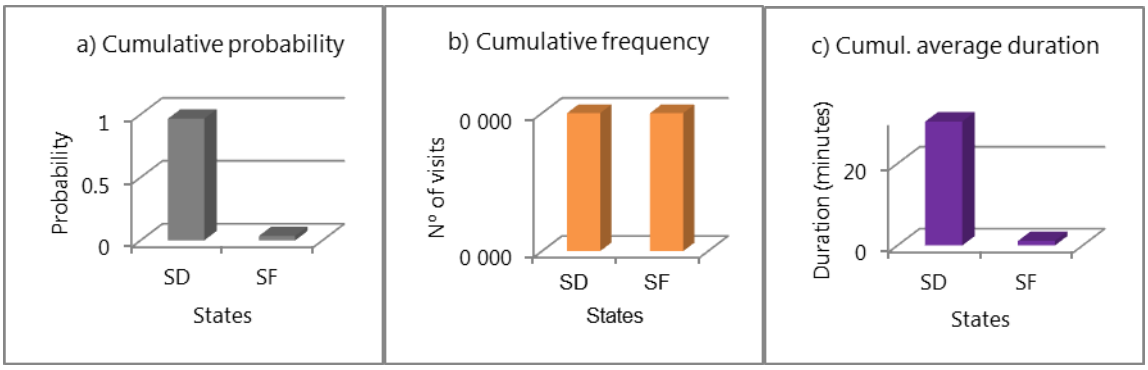

Figure 6. Cumulative values of aggregated states S_D and S_F: a) probability; b) frequency; and c) average residence time (minutes).

The graphs of Figure 6 shows that the frequencies of the states S_D and S_F are identical, but, as expected, the state S_D has a longer residence time and therefore it is more likely to occur.

3.5 Reliability indices

The simplified system model to a diagram with only two states allows us to obtain some performance indicators that would otherwise be difficult to obtain. Thus, the transition rates between states S_D and S_F may be obtained by:

$$\lambda = \frac{f_{S_D}}{P_{S_D}} = 0{,}033027005 \text{ failures/min} \quad \text{and} \quad \mu = \frac{f_{S_F}}{P_{S_F}} = 0{,}921865 \quad \text{repairs/min}$$

From the knowledge of the transition rates obtained by the state equations (Chapman-Kolmogorov differential equations):

$$P'_{S_D}(t) = -\lambda \times P_{S_D}(t) + \mu \times P_{S_F}(t) \quad \text{and} \quad P'_{S_F}(t) = \lambda \times P_{S_D}(t) - \mu \times P_{S_F}(t)$$

Solving this system of differential equations (using the Mathematica software) by assuming that the system is at state S_D at time t = 0, we obtain the probabilities of the states in the transient regime by:

$$P_{S_D}(t) = \frac{e^{t(-\lambda-\mu)}\lambda+\mu}{\lambda+\mu} \quad \text{and} \quad P_{S_F}(t) = -\frac{-1+e^{t(-\lambda-\mu)}\lambda}{\lambda+\mu}$$

Replacing the variables by their values for the transition rates above, we obtain:

$$P_{S_D}(t) = 1{,}04725\,(0{,}921857 + 0{,}033027e^{-0{,}954884t})$$

$$P_{S_F}(t) = -0{,}0345874(-1 + e^{-0{,}954884t})$$

Figure 7 shows the graphical representation of $P_{S_D}(t)$ for various values of t.

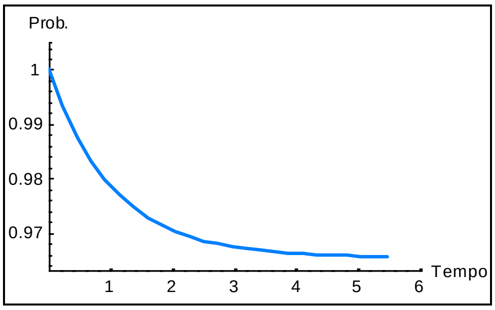

Figure 7. Probability *vs.* time for state S_D

Determining the limits of $P_{S_D}(t)$ and $P_{S_F}(t)$ as t tends to infinity we get the probabilities of states S_D and S_F in steady-state:

$$P_{S_D}(t) = \lim_{t\to\infty} P_{S_D}(t)(t) = 0{,}965413 \quad \text{and} \quad P_{S_F} = \lim_{t\to\infty} P_{S_F}(t) = 0{,}0345874$$

An alternative way to calculate this probability is to solve the system of equations (1). Thereby, we would obtain the same values as before:

$$P_{S_D} = \frac{\mu}{\lambda+\mu} = 0{,}965413 \quad \text{and} \quad P_{S_F} = \frac{\lambda}{\lambda+\mu} = 0{,}0345874$$

The probabilities P_{S_D} and P_{S_F} do not depend on the shape of the distributions that represent the processes of failure and repair in the simplified state diagram, but they depends on their average time of occurrence (in this case represented by the respective rates). Assuming that the processes are modeled by exponential distributions, with λ and μ rates, respectively, we can also estimate other performance indicators related to RAM factors, as shown in Table 7.

Table 7. Indicators of reliability in steady-state.

Reliability	Availability and Unavailability	Maintainability
$R(t) = e^{-0{,}03302t}$	$A(t) = P_{S_D}(t) = \frac{e^{t(-\lambda-\mu)}\lambda+\mu}{\lambda+\mu}$ $= 1{,}04725(0{,}921857 + 0{,}033027e^{-0{,}954884t})$	$f_\mu(t) = \mu e^{-\mu t}$
$f_\lambda(t) = 0{,}033027005\ e^{-0{,}03302t}$	$\overline{A}(t) = P_{S_F}(t) = -\frac{-1+e^{t(-\lambda-\mu)}\lambda}{\lambda+\mu}$ $= -0{,}0345874(-1 + e^{-0{,}954884t})$	$MTTR = \int_0^\infty t \times f_\mu(t)dt = \frac{1}{\mu} =$ $1{,}084758$ min
$F(t) = 1 - e^{-0{,}033027005t}$	$A(\infty) = \frac{MTBF}{MTBF+MTTR} = 0{,}965413$ $\overline{A}(\infty) = 1 - A(\infty) = 0{,}0345874$	$MTBF = \int_0^\infty R(t)dt = \frac{1}{\lambda} = 30{,}27825$ min Unavailability time = 518400 P_{S_F} = 17.929,90 min per year

In a more typical situation, the availability is calculated from the sum of the probabilities of all operating states of the model. Similarly, the availability is obtained by summing up the probabilities of failure states.

3.6 Critical analysis

According to the results obtained in this study, the turbine has a full operational availability of approximately 96.5%, a partial operational availability of 2.3% and an unavailability of 1.1%. Focusing the analysis on the state diagram of Figure 6, it appears that the opportunities for improving the availability of the system consist in reducing the probabilities of states S_{DP} and S_F. Such reduction may take place by means of maintenance actions, through a reduction in downtimes (unavailability times), or by improving the reliability of the components, reducing the frequency of failures.

As shown in the graphs of Figure 8, both states, S_{DP} and S_F, comprise several states of the wind turbine with very different values of probabilities that are mainly due to the time spent in these states.

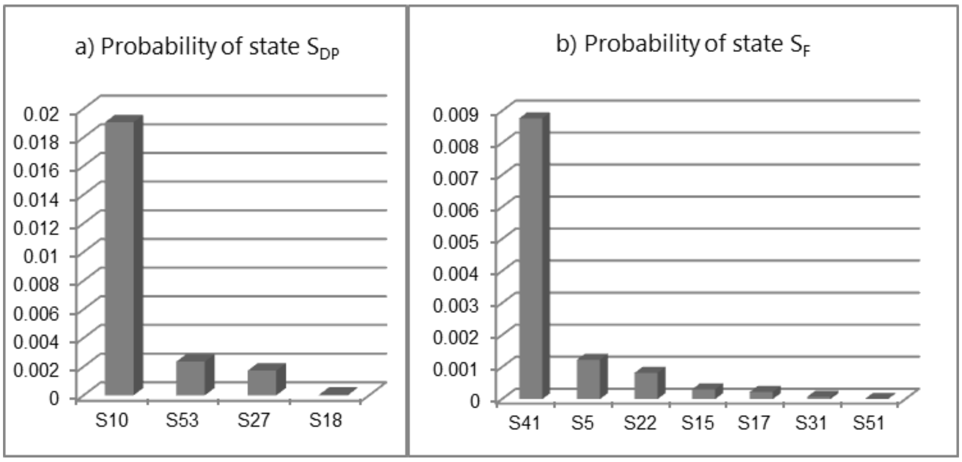

Figure 8. Probabilities of wind turbine states merged into aggregated states: a) S_{DP} and b) S_F.

The figure suggests that improvement opportunities can be found for states of partial operational readiness and operational availability.

The state that most contributes to the partial availability is state S_{10} which corresponds to the detection of ice on wind turbine blades. Ice, frost or snow caused by certain weather conditions can accumulate on wind turbines blades causing the occurrence of this state, and therefore a decrease in the efficiency of wind turbine or even the necessity of shut down the turbine. Accordingly, the maintenance team must perform a visual inspection and, if there is neither ice nor humidity, the wind turbine is manually restarted. On the other hand, if ice or humidity is detected, the restart is aborted and the wind turbine is placed in the state of unavailability, S_{31}. In this state, the wind turbine is heated to evaporate the ice and humidity before being restarted. It is a preventive protection operation of the generator, which, however, consumes energy thus reducing the production of the wind farm.

The state S_{10} (detection of ice) is the state that contributes most to the probability of the aggregate state of partial readiness S_{DP} (representing more than 80% probability) and so it is the state that should receive special attention by the team maintenance.

A similar analysis to the aggregated state of unavailability S_F identifies the state of the wind turbine S_{41} (protection circuit breaker tripped) as the one that contributes most to the aggregate state of failure S_F. All engines of the wind turbine have contactors, so that whenever an overcurrent is detected the wind turbine automatically shuts down to avoid damaging its main components. The restart of the wind turbine is made by after a maintenance inspection and verification of the cause of overcurrent.

From graph b) of Figure 6, about 77% of the wind turbine unavailability depends on state S_{41} (which in turn largely depends on the human intervention to reset the machine to its normal operation). State S_5, that exhibits the second highest probability among all the states of unavailability, also shows this situation: have a significant residence time and depends on the intervention of the maintenance team. That is, the states of the wind turbine that contribute most to the loss of availability are those states belonging to aggregate states S_{DP} and S_F whose residence times depend on the efficiency of maintenance teams.

4 Conclusions

The globalization of the economy and the increasingly demanding market, seeking products and systems with high performance at low cost, give rise to the need of minimizing failures and increasing the focus on reliability and maintainability functions due to their direct influence on the availability of products and technological systems.

RAM factors must be considered in all phases of the life cycle of a technological system to ensure optimum results in terms of life cycle cost. Among the costs associated with a wind system, operation and maintenance costs constitute an important fraction because they occur over a long period of time (about 25 years) and they directly affect the financial returns. Fortunately, wind farms owns extensive sets of data on the behavior (run, stop, crash, etc.) of its turbines, and so this fact can support the application of scientific analysis tools in order to help managers forming more efficient decisions at design and operational levels.

In this study, we evaluated the performance of wind turbines from the application of analysis techniques RAM to a data set of wind turbines in the states referring to two years of operation (2009 and 2010). The main findings were that the equipments exhibit high availability (greater than 95%), but there are still opportunities for improvement in terms of operation and maintenance policies as well as in terms of improving the reliability of critical components and parts. The cost of downtimes (opportunity costs for lost production) is of such magnitude, that very small gains in the availability of wind turbines (in the order of 1%) would allow a very significant increase in the turnover of the park.

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