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MODEL FOR THE ANALYSIS OF THE P-F INTERVAL IN PREDICTIVE OPTIMIZATION OF HYDROPOWER GENERATION PLANTS

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ABSTRACT

Hydropower plants have strict contractual requirements regarding availability and reliability in the production of electrical energy. In order to achieve this, there are different techniques of predictive maintenance, but for all of them there are two common problems (a) the time interval between in indicator of deterioration and the failure (P-F interval) and (b) the success rate of the inspection device (sensor). There is a gap in the literature about the optimal interval for different equipment and also about the success rate of sensors in each application.

In this paper, we propose a methodology based on data science in order to estimate the probable PF-interval using real data of failure, number failures in the past and a Monte Carlo simulation model. The model considers probability of time-to-failure of the equipment, probability of detection just before failure, decrease in probability of failure dependent on time interval before failure occurrence, cost of inspection, among others. This model is applied to a number of scenarios in order estimate the both success ratio and P-F interval using an algorithm specially developed to solve this problem.

We apply this model to a number of equipment in hydroelectric plants and construct rules-of-thumb for them in order to allow optimization of both successes of inspection programs and budget. This model is under way in the analysis of real data from a power generation company and initial results shows that they can be complemented with other research efforts in order to create, for example, a database with more complete information physical asset decision-makers.

1. INTRODUCTION

Hydropower plants have strict contractual requirements regarding availability and reliability in the production of electrical energy. In order to achieve this, companies make use of different techniques of predictive maintenance, to avoid time and cost of failures, such as vibration analysis, oil analysis, infrared thermography, acoustic/ultrasonic, electrical measures, etc. [1]. In case that failure is the end of a process, these techniques can identify that such failure is about to happen and then a preventive maintenance can be scheduled. For the application of all of these techniques there are two common problems (a) the time interval between an indicator of deterioration and the failure (P-F interval) and (b) the success rate of the inspection device (sensor).

One of the difficulties in RAM analysis (Reliability Availability and Maintainability analysis) is to model the efficiency of an inspection in order to identify a potential failure. For this problem, there is a gap in the literature about the predictive maintenance efficiency. For this reason, the objective of this paper is to present an approach to evaluate and set this efficiency during the validation process of an RAM analysis.

In this paper, we propose a methodology based on data science in order to estimate the probable PF-interval using real data of failure, number failures in the past and a Monte Carlo simulation model. The model considers probability of time-to-failure of the equipment, probability of detection just before failure, decrease in probability of failure dependent on time interval before failure occurrence, among others. We apply this model to a number of equipment in hydroelectric plants and construct rules-of-thumb for them in order to allow optimization of both successes of inspection programs and budget. This model is under way in the analysis of real data from a power generation company and initial results shows that they can be complemented with other research efforts in order to create, for example, a database with more complete information physical asset decision-makers.

This paper has 4 sections. In section 2 there is an overview of inspection (concepts, definition, etc.). Section 4 presents case application and results. Numerical data are not real because of confidentiality, although represent practical cases. Finally, section 4 presents final comments of this paper.

2. DETECTION PROBABILITY MODELING

For those failures that results from a degradation process (they do not happen suddenly), Moubray [2] presents the concept of decrease in asset's condition as illustrated in Figure 1.

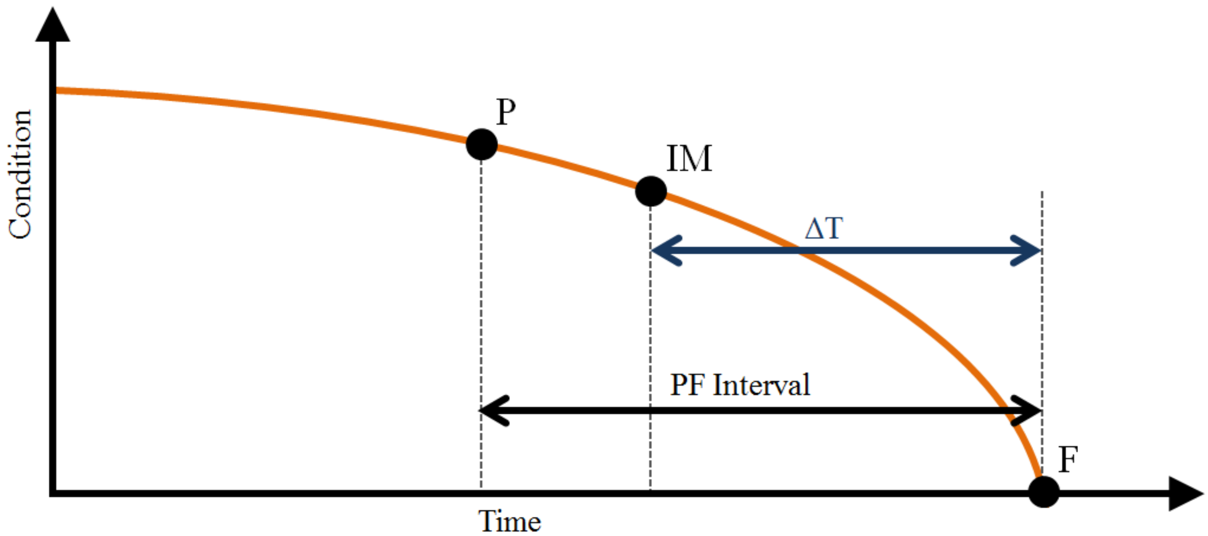


Figure 1 - P-F curve model (Source: adapted from [2])

The point "P" represents the moment when there is evidence that a failure is about to occur. This point is the limit of predictive technology. In order to move point P to left (farther from failure), one need more advanced predictive technology. Point "F" represents when the failure really occurs.

The PF interval is the distance in time between point "P" and "F". In Figure 1, additionally a point "IM" represents the inspection time, which depends on the inspection frequency. After the inspection, if there is any evidence that a failure is about to happen, it is possible to take action to prevent/avoid the consequences of the functional failure. In this case, inspection can be visual or by instrumentation.

The failure detection probability measures the efficiency of an inspection. In practice, there is a spectrum of probability to describe the PF curve. One way of equating this failure detection probability is with a linear model:

$$P(\Delta t) = \begin{cases} P_D\left(1 - \dfrac{\Delta t}{t_{PF}}\right) & for\ \Delta t \leq t_{PF} \\ 0 & for\ \Delta t > t_{PF} \end{cases} \tag{1}$$

where P_D represents the inspection's probability of detecting the failure immediately before its occurrence, t_{PF} is the PF interval and Δt the time difference between point IM and F (see Figure 1 again).

To illustrate the application of equation 1, consider that parameters $P_D = 100\%$ and $t_{PF} = 120$ hours are employed to define the curve displayed in Figure 2.

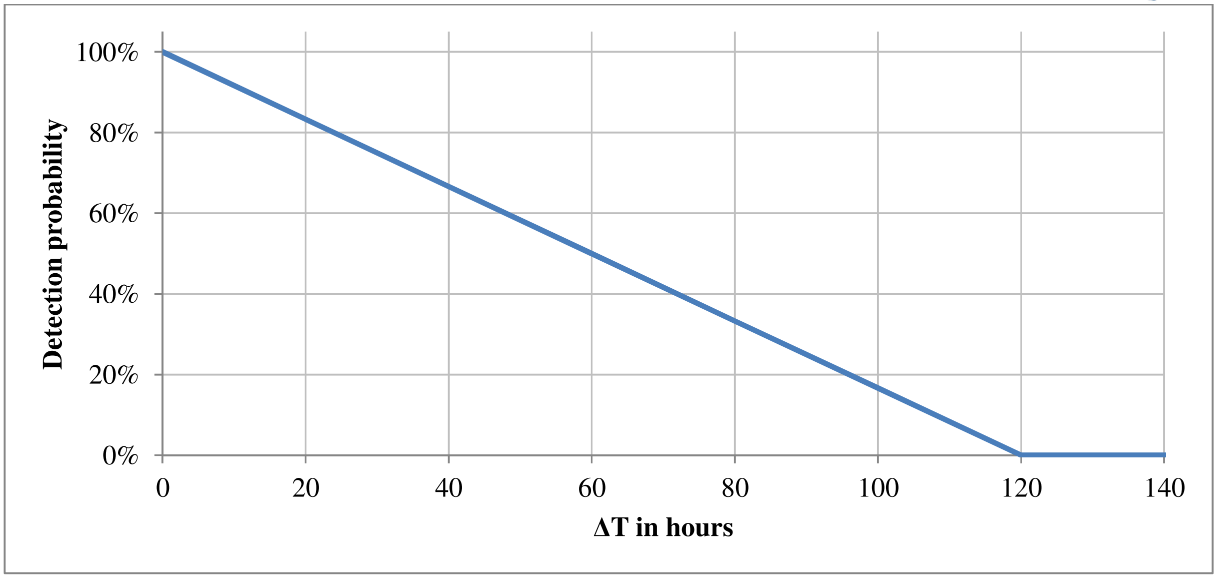


Figure 2 - Detection probability as function of Δt

In Figure 2 is easy to see that with linear model the detection probability decreases linearly until to reach 0% in the PF interval in the time interval larger than 120 hours far from failure. On the other case, just before the failure, the probability of detection is 100%.

3. NUMERICAL EXAMPLE AND DISCUSSIONS

The first numerical example considers a potential transformer with time to failure modeled by an exponential distribution with mean equal to 6.500 hours and time to repair negligible. If the inspection is performed each 730 hours and the PF curve model is linear with $P_D$equal to 100%, the relations between mean number of correctives and preventives maintenance in a lifetime of 10 years versus PF interval are expressed in Figure 3.

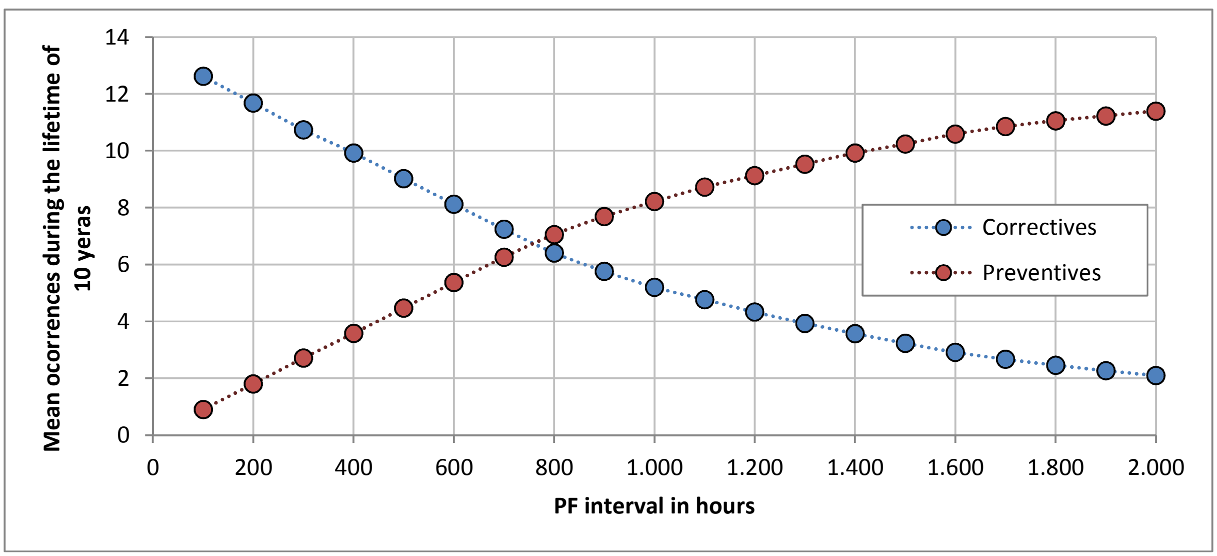


Figure 3 - Numbers of correctives and preventives versus PF interval.

The results of Figure 3 are based on 10.000 simulations in the software Availability Workbench. If the expected number of failures is about 8 in 10 years, the PF interval of 1.000 hours is a good estimation of the PF interval parameters. So, the analyst can adjust the PF interval parameter to validate the equipment/system performance.

In a power generation plant it is common to find subsystems with several components in series. In this sense and in order to supply a numerical example to discuss the proposed PF interval definition approach, first is considered one Reliability Block Diagram (RBD) in Figure 4.

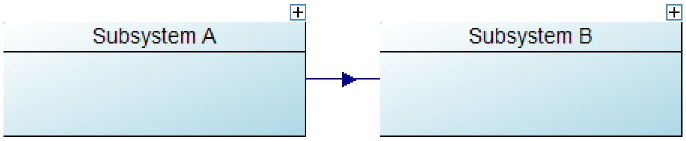
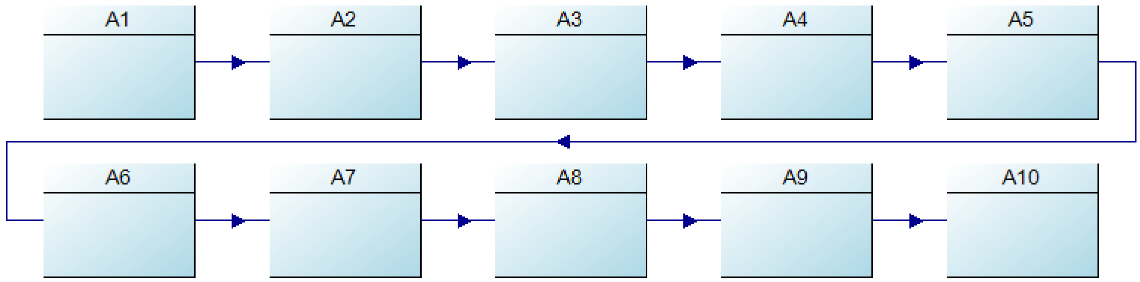
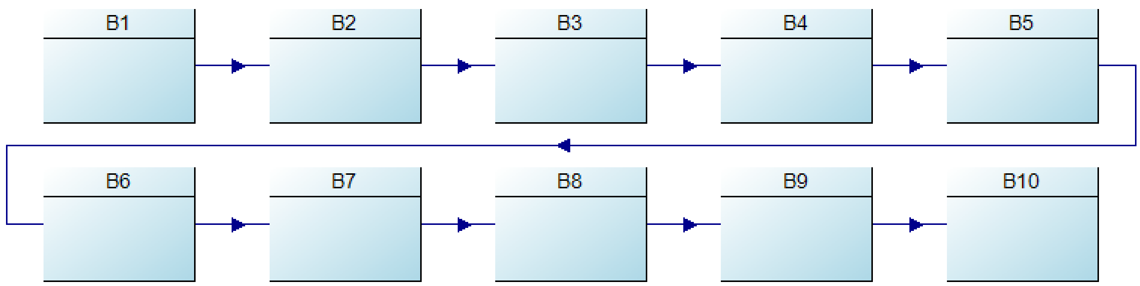


Figure 4 – Reliability Block Diagram of the System

In Figure 4, note that there are two subsystems in series. It means that the unavailability of any of the two subsystems implies in the system unavailability. Each of the subsystems A and B has a number of components as shown in Figure 5.



(a)



(b)

Figure 5 – Reliability Block Diagram of the Subsystem A and B.

Figure 5 (a) indicates that the subsystem A has 10 identical components of the type A. Similarly, Figure 5 (b) indicates that the subsystem B has 10 identical components of the type B. The following assumptions are considered in this study:

- For the component type A, the time to failure is modeled by an exponential with mean equal to 12.000 hours, corrective and preventive maintenance time are 120 hours and 48 hours, respectively, and the inspection interval is 730 hours;
- For the component type B, the time to failure is modeled by an exponential with mean equal to 26.000 hours, corrective and preventive maintenance time are 180 hours and 72 hours, respectively, and the inspection interval is 4.380 hours.

Considering 10 years of simulation and 1.000 simulations, the Table 1 summarizes, for the subsystem A, the mean downtime in hours as a function of the PF interval in hours for its related inspections.

Table 1 - Mean total downtime in hours of the subsystem A according to the respective PF interval associated with the inspection of the components of this subsystem.

PF interval (hours)	360	480	600	720	840	960	1.080
Mean total downtime (hours)	7.091	6.772	6.351	5.956	5.643	5.350	5.161

PF interval equal to 360 hours implies in a mean total downtime of the subsystem A equal to 7.091

hours. As the PF interval increases, the mean total downtime of the subsystem A increases too.
Similarly, Table 2 summarizes, for the subsystem B, the mean downtime in hours as a function of the PF interval in hours for its related inspections.

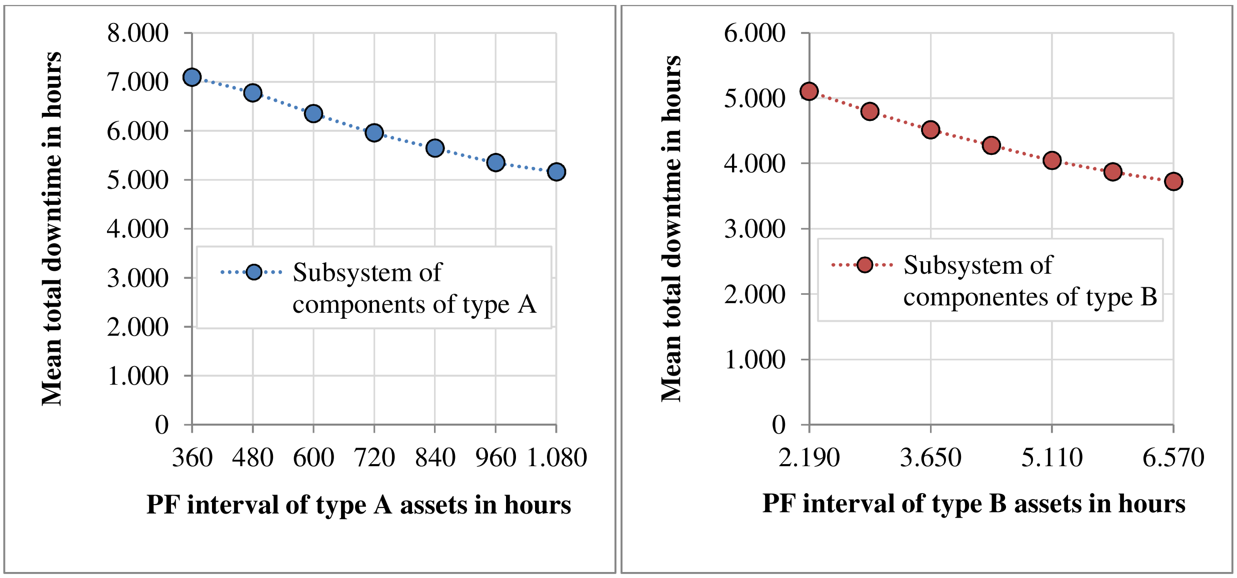
Table 2 – Mean total downtime in hours of the subsystem B according to the respective PF interval associated with the inspection of the components of this subsystem.

PF interval (hours)	2.190	2.920	3.650	4.380	5.110	5.840	6.570
Mean total downtime (hours)	5.103	4.794	4.516	4.278	4.046	3.869	3.721

PF interval equal to 2.190 hours implies in a mean total downtime of the subsystem B equal to 5.103 hours. Again, as the PF interval increases, the mean total downtime of the subsystem B increases too.

For both simulations (presented in Table 1 and 2), the range tested was based on plausible possibilities of PF interval. It means that, at this point, extra information, like analyst´s experiences, is important.

Figure 6 presents the data from Table 1 and 2 in form of chart.



(a) (b)

Figure 6 – Mean total downtime in hours of each subsystem according to the respective PF interval associated with the inspection of the components of the subsystem.

Note that both mean total downtime decreases with similar pattern.

During a validation processes, if the total downtime was expected to be around 6.000 hours for the subsystem A, a reasonable a PF interval is approximated to 720 hours. In other words, the total downtime observed in practice cannot be strongly different from the simulated after the validation. So the PF interval can be estimated to generate a reasonable mean total downtime.

Table 3 contains the impacts of the set of PF intervals, for type A and B, in the mean system total downtime.

Table 3 – Mean system total downtime (in hours) based on the PF intervals (in hours) of inspections associated with type A e B assets.

PF interval of type A assets	**PF interval of type B assets**						
	2.190	2.920	3.650	4.380	5.110	5.840	6.570
360	11.786	11.570	11.308	11.052	10.863	10.668	10.529
480	11.428	11.090	10.892	10.704	10.438	10.270	10.200
600	11.060	10.743	10.501	10.323	10.087	9.944	9.788
720	10.681	10.422	10.193	9.887	9.755	9.561	9.453
840	10.404	10.088	9.856	9.650	9.459	9.297	9.136

960	10.071	9.793	9.593	9.374	9.175	9.035	8.847
1.080	9.835	9.641	9.419	9.096	8.946	8.750	8.648

According to the sets studied the mean system downtime can range from 8.648 hours to 11.786 hours. The Figure 7 presents the Table 3 as a chart.

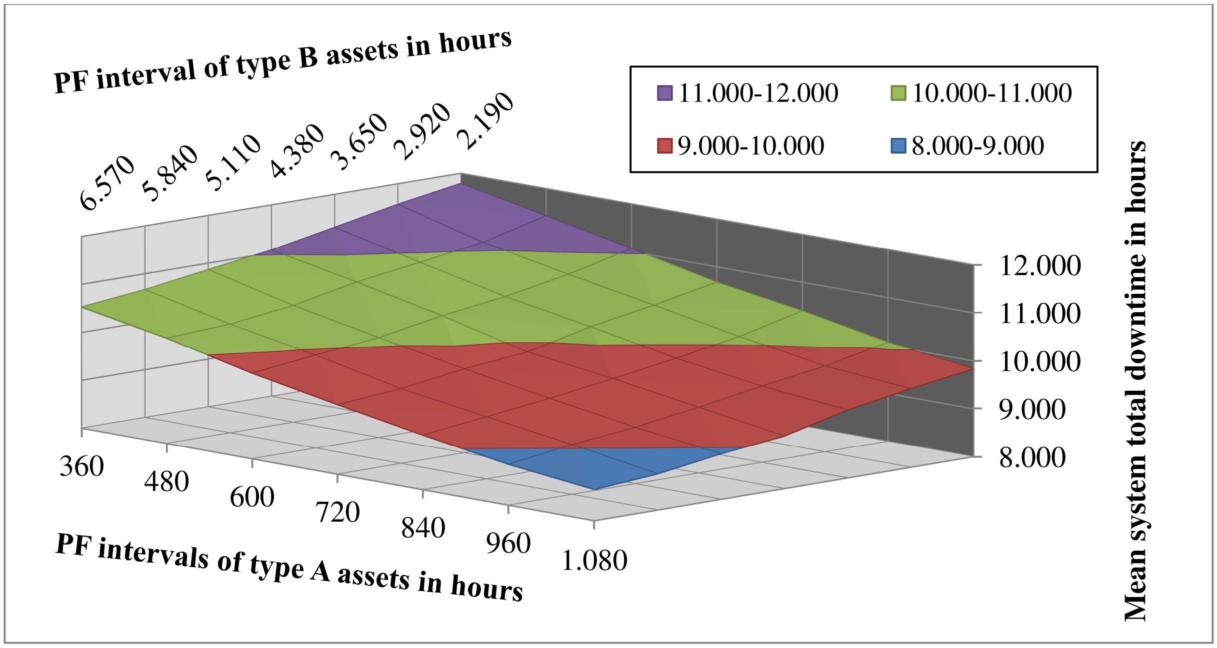


Figure 7 – Mean system total downtime (in hours) based on the PF intervals (in hours) of inspections associated with type A e B assets.

The different colors indicate the different ranges of mean system total downtime. It's possible to notice that different set of PF intervals can result in the same mean system total downtime. So, it´s important to have more than one target to validate the PF curve parameters, as the subsystems total downtime.

During the validation process some source of errors can make the definition of the PF intervals more complex, one example is the corrective maintenance delay time. In Figure 8 the plot contains the relationship between simulated mean system total downtime and logistic delay time of any corrective maintenance. This logistic delay time of corrective maintenance is the time spent between the failure moment and the initiation of the corrective maintenance.

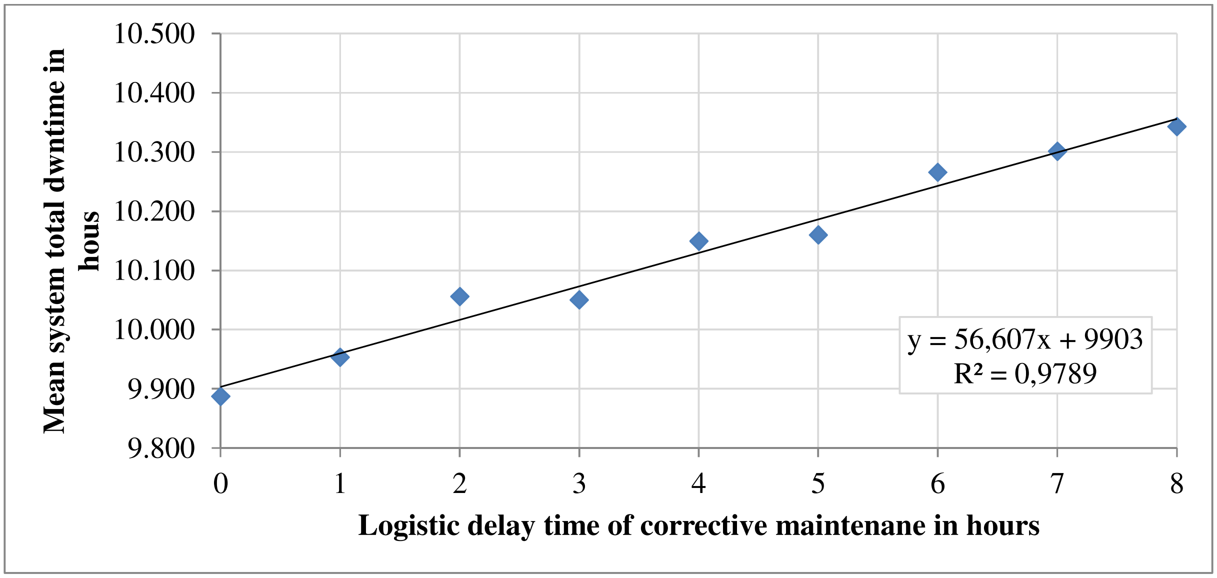


Figure 8 – Mean system total downtime due to logistic delay of corrective maintenance.

In Figure 8 is possible to notice that the mean system total downtime increases proportionally to the logistic delay time. Based on the expectation that more inspections used to identify a future failure must decrease the number of corrective maintenance, the logistic delay time affects the validation process too. So this is another variable which the analyst must be aware during the definition of PF interval. In other words, an unrealistic the corrective delay time can be misleading to the PF interval definition.

4. FINAL COMMENTS

The definition of the parameters of a PF curve is not trivial. This paper showed that, belong of using only the subjective assessment of the analyst team or information from the inspection system manufacturer, the validation process of model based on RBD simulation is an great opportunity to refine the definition of the PF curve parameters. Another important observation was that, during the validation process, to ignore some sources of error like logistic delay time of corrective maintenance must be misleading to PF curve parameters definition.

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REFERENCES

[1] GULATI, R. *Maintenance and reliability: Best practices*. Industrial Press, Inc. New York, NY, Estados Unidos, 2009.

[2] MOUBRAY, J. *Reliability centered maintenance II*. Butterworth-Heinemann, Jordan Hill, Oxford, Reino Unido, 1997.