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Optimizing Preventive Maintenance Policies: A Hydroelectric Power Plant Case Study

Fabio Henrique Pereira

Informatics and Knowledge Management Graduate Program, Universidade Nove de Julho, Brazil. E-mail: fabiohp@uni9.pro.br

Arthur Henrique de Andrade Melani

Department of Mechatronics and Mechanical Systems, University of São Paulo, Brazil. E-mail: melani@usp.br

Tiago Gaspar da Rosa

Mechanical Engineering Graduate Program, University of São Paulo, Brazil. E-mail: tiago.gaspar@usp.br

Fabio Norikazu Kashiwagi

Department of Mechatronics and Mechanical Systems, University of São Paulo, Brazil. E-mail: fabiokashiwagi1976@gmail.com

Marcos Antonio Coque Junior

Mechanical Engineering Graduate Program, University of São Paulo, Brazil. E-mail: mcoquejr@yahoo.com.br

Gilberto Francisco Martha de Souza

Department of Mechatronics and Mechanical Systems, University of São Paulo, Brazil. E-mail: gfmsouza@usp.br

Gisele Maria De Oliveira Salles

Companhia Paranaense de Energia – COPEL, Brazil. E-mail: gisele.salles@copel.com

Optimizing preventive maintenance (PM) policies consists of determining the optimal times for carrying out maintenance actions to minimize the process's total cost. The longer the time interval between preventive maintenance, the lower the corresponding cost. On the other hand, longer intervals between PMs increase the expected number of failures and, consequently, the need for corrective actions that increase the overall maintenance cost. Preventive maintenance actions are associated with a level of interventions, which can be defined as a weighted average of the number of tasks performed, the execution time, and the number of items replaced in the maintenance plan. Therefore, the objective of this work is to propose a method to determine the preventive maintenance intervals and the efficiency of these maintenance actions to minimize the total cost of a fixed horizon planning process. In general, the level of interventions is treated as a variable dependent on preventive maintenance time, which means that the longer the time interval between PMs, the greater the level of intervention of the maintenance action should be, in theory, and consequently, the greater its cost. In the optimization process proposed in this work, however, the level of interventions is treated as an independent variable of PM intervals, representing a contribution of this paper, and providing greater flexibility in the creation of maintenance plans. To validate the proposed method, it is applied to the preventive maintenance policies of a hydroelectric power plant in southern Brazil. Results show that optimizing maintenance intervals can significantly reduce the total cost of maintenance.

Keywords: Preventive Maintenance, Imperfect Maintenance, Hydroelectric Power Plant

1. Introduction

The critical role of an effective maintenance policy in ensuring a system's reliability, safety, and risk mitigation is widely recognized. It is imperative to establish a strategic plan for preventing unexpected disruptions or, should they occur, to facilitate prompt resolutions and maintain the system's optimal performance. Proper maintenance not only reduces expenses but also prolongs the system's lifespan and enhances efficiency (Panneerselvam 2012, Melani *et al.* 2018).

Preventive Maintenance (PM) is a vital strategy involving the systematic implementation of maintenance activities on equipment or systems to preclude unexpected malfunctions or failures. PM is crucial for maintaining the optimal operational condition of equipment and systems by addressing potential issues before they cause downtime or safety hazards (Melani *et al.* 2019). As a result, optimizing the intervals between PM tasks is essential for minimizing overall maintenance expenses.

Although many authors assume that, when performing PM activities on a given piece of equipment, it returns to As Good As New (AGAN) operation, this is not always the case. Imperfect maintenance is the maintenance activity classification that considers that the equipment can return in a state somewhere between AGAN and its pre-maintenance condition. Imperfect maintenance measures are associated with a level of intervention that considers the number of tasks performed, the execution duration, and the items replaced within the maintenance plan (van Noortwijk 2009). The level of intervention determines how close to AGAN condition will the equipment have after a given PM action.

When planning the frequency of PM activities for a given system, the objective is to minimize the total cost associated with maintenance. This total cost is dependent not only on the amount of planned PM activities in a given period, but also on the number of times the equipment will fail and have to undergo corrective maintenance. When performing such optimization activity, however, few authors explore the concept of imperfect maintenance.

To optimize PM policies considering imperfect maintenance activities, one must consider the level of intervention of each activity, the cost associated with each activity (considering that, the greater the severity, the greater the cost), and the time intervals between each PM activity.

In this paper, a method that treats the level of intervention of maintenance activities as an independent variable of PM durations is proposed. This approach offers increased flexibility in formulating maintenance plans by considering practical factors that may affect maintenance activities beyond the time interval between PMs. Additionally, the proposed method utilizes a reliability model incorporating imperfect preventive maintenance and a variable improvement factor based on age reduction. The improvement factor for each PM is determined by the maintenance action's level of intervention, which depends on the number of tasks performed and execution duration.

This study's primary application lies in optimizing the maintenance policy for heat exchangers in a hydroelectric power plant plagued by a specific failure mode: clogging due to the proliferation and encrustation of golden mussels. This invasive mollusk species has recently been introduced into the river where the plant is situated, causing recurrent failures in the plant's heat exchange system. As the heat exchange process utilizes river water, the mussels have encrusted themselves within the exchanger pipes, resulting in constant disruptions. The proposed method aims to establish an optimized maintenance policy to address this issue.

The developed maintenance framework not only determines the optimal timing for preventive maintenance and the corresponding level of intervention but also identifies the optimal number of maintenance activities to minimize the total maintenance cost in a fixed user-specified planning horizon. Genetic algorithm solutions are employed for representation and decoding, designed to simultaneously evaluate the timing, level of intervention, and quantity of maintenance activities.

2. Imperfect Maintenance

The concept of imperfect maintenance has piqued the interest of researchers since the latter half of the 1970s, with seminal contributions from notable researchers such as Kay (1976), Chaudhuri and Sahu (1977), Chan and Downs (1978), and Nakagawa (1979). Kay (1976) focused on the efficacy of preventive maintenance. Chaudhuri and Sahu (1977) proposed a model for determining the optimal preventive maintenance intervals for both perfect and imperfect PM. Chan and Downs (1978) developed two criteria for preventive maintenance analysis, employing a state transition diagram to depict preventive maintenance, considering a probability p of not restoring a component to an As Good As New condition.

Nakagawa (1987) has been particularly engaged in this area, taking the assumption of imperfect preventive maintenance into account when defining optimal preventive maintenance policies. Although most of the research on imperfect maintenance focuses on single-unit systems (Wang and Pham 2006), this concept can also be applied to multi-component systems, which are more commonly encountered in real-world problems.

Recent literature highlights a shift towards practical implications of imperfect maintenance. Sanchez et al. (2009) addressed the optimization of testing and maintenance activities with uncertainty in imperfect maintenance modeling and emphasized the importance of accounting for uncertainties in imperfect maintenance modeling, as they affect system unavailability and cost. Mabrouk et al. (2016) presented a model for determining the optimal PM scheduling strategy for leased equipment, considering that both PM and CM are imperfect, and incorporated penalty costs into the model. Pandey et al. (2016) proposed a mathematical model for decision-making on selective maintenance actions under imperfect repair for binary systems, focusing on both the optimal utilization of available resources and maximizing the reliability of the subsequent mission.

Le and Tan (2013) examined the optimal maintenance strategy for systems subjected to degradation conditions and imperfect maintenance, recommending a combined approach that incorporates both inspection and continuous monitoring activities to enhance system reliability. As evidenced by the volume of recent publications, interest in imperfect maintenance persists, and researchers are becoming increasingly conscious of the necessity to consider this form of maintenance in both theoretical and practical issues.

3. The Proposed Method

The methodological procedure adopted in this work can be divided into 1) the adjustment of the reliability model from the actual data and 2) the imperfect preventive maintenance optimization that consists of determining the number, times, and level of intervention for preventive maintenances, that minimizes the total maintenance cost in a fixed planning horizon.

3.1 Adjustment of the reliability model

The reliability model is based on a non-homogeneous Poisson process (NHPP), with the traditional Power Law to characterize the failure intensity function, according to equation (1),

$$u(t) = \frac{1}{\lambda^{\beta}} \cdot \beta \cdot t^{(\beta-1)} \tag{1}$$

So, the adjustment of the model consists of estimating model parameters λ and β (λ is the parameter of scale and can be interpreted as time during which exactly a failure is expected to occur, and β is the parameter of shape and it represents the variability of the expected number of faults compared to time). The parameters λ and β are used to define the function that describes the accumulated number of expected failures to time t.

The proposed model also considers the imperfection of preventive maintenance, which means that it is also necessary to estimate the improvement factor $a(s_j)$ that represents the influence of maintenance action on system failure intensity. In this paper, the improvement factor is based on age reduction, and it is defined as a function of the level of intervention s, according to equation (2) in which s_j is the level of intervention of the j-th preventive maintenance action (j=1, …, c).

$$a(s_j) = 1 - EXP(-s_j \cdot \theta), j = 1, \ldots, c \tag{2}$$

The failure intensity function is rewritten by applying the improvement factor $a(s_j)$ after each preventive maintenance action in the instant T_j, according to equation (3),

$$u(t) = \frac{1}{\lambda^{\beta}} \cdot \beta \cdot (t - a(s_j) \cdot T_{j-1})^{(\beta-1)}, \quad T_{j-1} \le t < T_j \tag{3}$$

Thus, the age of the system is adjusted to an intermediate condition proportional to the factor $a(s_j)$.

The adjustment of the reliability model is performed by obtaining the value of the parameters λ, β and θ using the traditional maximum likelihood estimation method, defined as equation (4):

$$L(\lambda,\beta,\theta)=\prod_{j=1}^{c}\left[\prod_{i=1}^{n_j}\frac{1}{\lambda^{\beta}}\cdot\beta\cdot(t_{j,i}-a(s_{j-1})T_{j-1})^{\beta-1}\right] \cdot EXP\left[-\sum_{j=1}^{c}\left(\frac{1}{\lambda^{\beta}}\cdot(T_j-a(s_{j-1})T_{j-1})^{\beta}-\frac{1}{\lambda^{\beta}}\cdot((1-a(s_{j-1}))T_{j-1})^{\beta}\right)\right] \tag{4}$$

in which n_j is the number of failures in j-th PM cycle at times $t_{j,i}$.

3.2 Imperfect preventive maintenance optimization

The second stage of the optimization process consists of finding values for the number of preventive maintenance and their respective times and intervention levels, considering a planning horizon of 180 days. Each candidate solution is associated to a total cost, which is obtained by adding the preventive and corrective maintenance costs along the planning horizon (180 days).

This stage of optimization was performed using the genetic algorithm, following the steps illustrated in the pseudocode of Figure 1. Each element $X=\{x_0,\cdots,x_{N-1}\}$ in a set of candidate solutions, called population, is encoded as a set of decimal values (value encoding). Such values are used to determines the number of PM activities (c), and the times and level of intervention for these activities, T_j and s_j, for $j=1,\ldots,c$, according to the decoding process defined in the algorithm of Figure 2.

It is noteworthy that other optimization approaches, such as those based on exact methods, for example, could be applied to solve this problem. In particular, the application of the Nelder-Mead method, commonly used in nonlinear optimization problems as addressed in Lin and Pham (2022), did not produce better results compared to AG for this application. In addition, analytical methods that require the probability of failure to be constant over time cannot be applied to the problems in which non-homogeneous counting processes are necessary, such as the examples dealt with in this work (Hafver et al., 2019).

```
START
Generate an initial population
Compute fitness of individuals
REPEAT
    Selection
    Crossover
    Mutation
    Compute fitness
UNTIL stop criterion is satisfied
STOP
```

Figure 1. Genetic algorithm pseudocode.

Algorithm: Decoding process
Input: candidate solution X
admitted intervention levels $S^*=\{s_1^*,\ldots,s_v^*\}$
basic time interval n
Output: c; $T=\{T_1,T_2,\ldots,T_c\}$; $S=\{s_1,s_2,\ldots,s_c\}$

$c=0$; $T=\emptyset$; $S=\emptyset$
for all $x_i\in X$
Decompose x_i in integer part $\lfloor x_i\rfloor$ and fractional part $\{x_i\}$: $\{x_i\}=x_i-\lfloor x_i\rfloor$
if $mod(\lfloor x_i\rfloor,2)==1$
$c=c+1$
$s_c=s^*_{(\lfloor x_i\rfloor+1)/2}$
$T_c=n(i+\{x_i\})$
$T=T\cup\{T_c\}$ e $S=S\cup\{s_c\}$
end if
end for

Figure 2. Proposed decoding process.

In Figure 2, the admitted intervention levels depend on the application and must be provided by the user. The basic time interval is defined here as the minimum time interval that contains a single preventive maintenance action (in the case of this work equal to 7 days).

Each element x_i of a candidate solution X is defined in the interval $(0;2v)$, in which v is the number of admitted intervention levels, in order ensure equal probability for even and odd values.

The decimal part $\{x_i\}$ of the number x_i represents a fraction of the basic time interval n and determines the exact day to perform the preventive maintenance.

After the decoding process, solutions are evaluated by calculating their fitness values according to the equation (5)

$$C_{TOT}(T,S,c) = \sum_{j=1}^{c} C_{PM}(s_j) + E[N(t)]\, C_{CM} \quad (5)$$

in which C_{PM} and C_{CM} means the preventive and corrective maintenance costs, respectively, and $E[N(t)]$ represents the expected number of failures during the planning horizon *N*.

4. Case Study

The case study addressed consists of three heat exchangers located in the hydroelectric power plant. Although similar equipment and work under similar conditions, the location of equipment on the riverbed can influence the process encrustation of golden mussels, which suggests that heat exchangers data will be evaluated separately. Failure data obtained for 300 days of observation are presented in Table 1 for k = 1, 2, 3 exchangers.

Table 1. Heat exchangers failure data

k=1			*k*=2			*k*=3		
Time *t* (days)	Event	*s*	Time *t* (days)	Event	*s*	Time *t* (days)	Event	*S*
0.00	Start	-	0.00	Start	-	0.00	Start	-
39.68	Failure	-	29.56	Failure	-	52.13	Failure	-
51.99	Failure	-	48.12	Failure	-	75.27	Failure	-
64.76	Failure	-	60.00	PM	0.8	89.45	Failure	-
80.00	PM	1.0	99.78	Failure	-	105.69	Failure	-
127.74	Failure	-	125.96	Failure	-	120.00	PM	1.0
144.21	Failure	-	140.00	PM	0.8	174.89	Failure	-
154.88	Failure	-	194.21	Failure	-	217.62	Failure	-
160.00	PM	1.0	227.26	Failure	-	233.97	Failure	-
234.88	Failure	-	233.97	Failure	-	240.00	PM	0.8
263.97	Failure	-	240.00	PM	0.8	284.37	Failure	-
285.35	Failure	-	294.88	Failure	-	300.00	End	-
300.00	End	-	300.00	End	-			

Additionally, corrective maintenance costs were set at $C_{CM} = 30000$ monetary units and the cost of preventive maintenance defined as a function of the level of intervention s, according to equation (3), which can be adjusted according to the problem,

$$C_{PM} = 1500 * s + 500 \quad (3)$$

All results presented here were obtained applying the genetic algorithm with parameters empirically defined according to Table 2. The results are presented as the average of 10 replications for each example with the respective sampling error ε with a level confidence of 95%, for the adjusted parameters of model.

Table 2. Genetic algorithm parameters

Parameter	Value
Number of iterations	100
Population size	100
Mutation rate	1%
Crossover rate	90%
Crossover operator	Two-point
Elitism rate	5%

First, we present the model adjustment results for the three cases discussed in this work. In Table 3 are the average values for parameters λ, β, θ in ten runs, which are used for optimization of predictive maintenance times and intervention levels in the second stage of optimization. The model adjustment results show a similarity in the values of λ and β for the three equipment, but a significant variation in parameter θ. It is worth remembering that this parameter is directly related to the preventive maintenance improvement factor, so the results indicate greater effectiveness of preventive maintenance in this case. A deeper discussion of this result may be based on the analysis of the results of optimization of time and intervention levels of preventive maintenance, as shown in Table 4. In this case, we present the results obtained in the ten replications of the genetic algorithm as variations in the responses are characteristic of this method.

Table 3. Model adjustment results

k	Measure	λ	β	θ
1	Mean	100.0816	1.9865	0.9690
	ε	0.1176	0.0038	0.0189
2	Mean	100.4445	1.9834	1.1862
	ε	0.2237	0.0108	0.0333
3	Mean	100.7491	1.9796	1.6559
	ε	0.3356	0.0109	0.0408

Despite variations in different algorithm executions, it is possible to see the effects of preventive maintenance in the three cases. It can be observed, for example, that the indicated number of preventive maintenance (c) seems to be directly proportional to the effectiveness of the maintenances.

Thus, the higher the value of the parameter θ, the higher the indicated number of maintenances, which resulted in most often values (mode) equal to 4, 5 and 6 to k = 1, 2 and 3, respectively (θ of 0.9690, 1.1862 and 1.6559). This effect can also be observed in the admitted intervention levels to each equipment. While heat exchangers 1 and 2 generally require an intervention of 100%, the equipment k=3 admits interventions of 60% and 70%, for example. Interestingly, for k=3, lower intervention levels maintenance is indicated at the beginning of the planning horizon, maybe due to the higher reliability at the beginning of the analysis period and greater effectiveness of preventive maintenance in this case (higher value of θ).

It is also important to comment the results regarding total maintenance costs in each case. It is noted that a greater number of preventive maintenances represent a reduction in the total cost that is dependent on the effectiveness of this action. This behavior is due to the reduction of the expected number of failures after preventive maintenance, which is also valid for maintenance actions with lower intervention levels, even if the effect is less pronounced in these cases.

5. Conclusions

In this paper, we presented a method for optimizing preventive maintenance policies, considering both the time intervals between maintenance actions and the intervention levels of these actions as independent variables. The proposed approach allowed for greater flexibility in the creation of maintenance plans and contributed to minimizing the total cost during a fixed user-defined planning horizon. The reliability model considered imperfect maintenance and incorporated a variable improvement factor based on age reduction.

The case study, focused on heat exchangers in a hydroelectric power plant in southern Brazil, demonstrated the applicability and effectiveness of the proposed method. It provided valuable insights into the relationship between the effectiveness of preventive maintenance and the optimal number of maintenance actions. Furthermore, it revealed that lower intervention level of maintenance actions might still be beneficial in reducing total maintenance costs, depending on the equipment's characteristics and maintenance effectiveness.

The results obtained in this work support the relevance of considering imperfect maintenance in the development of optimized maintenance plans. The ability to treat intervention level as an independent variable of PM intervals represents a significant contribution, as it provides a more practical and flexible approach for dealing with real-world maintenance scenarios.

Future research could explore the applicability of this method to other industrial sectors and equipment types and investigate the incorporation of additional factors, such as environmental or operational conditions, in the optimization process.

Table 4. Optimization results of preventive maintenance times and intervention levels, for a planning horizon of N=180 days. Best results are highlighted.

k	c	T_j	s_j	$C_{TOT}(T_j, s_j, c)$
1	4	40, 76, 115, 139	1.0, 1.0, 1.0, 1.0	**309.77*N**
	4	43, 82, 112, 143	1.0, 1.0, 1.0, 1.0	318.28*N
	5	27, 57, 80, 113, 147	1.0, 1.0, 1.0, 0.9, 1.0	318.32*N
	5	20, 56, 83, 120, 137	0.8, 1.0, 1.0, 1.0, 1.0	320.07*N
	4	40, 80, 114, 149	1.0, 1.0, 1.0, 1.0	314.02*N
	4	27, 60, 97, 141	0.9, 1.0, 1.0, 1.0	318.39*N
	4	44, 74, 112, 155	1.0, 1.0, 1.0, 1.0,	328.89*N
	5	22, 47, 87, 128, 161	0.8, 1.0, 1.0, 1.0, 1.0	319.25*N
	4	26, 65, 103, 142	1.0, 1.0, 1.0, 1.0	326.45*N
	4	27, 64, 105, 143	1.0, 1.0, 1.0, 1.0	318.33*N
2	5	32, 62, 92, 116, 145	1.0, 1.0, 1.0, 1.0, 1.0	296.93*N
	5	35, 54, 88, 119, 150	0.9, 1.0, 1.0, 1.0, 1.0	275.19*N
	5	34, 57, 85, 116, 144	0.9, 1.0, 1.0, 1.0, 1.0	292.29*N
	6	35, 58, 80, 103, 126, 151	1.0, 1.0, 1.0, 1.0, 1.0, 1.0	283.19*N
	5	36, 61, 100, 126, 157	0.9, 1.0, 1.0, 1.0, 1.0	297.37*N
	5	25, 54, 88, 126, 155	1.0, 1.0, 1.0, 1.0, 1.0	276.54*N
	5	29, 54, 85, 117, 149	1.0, 1.0, 1.0, 1.0, 1.0	281.67*N
	5	35, 56, 84, 103, 142	0.9, 1.0, 1.0, 1.0, 1.0	292.19*N
	5	29, 54, 80, 111, 149	1.0, 0.9, 1.0, 1.0, 1.0	274.84*N
	5	30, 61, 91, 118, 142	1.0, 1.0, 1.0, 1.0, 1.0	**274.21*N**
3	6	22, 43, 71, 94, 121, 154	0.7, 1.0, 1.0, 1.0, 1.0, 1.0	**224.36*N**
	5	36, 58, 91, 126, 153	1.0, 1.0, 1.0, 1.0, 1.0	234.33*N
	6	23, 42, 65, 92, 117, 148	0.6, 1.0, 1.0, 1.0, 1.0, 1.0	235.90*N
	5	25, 54, 82, 117, 154	1.0, 1.0, 1.0, 1.0, 1.0	243.13*N
	6	28, 50, 75, 100, 125, 163	0.9, 1.0, 1.0, 1.0, 1.0, 0.9	244.08*N
	6	22, 44, 69, 107, 134, 161	0.7, 1.0, 1.0, 0.9, 1.0, 1.0	234.60*N
	6	30, 54, 80, 103, 128, 150	0.8, 1.0, 1.0, 1.0, 1.0, 1.0	232.76*N
	5	30, 61, 91, 119, 149	1.0, 1.0, 1.0, 1.0, 1.0	226.10*N
	6	22, 44, 66, 93, 116, 147	0.7, 1.0, 1.0, 1.0, 1.0, 1.0	227.80*N
	5	26, 50, 73, 107, 146	0.8, 1.0, 1.0, 1.0, 1.0	234.27*N

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