Optimal maintenance management for synchronous generators: a condition-based approach to predict and assess equipment wear

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Abstract. Currently, effective and early detection of potential failures is of paramount importance in power generation systems, posing a significant challenge for generating companies. This article proposes optimal maintenance policies using a condition-based maintenance (CBM) architecture for a case study based on a synchronous generator. These policies are defined based on the estimated degradation index of the different components of the synchronous generator. The results obtained demonstrate that the proposed model is capable of suggesting an accurate optimal maintenance policy by relating the severity of component damage to the average maintenance cost.

1 Introduction

Usually, the working environment to which synchronous generators are exposed within power plants tends to be demanding. This implies that system components undergo a certain level of degradation in performance as operating time increases. When this degradation exceeds a specified tolerance threshold, unexpected failures begin to occur if not addressed promptly [1]. Nowadays, timely maintenance management to reduce associated costs is a topic of significant interest for generating companies. They aim to substantially reduce the total maintenance cost and improve system availability. A model analyzing quantitative optimization for the maintenance of a generation system is presented in [2], and conditions enabling reliable monitoring are described in [3].

Over the years, several studies have attempted to establish the correct maintenance policy for power generation systems, resulting in a combination of guidelines and strategic actions for preventive, corrective, and predictive maintenance [4], [5].

In recent years, Condition-Based Maintenance (CBM) has become prominent in efforts to reduce downtime and maintenance costs. CBM can be implemented through continuous monitoring of machine state and effective maintenance scheduling. In other words, maintenance is recommended when any abnormal behavior in system performance is anticipated. Consequently, constant monitoring of system states has become a crucial element to improve production and profits in industries, avoiding costly losses in such extensive systems [6]. A model describing the reliability acquired by systems with degrading components and providing guidelines to minimize maintenance costs, strengthening CBM policies, is described in [7].

The study in [8] presents models of performance degradation of components in a generation system and their assumptions, as well as a maintenance cost function for the condition in which a specific component is analyzed. Moreover, within the proposal to optimize predictive maintenance schemes based on condition (continuous monitoring) for a generation system, [9] suggests a model developed with necessary considerations that balance maintenance priority against the possibility of an imminent failure. It is worth noting that a degradation process can be described using various mathematical tools, including a continuous distribution function, the Markov decision process, the semi-Markov decision process, and others.

Condition-based maintenance (CBM) is carried out through a system-state inspection to determine the degree of component degradation, identify potential failures, and make maintenance decisions [10]. In [11], an application of the Gamma process in modeling maintenance of systems with degradation is summarized, while [12] defines the system's performance level, divided into several discrete states. This establishes a continuous-time polymorphic Markov degradation process model that optimizes the detection cycle and maintenance threshold of the system. Finally, [13] and [14] emphasize the importance of optimizing maintenance for multicomponent systems, indicating the need to consider the economic correlation between components and the use of proportional hazard models and artificial neural network methods to study multicomponent system maintenance issues.

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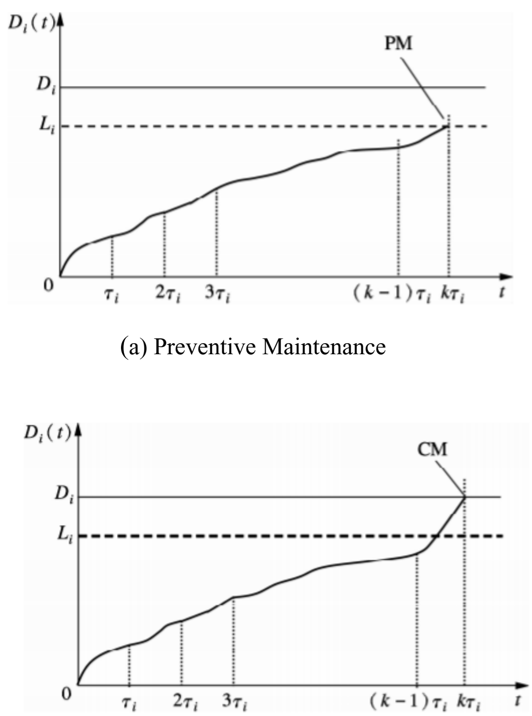
This work presents an approach to optimize the maintenance of components whose degradation can be classified according to the severity of damage. It is essential to note that the maintenance of these components often relies on different condition-based maintenance strategies. Based on the renewal process theory, this research considers the economic correlation between components and then analyzes the optimal detection cycle for a system that examines multiple components, as evidenced in the chosen case study.

2 Methodology

2.1 Performance degradation model and its assumptions

This document presents a well-established framework for implementing maintenance ideas for components of a smooth rotor synchronous generator. Figure 1 is a schematic diagram of the repair process and performance degradation of the components. In the figure, D_i indicates the failure threshold and post-maintenance threshold of the element; L_i is the threshold for preventive maintenance; i represents the ith component (i = 1, 2, ..., I) and I is the number of all the components in the system. The random variable, $D_i(t)$ represents the degraded state of component i at time t, where $D_i(t) = 0$, means the component is in a completely new state. Without preventive maintenance, the performance of the components will continue to degrade over time, implying that when $D_i(t) \geq D_i$ it would indicate an imminent failure of the component.



(a) Preventive Maintenance

(b) Subsequent or Corrective Maintenance

Fig. 1. Schematic diagram of single component performance degradation and its threshold.

A detection is performed at equal intervals in the component's state, and the detection period is established as τ_i , The detection points are respectively $\{\tau_i, 2\tau_i, 3\tau_i \dots, k\tau_i, \dots \dots\}$, Through this, we can obtain the state of the components at each inspection point and make the following maintenance decisions based on the degradation of the components with the following scenarios: I) When $L_i \leq D_i(t) < D_i$ preventive maintenance should be carried out, as shown in Figure 1(a); II) When $D_i(t) \geq D_i$ corrective maintenance should be performed, as shown in Figure 1(b); III) When $D_i(t) < L_i$ the generator continues its normal operation since the component has not surpassed the established wear threshold.

2.2 Renewal process theory

i) Counting Process

We establish the assumption that repaired components are put into use when t = 0. That is, after a failure occurs, the component has been restored to a normal state through maintenance, and its maintenance time is considered negligible. This process repeats until establishing a sequence of the component's failure time. Let $N(t)$ be the number of failures in the time interval $[0\,, t\,]$ responding to a random process $[N(t), t \geq 0\,]$ like the counting process described in [15]. This process considers a system defined as a correlation of two types of components, where the number of failures of each component is described as a stochastic process, with one process depending on the other.

ii) Renewal Process

If the occurrence intervals of all failures in a counting process are independent of each other, and the time between failures follows an exponential distribution with parameter λ, the counting process corresponds to a homogeneous Poisson process. This homogeneous Poisson process must satisfy the following conditions: 1) $N(0) = 0$; 2) $N(t)$ is an independent increment of the previous event $N(t-1)$; 3) the parameter t is defined as the length of any interval, and the number of failure events in this interval follows a distribution of λt, meaning there exists, for any $t \geq 0$

$$P_r[N(t+s) - N(s) = n] = \frac{(\lambda t)^n}{n!} e^{-\lambda t} \quad (1)$$

When the arrival time intervals of the homogeneous Poisson process are independent, the distribution function is arbitrary, and they are identically distributed, the resulting counting process is called a renewal process. For this counting process, we establish $\{X_n,\ n = 1, 2, \dots\}$ which is a series of mutually independent and identically distributed non-negative random variables with a common distribution function $F(x)$, here, T_n is the time between event $n-1$ and the event n. For this counting process, we establish a value for mean μ and variance of δ^2, Then, the moment when the n^{th0} event occurs is given by:

$$S_n = \sum_{k=i}^{n} T_k \quad (2)$$

By definition, if $S_0 = 0$, then $N(t) = sup\,\{n: S_n \leq t\}$ in the counting process; similarly, we will refer to the renewal process as $[N(t), t \geq 0\,]$. The stochastic properties of the process can be fully described by the common distribution $F(x)$ of X_n based on the law of large numbers, knowing that: $n \to \infty, \frac{S_n}{n} \to \mu$.

Let $F(t)$ be the cumulative probability distribution at the time of continuous updating, and $c(t)$ defines the cost of an updating time. According to the updating theory proposed in [16], [17], the average cost per unit of time is given by:

$$\lim_{t\to\infty} \frac{E[K(t)]}{t} = \frac{\int_0^\infty c(t)dF(t)}{\int_0^\infty t\,dF(t)} \tag{3}$$

where, $E[K(t)]$ represents the expected total cost.

2.3 Maintenance cost function for a single component's condition

In this section, a random effects model will be used to describe the degradation of component performance, and the expression of the function is given by:

$$D_i(t) = \;A_i + \theta_i t^{B_i} \tag{4}$$

In the formula, A_i represents the initial degradation of the component, such as a signal of wear, vibration, or any other variant considered as a potential cause of failure; t is the time variable; B_i indicates the degradation level of the component, where a higher value leads to a faster degradation rate and increases the probability of component failure.

The probability that the amount of degradation exceeds the threshold “x” al the time “t” is given by:

$$P|D_i(t) \geq x| = 1 - F_{\theta_i}\left(\frac{D_i - A_i}{t^{B_i}}\right) \tag{5}$$

where, F_{θ_i} is the cumulative density function evaluated at θ_i. This article assumes that F_{θ_i} follows a normal distribution with mean μ_{θ_i} and variance σ_{θ_i}.

Within the maintenance costs, the following will be included: inspection costs $C_{I(i)}$, preventive maintenance costs $C_{P(i)}$, corrective maintenance costs $C_{R(i)}$, downtime cost rate $C_{D(i)}$, minimum cost of downtime, and others $C_{M(i)}$. Assuming that both preventive and post-maintenance can return the component to the initial state, the life cycle is defined as the time interval from the initial state to the first component updating activity. The occurrence of multiple consecutive life cycles constitutes an updating process. The long-term average cost rate of the components can be expressed as:

$$Z_i(\tau_i) = \frac{E[C(\tau_i)]}{E[W(\tau_i)]} \tag{6}$$

where, $E[C(\tau_i)]$ is the average maintenance cost of component i over its total lifetime; $E[W(\tau_i)]$ is the average lifecycle of component i, and $E[C(\tau_i)]$ can be expressed as:

$$E[C(\tau_i)] = C_{I(i)}\,E_i[N] + C_{P(i)}\,P_{P(i)} + C_{R(i)}\,P_{R(i)} + C_{D(i)}E_i + C_{M(i)}E_{M(i)}[N] \tag{7}$$

Here:

$C_{I(i)}\;E_i[N]$ is the cost of testing, where $C_{I(i)}$ is the cost of a single test, $E_i[N]$ is the cost of the average number of inspections, and N is the total number of parts.

$C_{P(i)}\;P_{P(i)}$ are the costs of preventive maintenance, where $C_{P(i)}$ is the cost of a single preventive maintenance, and $P_{P(i)}$ is the probability of having to perform preventive maintenance on the component.

$C_{R(i)}\;P_{R(i)}$ is the cost of corrective maintenance, i.e., when the component fails, where $C_{R(i)}$ is the cost of a single corrective maintenance, and $P_{R(i)}$ is the probability of having to perform corrective maintenance on the component,

$C_{D(i)}\;E_i$ is used for the cost of downtime, where $C_{D(i)}$ is the cost of downtime per unit of time, and, E_i is the average downtime when the component undergoes maintenance.

$C_{M(i)}\;E_{M(i)}[N]$ is the cost of minimum maintenance, where, $C_{M(i)}$ is the cost of a minimum maintenance, and, $E_{M(i)}[N]$ is the minimum number of repairs for the component.

The calculation for each parameter is detailed below:

- Average Number of Inspections $E_i[N]$

If the component needs preventive or post-maintenance at the k[th] inspection point, a renewal process must be completed by establishing the intervals of its useful life. Assuming the component has a total of k inspection activities during its life cycle, then $E_i[N]$ is defined as:

$$E_i[N] = \sum_{k=1}^{n} \mathrm{kP(N\;=\;k)} \tag{8}$$

where P (N = k) denotes the probability indicating the update at k[th] detection point, leading to the following two component updating states:

$$E_{i1}^k = \{D_i((k-1)\tau_i) < L_i\} \cap \{L_i \leq D_i(k\tau_i) < D_i\} \tag{9}$$

$$E_{i2}^k = \{D_i((k-1)\tau_i) < L_i\} \cap \{D_i(k\tau_i) \geq D_i\} \tag{10}$$

Then, the situation in which the component $k\tau_i$ will not be replaced is defined by:

$$E_{i3}^k = \{D_i((k-1)\tau_i) < L_i\} \cap \{D_i(k\tau_i) < L_i\}$$

This is because:

$$P = D_i\big((k-1)\tau_i < L_i\big) = \;F_{\theta_i}\left(\frac{L_i - A_i}{((k-1)\tau_i)^{B_i}}\right)$$

For the probability that the component updates its state at the k[th] detection point, will be defined as:

$$\mathrm{P(N = k)} = P\big\{D_i\big((k-1)\tau_i < L_i\big)\big\} - P\{D_i(k\tau_i) < L_i\} \tag{11}$$

$$P(N = k) = F_{\theta_i}\left(\frac{L_i - A_i}{((k-1)\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{L_i - A_i}{(k\tau_i)^{B_i}}\right) \quad (12)$$

Thus, the average number of inspections $E_i[N]$ can be expressed as:

$$E_i[N] = \sum_{k=1}^{\infty} k\left\{F_{\theta_i}\left(\frac{L_i - A_i}{((k-1)\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{L_i - A_i}{(k\tau_i)^{B_i}}\right)\right\} \quad (13)$$

- Determination of Maintenance Probabilities

The probability of preventive maintenance for components and the probability of corrective or post-maintenance for components are at $k\tau_i$, Also, the probability that the failure threshold is reached before D_i is:

$$P\{D_i(k\tau_i > D_i)\} = P\{T_{D_i} < k\tau_i\} \quad (14)$$

The component will reach the preventive maintenance condition at the threshold time located at position $(k-1)\tau_i$ and $k\tau_i$, whose probability is given by:

$$P\{D_i((k-1)\tau_i \leq L_i < D_i(k\tau_i))\} = P\{(k-1)\tau_i \leq T_{L_i} < k\tau_i\} \quad (15)$$

where the preventive maintenance threshold is reached within the interval $(k-1)\tau_i$, when it has a value Li. For this, we will define the situations raised in the previous section:

① If $L_i \leq D_i(k\tau_i) < D_i$, preventive maintenance must be performed, and its probability is given by:

$$P_{P(i)} = \sum_{k=1}^{\infty} P\{D_i((k-1)\tau_i) < L_i, L_i \leq D_i(k\tau_i) < D_i\} \quad (16)$$

② If $D_i(k\tau_i) \geq D_i$, corrective or post-maintenance must be performed, and its probability is given by:

$$P_{R(i)} = \sum_{k=1}^{\infty} P\{D_i((k-1)\tau_i) < L_i, D_i(k\tau_i) \geq D_i\} \quad (17)$$

Knowing that:

$$P_{P(i)} + P_{R(i)} = \sum_{k=1}^{\infty} F_{\theta_i}\left(\frac{D_i - A_i}{((k-1)\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{D_i - A_i}{(k\tau_i)^{B_i}}\right)$$

Establishment of Cases for Preventive Maintenance Probability:

$$k < \frac{D_i - A_i}{D_i - L_i};\ P_{P(i)} = \sum_{k=1}^{\infty}\left(F_{\theta_i}\left(\frac{D_i - A_i}{(k\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{L_i - A_i}{(k\tau_i)^{B_i}}\right)\right) \quad (18)$$

$$k \geq \frac{D_i - A_i}{D_i - L_i};\ P_{P(i)} = \sum_{k=1}^{\infty}\left(F_{\theta_i}\left(\frac{L_i - A_i}{((k-1)\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{L_i - A_i}{(k\tau_i)^{B_i}}\right)\right) \quad (19)$$

As established in formula (17), the value for $P_{R(i)}$ can be estimated.

- Average Downtime of Components $E_i\ [T, k\tau_i]$

If the component fails at time T and this is within the limits of $(k-1)\tau_i < T \leq k\tau_i$, it means that the synchronous generator will be in a state of downtime until the next inspection point is repaired, obtaining the average downtime of the identified components.

The expression for E_i is defined as:

$$E_i[\xi] = \sum_{k=1}^{\infty}\left(\int_{(k-1)\tau_i}^{k\tau_i}(k\tau_i - t)\, dF(t)\right) P\left(E_{i2}^{k}\right) \quad (20)$$

where:

$$F_i(t) = 1 - R_i(t) = 1 - F_{\theta_i}\left(\frac{D_i - A_i}{t}\right)$$

- Minimum Number of Repaired Components $E_{M(i)}[N]$

When the component's state update occurs at $k\tau_i$ it is possible to perform minimum maintenance at the first inspection time k-1 of the component, and the expression is defined as:

$$E_{Mi}[N] = \sum_{k=1}^{\infty}(k-1).\left[1 - \prod_{i=1}^{N} P(D_i(k-1)\tau_i < L_i)\right] \quad (21)$$

- Average Cycle Life $E[W(\tau_i)]$

$$E[W(\tau_i)] = \sum_{k=1}^{\infty} k\tau_i\, P(N = k) = \sum_{k=1}^{\infty} k\tau_i\left(F_{\theta_i}\left(\frac{L_i - A_i}{((k-1)\tau_i)^{B_i}}\right) - F_{\theta_i}\left(\frac{L_i - A_i}{(k\tau_i)^{B_i}}\right)\right) \quad (22)$$

By substituting various parameters into equation (6), the long-term average moving cost rate of the components $Z(\tau_i)$ can be obtained.

2.4 Decision for maintenance of multicomponent system:

For systems that integrate multiple components, the regular maintenance method is generally adopted, and the maintenance strategy is as follows [18]:

Determine the component failure detection interval, which is defined by λ according to the state maintenance test.

Make maintenance decisions based on the state of a single component. If the state parameter D_i of a component at the detection point satisfies the condition $L_i \leq D_i(T) < D_i$, then preventive maintenance must be performed; if $D_i(T) \geq D_i$ then corrective or post-maintenance must be performed, and the component failure is updated.

Timely maintenance decision policies for multiple components. When $D_i(T) < L_i$, minimal maintenance will be performed for component i, and preventive maintenance will be performed on related components.

Considering the economic correlation between the components of the synchronous generator, the multicomponent synchronous generator's average multicomponent maintenance cost rate can be expressed as:

$$Z_{sys}(\tau) = \frac{[N-\omega(N-1)]R}{\tau} + \sum_{i\epsilon N} Z_i(\tau) \quad (23)$$

In the formula, $Z_{sys}(\tau)$ is the average maintenance cost rate of the synchronous generator; ω is the economic correlation coefficient between components of the generator, $\omega = 0 \sim 1$; R is the fixed cost for preventive maintenance or post-facto maintenance; τ is the unified inspection for each generator element (can be one or several at once); $Z_i(\tau)$ is the average maintenance cost rate of component i when the detection period is τ.

3 Case study

In this section, we will validate the methodological proposal by analyzing a synchronous generator powered by a steam turbine. This case study corresponds to the smooth rotor synchronous generator at the Trinitaria Thermal Power Plant, owned by the Electric Corporation of Ecuador (CELEC EP) in Guayaquil, Ecuador. The key characteristics of the generator are summarized in Table 1.

Table 1. Main characteristics of the Trinitaria power plant synchronous generator.

Manufacturer:	ABB, WX18Z-090LL
Nominal apparent power:	156,500 KVA
Nominal active power:	133,025 KW
Cooling:	Air-cooled
Insulation class:	F
Voltage:	13,800 V.
Operating voltage range:	± 5 %
Rotor: Cilíndrico	2 poles
Nominal current:	6,547 A.
Power Factor:	0.85
Number of phases	3
Frequency:	60 Hz.
Speed:	3600 RPM
Efficiency (at nominal power and power factor = 0.85):	98.6 %

For this particular case, a brief analysis of its operation under steady-state conditions will be conducted, using the model proposed in [19] as a reference. This model will enable us to gather relevant data, such as operating voltages and currents, steady-state generator speed, mechanical and electrical powers, and others. The acquisition of these data will provide us with a historical database, which will be used to construct our model for estimating component wear and allowable thresholds before failure based on the equations described in Section II.

An experimental mathematical model that closely approximates the actual conditions in the Trinitaria Thermal Power Plant is shown in Fig. 2 [19]. It is worth noting that this model replicates the entire Trinitaria Thermal Power Plant. However, for the purposes of this study, we will focus solely on using the generator model to facilitate our analysis of the wear exhibited by various components (bearings, exciter, and winding).

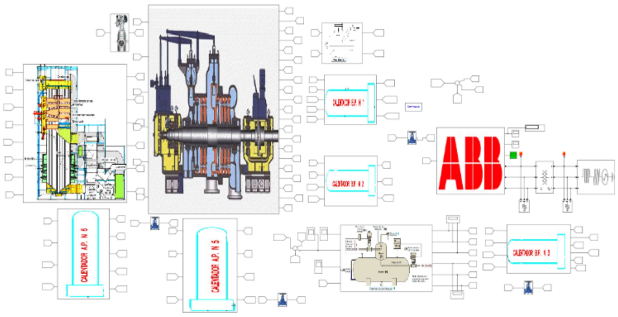


Fig. 2. Equivalent Mathematical Model of the Trinitaria Thermal Power Plant.

4 Simulation methodology

For the purposes of this study, it is essential to have the operational history of the synchronous generator. The model used to simulate the synchronous generator of the Trinitaria thermal power plant is shown in Figure 2. The data were obtained by simulating the normal operation of the generator and estimating the conditions leading to component wear over a time period T. Fig. 3 shows the operational condition of the synchronous generator in steady state, also known as a permanent regime, where stator currents, field current, and electromechanical torque in p.u. are depicted.

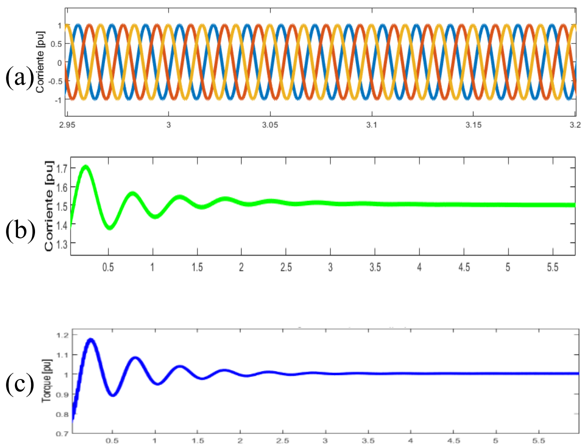


Fig. 3. Normal Operation or Steady State of the Synchronous Generator: (a) Stator currents, (b) Field current, (c) Electromechanical torque.

This model can be idealized to analyze wear conditions based on the scheme presented in Fig. 1, allowing us to estimate data related to the degradation of component performance and the repair and maintenance process. In Fig. 4 illustrates how components deterioration affects the normal operation of the generator. The graph also demonstrates the approach to imminent failure, considerations for maintenance are not taken into account.

Each failure and component degradation scenario has been considered for estimating failure times. This enables us to predict, using the proposed model, the failures that may occur in the predefined components of the generator. It provides timely insights for maintenance decision-making.

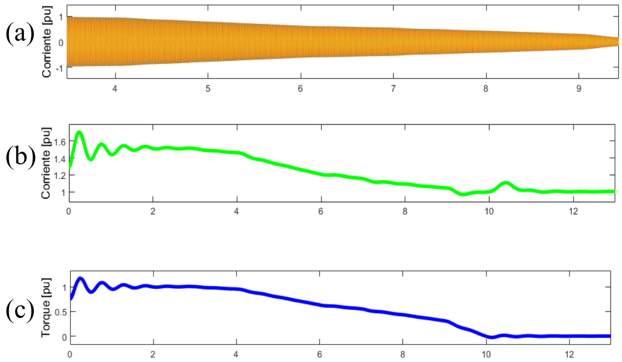


Fig. 4. Operation of the Synchronous Generator Considering Component Deterioration:(a) Stator currents, (b) Field current, (c) Electromechanical torque.

We assume that the initial degradation of the three components is zero, and the maintenance and degradation parameters are shown in Table 2.

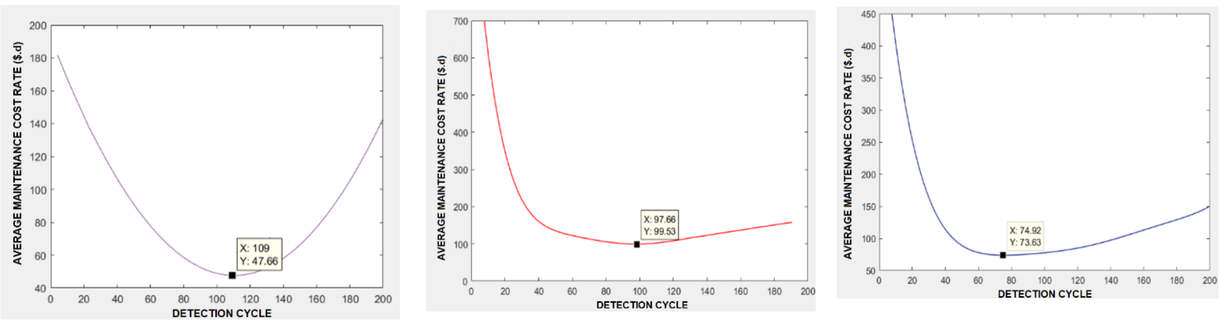
Table 2. Synchronous generator degradation parameters and maintenance costs.

Maintenance Costs/ dollars	Component		
	Bearings	Stator Winding	Exciter
$C_{P(i)}$	1080	2315	1543
$C_{R(i)}$	4630	10802	7716
$C_{I(i)}$	154	154	154
$C_{D(i)}$	1111	1111	1111
$C_{M(i)}$	309	772	463
R	7716	7716	7716
Degradation			
D_i	100	200	0,08
L_i	90	190	150
μ_{θ_i}	0,08	0,12	140
σ_{θ_i}	0,015	0,015	0,015
B_i	1	1	1

The degradation parameters for the components shown in Table 2 are calculated using equations (4)-(5).

5 Results

The proposed CBM (Condition-Based Maintenance) in this work is valid for a 133,025 KW, 13,800 V, 60 Hz synchronous generator, cylindrical rotor with 2 poles and 3600 RPM. From equation (6), the independent average maintenance cost, rate, and optimal inspection cycle curve for the three components are obtained, as shown in Figure 5. The optimal inspection periods for bearings, stator winding, and exciter are 109, 98, and 75 days, respectively. The average maintenance cost rates for each period were 47.66, 99.53, and 73.26 dollars/day. To obtain the results of the above calculations, the analysis was considered as independent components. For the execution of optimal maintenance of the synchronous generator of this thermal generation plant, it can be solved using equation (23).



(a) Bearings (b) Stator Winding (c) Exciter

Fig. 5. Detection cycle cost rate curve of each component.

The relationship between the maintenance cost of various components and the inspection cycle is presented in Figure 6. Considering the economic relevance of the components, the optimal inspection period for the synchronous generator is no longer the optimal inspection period for each component. The optimal inspection period now is 86 days, and the average maintenance cost rate for the entire life cycle is 4.873 dollars/day. In Figure 6, we can observe the following: i) When the maintenance period is less than 40 days, the average maintenance cost rate of the system decreases rapidly with the increase of the original inspection cycle. This is because the detection frequency is too high, leading to excessive detection and an increase in the average maintenance cost rate. ii) When the detection period is greater than the optimal detection period (86 days), the average cost rate increases as the detection period increases. This is because the inspection cycle is too long, and there is a lot of downtime due to the inability to repair in time, which increases the average maintenance cost rate.

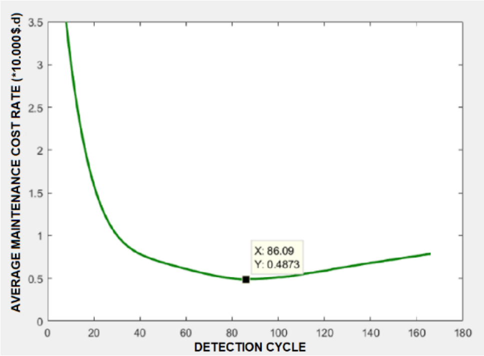


Fig. 6. Detection cycle cost rate curve of each component

The maintenance activities of the components of the synchronous generator will result in corresponding idle cost rates. For this, the rate will be maintained for the values of other parameters without change, and the value of $C_{D(i)}$ will be replaced. The relationship between the total average maintenance cost rate and the detection cycle for the synchronous generator under different idle costs is obtained from equations (6)-(13), as shown in Figure 7.

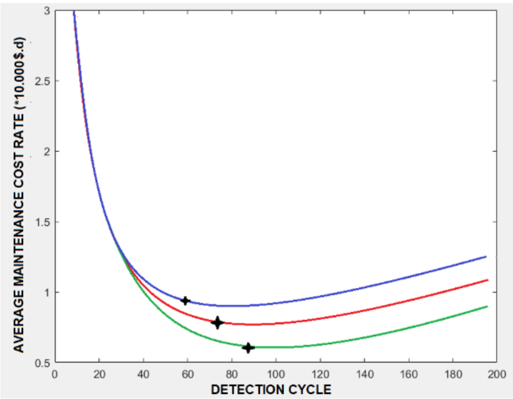


Fig. 7. Effect of idle time cost rate on the optimal detection period of the synchronous generator

It can be seen in Figure 7 that when the idle cost rate is 536, 1125, and 1688 dollars, respectively, the corresponding optimal detection periods of the synchronous generator are 59, 74, and 84 days, respectively.

6 Conclusions

The early detection of failures in generators of power generation systems is of vital importance, so representations that allow a successful and reliable study without requiring the shutdown of machinery for subsequent review are the subject of studies aimed at improving optimal maintenance policies, considering the different costs that this would imply.

Condition-Based Maintenance proposes the detection of failures when they have not reached a harmful level, evaluating the costs that would imply not acting in a timely manner based on the prediction of future states for the components taken from the generator when it is in normal operation, also called a steady state.

This work takes the synchronous generator of the Trinitaria system's thermal generation plant and analyzes it as a whole, defining the components that are constantly monitored by maintenance personnel in the generation plant. Additionally, it establishes a long-term average cost rate model for generators based on the updating process, considers the economic relevance between maintenance activities of components, establishes a condition-based maintenance model by analyzing multiple generator components, and studies the optimal detection cycle of the system.

According to Figure 7, the following conclusions can be drawn:

- As the idle time cost rate per unit time increases, the optimal detection period decreases. This is because when the idle time cost rate per unit time increases, to ensure the optimal average cost rate, it is necessary to increase the detection frequency to shorten downtime and shorten the detection cycle.
- As the cost rate of loss time due to inactivity per unit time increases, the optimal average cost rate will show an increasing trend. By changing the value of the fixed maintenance cost R, the relationship between the average maintenance cost rate of the synchronous generator and the inspection cycle under different fixed maintenance costs can be obtained. At different values of fixed maintenance cost R, the optimal inspection periods for the analyzed generator as a system containing various components are defined. Obviously, as the fixed maintenance cost R increases, the maintenance cycle of the synchronous generator will increase, in order to reduce system maintenance times during the life cycle and reduce maintenance costs.

The results show that the maintenance optimization model can effectively describe the optimization problem of synchronous generator maintenance. Making correct decisions will allow us to act in a timely manner for the maintenance of the machine without incurring unnecessary stops, based on the costs that the optimal inspection cycles would imply. In subsequent research, the maintenance model can consider factors such as the law of degradation of component performance and dynamic maintenance of the three analyzed components together in this document. In addition, all the massive historical data that can be obtained from the personnel of the generation plant through constant monitoring has practical added value when designing a plan that clearly defines policies for optimal condition-based maintenance.

This article also presents the economic correlation coefficient λ to describe the economic correlation between components. According to equation (23), the relationship between the average maintenance cost rate of the synchronous generator as a multicomponent system and the economic correlation coefficient of the components can be obtained.

In Figure 8, it is observed that when the economic correlation coefficient λ=1, the economic correlation between components is the highest, and the average maintenance cost rate of the system is the lowest. Therefore, considering the economic correlation between components, it is possible to reduce maintenance costs when treating the generator as an integrated system of various components.

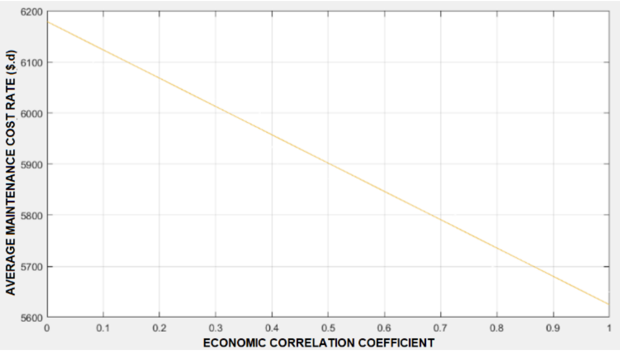


Fig. 8. Relationship between the average maintenance cost rate and the economic correlation coefficient of the components

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