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Optimizing PM Intervals for Manufacturing Industries Using Delay-time Analysis and MOGA

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Abstract

Overall productivity and profitability are directly affected by the adopted maintenance policy for any manufacturing industry. It should maximize the availability of the system and minimize operating costs. This article attempts to develop a preventive maintenance (PM) model based on delay-time analysis to reduce the downtime and cost of maintenance activities. The developed maintenance model is optimized using a multi-objective genetic algorithm (MOGA) to determine the optimal maintenance frequency. Further, sensitivity analysis is performed to verify the consistency of the proposed model. Lastly, the model's applicability is tested by implementing it in a foundry unit, and a drastic reduction in overall maintenance downtime and cost almost by 71.69% is achieved.

Keywords: Preventive maintenance (PM); Delay-time analysis (DTA); Maintenance downtime; Maintenance cost; Multi-objective genetic algorithm (MOGA).

1. Introduction

Mechanical systems and their components deteriorate with time [1]. Therefore, timely maintenance is required to avoid malfunctioning. However, in most organizations, maintenance is either overlooked or overperformed. In either case, substantial time and money are wasted, which ultimately affects the productivity and revenue of the organization. Moreover, maintenance is attributed to the quality of the products manufactured in any industry. According to a study, solely maintenance operations account for around 28% of entire production costs in any business[2]. Furthermore, maintenance cost has the largest share after energy costs of any operational budget [3, 4]. Therefore, it is required to perform adequate and timely maintenance to reduce the number of failures, thus increasing the reliability of machines and equipment.

Maintenance is the set of activities performed on a system to restore or retain it to a state where it can perform its intended functions [5]. These activities generally involve inspection, cleaning, lubrication, adjustment, alignment, and repair/or replacement of wear-out components/or subcomponents to keep the facility/equipment in working condition and avoid unexpected failure during operation [6]. Two approaches were adopted to perform maintenance in any facility based on this. These are continuous and periodic maintenance [7, 8]. In the first approach, equipment is continuously and rigorously monitored using a sensor-based monitoring system and warns whenever something happens wrong. The latter method involves the empirical and statistical analysis of equipment failure data [7]. But both approaches have certain limitations. Continuous condition monitoring is quite expensive, and noise can be generated due to imprecise diagnosis. However, periodic maintenance is cost-effective, but has a risk in terms of the possibility of some failure in between two successive maintenance activities [7, 8]. Therefore, the main problem faced by any industry is determining an effective maintenance policy that will improve overall productivity and profitability [9].

Numerous models have been developed to determine an effective maintenance policy [6, 10-16]. Preventive maintenance (PM) is the most studied maintenance policy [10, 11]. An effective PM policy is performed at a planned time interval to prevent potential failures. For any PM program, determining the inspection interval is one of the prime necessities [10]. The inspection interval should be fixed to minimize the cost of performing PM activities [12]. If the inspection interval is too short, it will increase the inspection cost and the facility's downtime, thus affecting the system's overall productivity. Alternatively, if it is too long again, the cost of PM and the system's downtime increases due to the probability of failure [12]. Therefore, it is required to optimize the PM interval to minimize the cost and the downtime due to PM activities [13].

Therefore, this research attempts to develop a PM model that minimizes the total maintenance downtime and the cost associated with maintenance by using a heuristic method. In this regard, mathematical models are developed to find the downtime and cost associated with the maintenance activities using delay-time analysis [14-16]. Further, the optimal maintenance frequency is determined by optimizing the developed models using a multi-

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objective genetic algorithm (MOGA) that simultaneously minimizes the downtime and cost. Additionally, sensitivity analysis is performed to verify the consistency of the proposed model. The proposed model is further applied in a foundry unit to optimize the PM policy of one of the most failure-prone equipment.

2. Mathematical Model

This study developed the mathematical model based on delay time analysis (DTA) proposed by Christer and Walker in 1984 [17]. According to DTA, every component sounds abnormal before it breakdowns. Figure 1 elaborates on the DTA concept. The line represents the timeline, and the two circles on the timeline represent the initiation of the defect (white circle) and actual failure (black circle). The time between the initiation of the defect and actual failure is known as the delay time (h) [17]. According to the DTA concept, any fault occurring in the time interval (0, T) has a delay time Δh within the interval (h, h+Δh) with the probability of f(h)Δh. If the fault arises in the period (0, T–h), it will be repaired as a breakdown repair; otherwise, as an inspection repair, as shown in Figure 2.

The probability of breakdown b(T) due to the occurrence of a fault within a period (0, T) can be expressed as [17]:

$$b(T) = \int_{h=0}^{T} \frac{(T-h)}{T} f(h)dh \quad (1)$$

The expected downtime per unit time D(T) for a given probability for breakdown failure b(T) is expressed as:

$$D(T) = \frac{D_i + K_f T b(T) D_b}{T + D_i} \quad (2)$$

where D_i is average inspection downtime incurred in the inspection of the equipment, D_b is average breakdown repair downtime involved in repair/replacement of the equipment failed due to sudden failure, K_f is arrival rate of a defect per unit time, which is the average time a defect arises over a period, T is the time interval between inspections.

Similarly, the expected maintenance cost per unit time C(T) of the equipment with an inspection of period T is expressed as:

$$C(T) = \frac{K_f T C_b b(T) + C_{ir}[1 - b(T)] + C_i}{T + D_i} \quad (3)$$

where C_b is breakdown repair cost, C_{ir} is inspection and repair cost, C_i is inspection cost.

In this study, the probability distribution function of delay time f(h) follows an exponential distribution. Therefore,

$$f(h) = \frac{1}{\theta} e^{-h/\theta} \quad (4)$$

where θ is the mean time between failures (MTBF). It is the mean operating time between subsequent failures of equipment.

From Eq. (1) and (4):

$$b(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right)\left(\frac{1}{\theta} e^{-h/\theta}\right) dh \quad (5)$$

Further putting the value of Eq. (5) in Eq. (2) and (3) and simplifying, we have:

$$D(T) = \frac{D_i + K_f T\{\theta(e^{-T/\theta} - 1) + T\} D_b}{T + D_i} \quad (6)$$

$$C(T) = \frac{K_f T C_b\{\theta(e^{-T/\theta} - 1) + T\} + C_{ir}[1 - \{\theta(e^{-T/\theta} - 1) + T\}] + C_i}{T + D_i} \quad (7)$$

Therefore, the mathematical model for estimating the optimum maintenance schedule is:

$$Minimize D(T) = \frac{D_i + K_f T\left\{\theta\left(e^{-\frac{T}{\theta}} - 1\right) + T\right\} D_b}{T + D_i} \quad (8)$$

$$C(T) = \frac{K_f T C_b\left\{\theta(e^{-\frac{T}{\theta}} - 1) + T\right\} + C_{ir}\left[1 - \left\{\theta(e^{-\frac{T}{\theta}} - 1) + T\right\}\right] + C_i}{T + D_i}$$

$s.t. t_1 \le T \le t_2$
$d_{i_1} \le D_i \le d_{i_2}$
$k_{f_1} \le K_f \le k_{f_2}$
$\theta_1 \le \theta \le \theta_2$
$d_{b_1} \le D_b \le d_{b_2}$
$c_{b_1} \le C_b \le c_{b_2}$
$c_{ir_1} \le C_{ir} \le c_{ir_2}$
$c_{i_1} \le C_i \le c_{i_2}$

where t_1 and t_2 are the lower and upper limit of time interval, T; d_{i1} and d_{i2} are the lower and upper limit of average inspection downtime, D_i; d_{b1} and d_{b2} are the lower and upper limit of average breakdown repair downtime, D_b; k_{f1} and k_{f2} are the lower and upper limit of the arrival rate of a defect per unit time, K_f; θ_1 and θ_1 are the lower and upper limit of MTBF, θ; C_{b1} and C_{b2} are the lower and upper limit of the breakdown repair cost; C_{ir1} and C_{ir2} are the lower and upper limit of inspection and repair cost; C_{i1} and C_{i2} are the lower and upper limit of inspection cost.

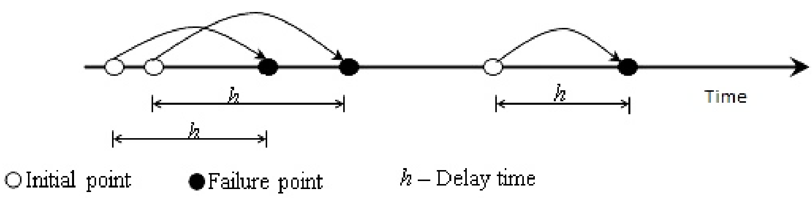

Figure 1. Delay time

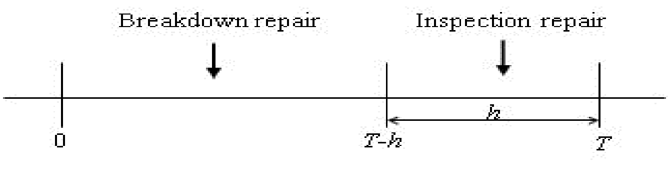

Figure 2. Repair type

3. Multi-Objective Genetic Algorithm (MOGA)

Holland initially proposed the Genetic Algorithm (GA) in the 1960s [18], and his colleagues and students further refined it at the University of Michigan between the 1960s and 1970s [19]. The concept of GA is based on the evolutionism theory that explains the origin of species [18-20]. Traditionally, GA has been applied to single-objective optimization problems. However, today GA is successfully used to optimize practical issues where two or more objectives [20].

In the last few decades, several variants of GA were introduced to solve different real problems having more than one objective [21-24]. Among them, MOGA was successfully used by various researchers to find the Pareto-based optimal solutions for various real engineering problems. MOGA was first proposed by Fonseca and Fleming, 1993, emphasizing the use of Pareto-based ranking and niching methods to search the true Pareto front without affecting the diversity of the population [25]. In MOGA, every solution linked with each objective can be considered as an elite individual. Therefore, there are *n* elite individuals for any objective. These solutions are preserved to the subsequent generation in genetic algorithms [20]. The pseudo-code of MOGA used in this study is depicted in Figure 3.

4. Methodology

The proposed methodology to determine the optimal inspection interval by reducing the downtime and cost associated with preventive maintenance is depicted in Figure 4. The first step involves a thorough analysis of the entire process to understand better and identify the problems. A better understanding of the process is the prime requirement in developing any maintenance model. Insufficient or inadequate knowledge of the process may create confusion in selecting the problem. Moreover, during the problem identification stage, care should be takento classify the occurred breakdown as a maintenance issue, an engineering issue, or an operator issue. After an assortment of the problem, appropriate data shall be collected from the maintenance department or the specific shop itself. Following data are required as defined by the mathematical model:

- Average inspection downtime, d_i.
- Average breakdown repair downtime, d_b.
- The arrival rate of defect per unit time, k_f.
- Mean-time between the failures (MTBF), θ.
- Inspection cost, C_i.
- Inspection and repair cost, C_{ir}.
- Breakdown repair cost, C_b.

After collecting valuable information about the problem, mathematical models are formulated and further optimized using MOGA to estimate the optimum inspection schedule based on minimum downtime and maintenance costs.

5. Case Study

The effectiveness of the proposed maintenance model is being investigated through a case study of a leading foundry unit situated in southern India. The proposed model has been implemented to schedule the maintenance activities performed on one of the failure-prone systems, shot blasting machine, which minimizes its cost and downtime. A shot blasting machine is used to clean the surface of the casting after cooling, knock-out, and de-gating. In the existing setup, an overhead rail wheel blasting type shot blasting machine is used in which jets of small metal balls are imposed on the castings to clean their surfaces. It required approximately 10 - 15 minutes to clean 20-30 castings, or 1 ton/hanger (maximum), depending upon the size of castings at a time. The significant parts of the machine are blasting wheels, re-claimer and dust collector, blast system, direct-pressure system, suction (siphon) system.

```
START:
Input: Algorithm control parameters
Output: Pareto Front
Initialize generation counter g=0
Initialize population
Initialize control parameters
Initialize Elite Solution
While g<g_max do
        Perform non-dominated sorting
        Select individual for mating pool
        Perform crossover
        Perform mutation
Perform Elitism
Assign current generation=new generation
Estimate F*=nondominated pareto front of current generation
Assign, {Elite Solution} = {Elite Solution} ∪ F*
Increment the generation g=g+1
End while
Print {Elite Solution}
STOP
```

Figure 3. Pseudo-code for MOGA

In the current maintenance plan, each major part is inspected per shift to identify problems, if any, which takes around half an hour (a total of one and a half hours daily). Additionally, regular planned maintenance and any subsequent adjustments or repairs have been carried out per month and take approximately eight hours. Thus, the total downtime of the shot-blasting machine is approximately 53 hours per month (1.5 × 30 + 8 hours) which costs about ₹ 13,250/- per month (@ ₹ 250/hr.). Although, occasional breakdown also occurs due to the sudden failure of one or more of these parts. This increases the total downtime as well as the cost of maintenance. The information related to maintenance downtime and their cost parameters is listed in Table 1.

6. Result and Discussion

The MOGA solver in MATLAB 2015a was used to optimize the preventive maintenance frequency in this investigation. The variables were converted to binary coding by generating mathematical models as M-files and then optimized with the "gamultiobj" optimization tool, which uses a multi-objective genetic algorithm. The optimal solutions from the MOGA solver are obtained with the following parameter settings. Population size – 200, Selection function – Tournament, selection size – 2, crossover rate - 0.8, mutation function - constraint dependent, Pareto front population fraction - 0.35, stopping criteria - 100*No. of variables. The corresponding code is depicted in Figure 5.

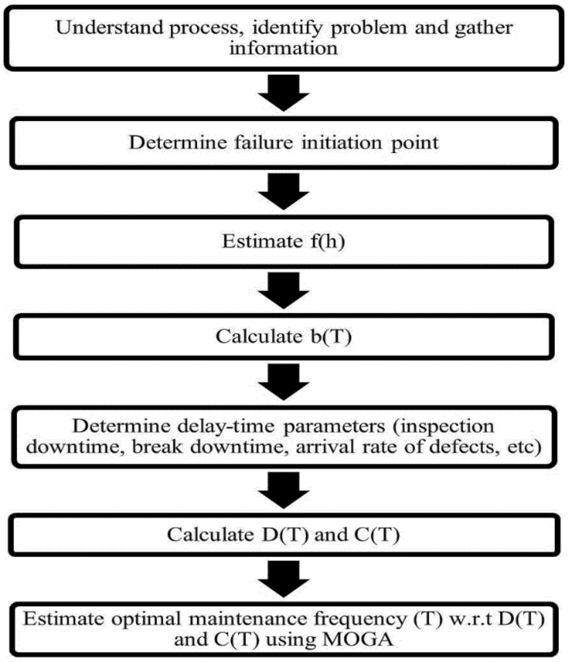

Figure 4. Flow chart of the methodology adopted

Table 1. Maintenance downtime and cost parameters

S. No.	Major Parts	k_f	θ	d_i	d_b	C_i	C_{ir}	C_b
1.	Blasting Wheels	0.26	365	0.33	7	500	2200	22000
2.	Re-claimer and dust collector	0.33	290	0.25	3	150	1300	12000
3.	Blast System	0.29	230	0.17	3	280	2200	18000
4.	Direct-pressure systems	0.41	85	0.04	0.33	100	1500	10000
5.	Suction (siphon) systems	0.36	30	0.04	0.33	80	1200	5000

```
clear; clc;close all;
fun = @moo_objective_functions;
nvars=8;
A=[]; b=[]; Aeq=[]; beq=[];
lb=[0 0.041 0.26 270 0.33 5000 1200 80]; ub=[120 0.333 0.41 730 7 22000 2200 500];
[x,fval,exitflag,output] = gamultiobj(fun,nvars,A,b,Aeq,beq,lb,ub)
D_T = fval(:,1);
C_T = fval(:,2);
% plot(D_T,C_T,'*-')
T = x(:,1);
D_i = x(:,2);
K_f = x(:,3);
theta=x(:,4);
D_b = x(:,5);
C_b = x(:,6);
C_ir = x(:,7);
C_i=x(:,8);
T1 = table(D_T,C_T,T,D_i,K_f,theta,D_b,C_b,C_ir,C_i)
T_sorted = sortrows(T1,{'D_T'})
D_T_sorted = T_sorted.D_T;
C_T_sorted = T_sorted.C_T;
plot(D_T_sorted,C_T_sorted,'*-')
xlabel('D(T)')
ylabel('C(T)')
title('Pareto Front')
function f = moo_objective_functions (x)
T = x(1); D_i = x(2); K_f = x(3);theta=x(4);
D_b = x(5); C_b = x(6); C_ir = x(7);C_i=x(8);
f(1) = (D_i+K_f*T*(theta*(exp(-T/theta)-1)+T)*D_b)./(T+D_i);
f(2) = (K_f*T*C_b*(theta*(exp(-T/theta)-1)+T)+C_ir*(1-(theta*(exp(-T/theta)-1)+T))+C_i)./(T+D_i);
end
```

Figure 5. MOGA code

Figure 6 shows the Pareto front for D(T) vs. C(T), in which each point in the Pareto front is a non-dominated solution concerning others. From the detailed study of the graph, it can be concluded that both responses' optimum value is satisfied when the PM frequency is six days. The optimal maintenance downtime is 1.38 hrs./day with a maintenance cost of ₹ 375/- per day. This reduces the total downtime and maintenance cost by approximately 71.69%.

6.1. Sensitivity Analysis

Further, sensitivity analysis has been performed to verify the consistency of the model. For this, some critical parameters (such as k_f, λ, C_i and C_{ir}) that affect the solution have been varied by 5 and 10%. The results of sensitivity analysis are depicted in Table 2. It can be concluded that the increase and decrease of variables resulted in small changes in the maintenance downtime D(T), maintenance cost C(T), and inspection interval (T). Therefore, the optimum preventive maintenance (PM) schedule for the shot-blasting machine is 6 days, in which both the maintenance downtime and maintenance cost are minimum. Figure 7 shows the graphical representation of the sensitivity analysis.

7. Conclusion

This research aimed to use multiple objectives in determining the optimal PM interval. Two criteria, maintenance cost and downtime were selected to assess the PM interval's performance. DTA approach was used to develop the mathematical relationship between the PM intervals and the corresponding criteria. Further, the mathematical models were optimized using MOGA to determine the best PM interval that minimizes the maintenance cost and downtime. The proposed maintenance model was applied in a foundry unit to optimize the PM interval of the shot-blasting machine. The results concluded that the optimum PM interval should be 6 days to satisfy both criteria simultaneously. This reduces the overall maintenance downtime and cost by nearly 71.69%.

Additionally, the sensitivity analysis of the results was carried out to verify the consistency of the proposed model. Furthermore, the developed model can be helpful for any discrete industry. It helps reduce the downtime of the production facility and reduce maintenance and inspection costs. Also, this model enables the maintenance person to decide on periodic maintenance of the production facility to increase productivity.

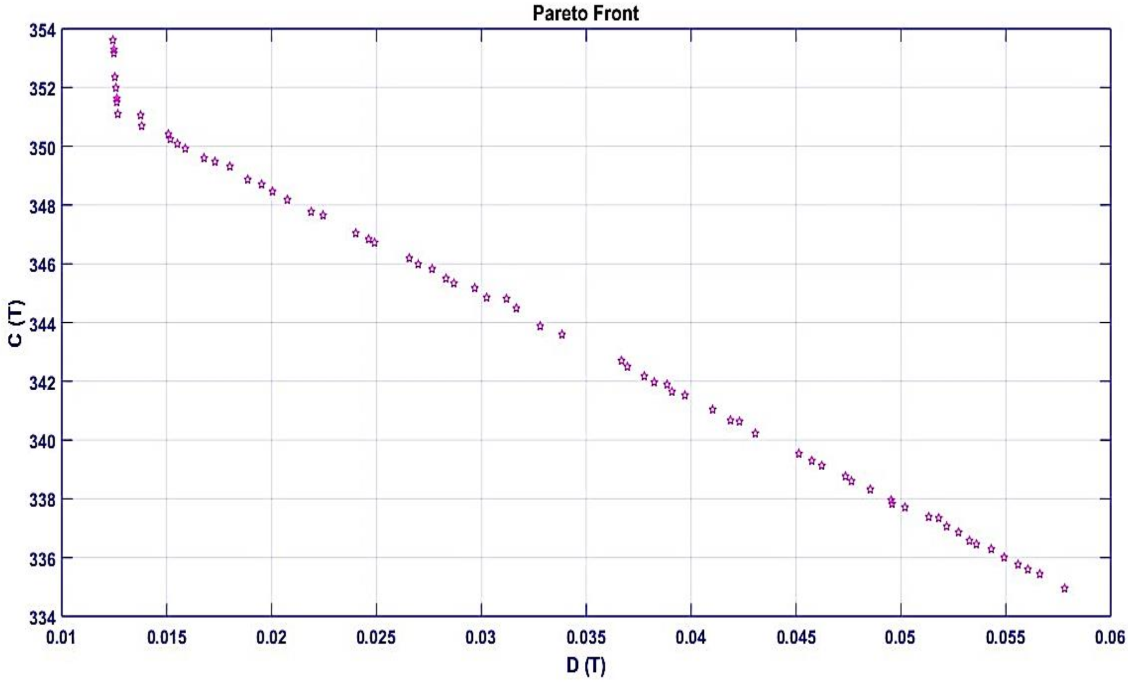

Figure 6. Pareto optimal front for D(T) vs. C(T)

Table 2. Results of sensitivity analysis

Case No.	T (Days)	D (T) (Hrs.)	C (T) (₹)
C1 (Increased by 5%)	6.65	0.0544	294.82
C2 (Increased by 10%)	6.03	0.0628	265.91
C3 (No Change)	6.09	0.0578	334.95
C4 (Decreased by 5%)	6.69	0.0551	313.25
C5 (Decreased by 10%)	6.60	0.0543	311.03

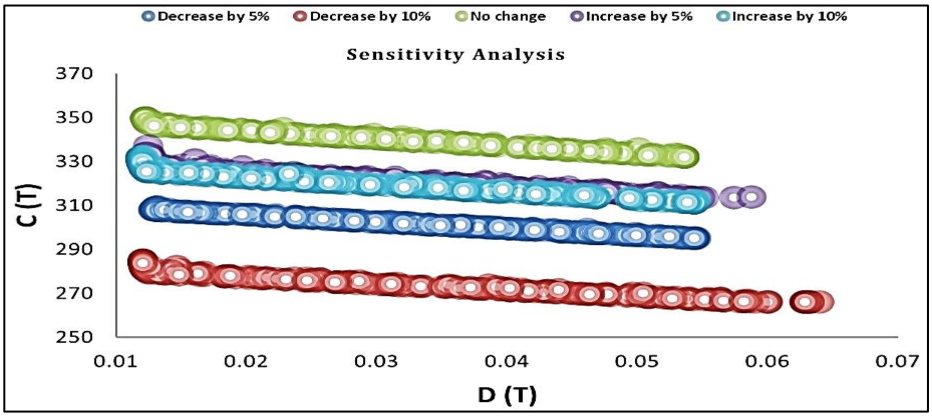

Figure 7. Sensitivity analysis

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