Hybrid Tool for Optimal Preventive Maintenance Schedule for Deteriorating Systems

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Abstract: This paper statistically establishes the feasibility of using Simulated Annealing as compared to traditional method for the wide range of deteriorating systems and hence presents a Simulated Annealing assisted hybrid tool to determine optimal PM schedule for maximizing availability of deteriorating systems. The proposed method carries out initially the Weibull analysis on the failure data collected, checks for feasibility of PM and if PM is found feasible it searches for global optimal schedule for PM using SA. The results obtained from SA are statistically compared with those obtained using traditional method (Integrated Graphical model) using inferential statistics. As the findings are quite encouraging, the proposed hybrid tool can be conveniently used for deciding PM strategy.

Keywords: Simulated annealing, maintenance scheduling, optimal schedule, availability, model adequacy

1. Introduction

There are certain fundamental anomalies in assessing the frequency with which preventive maintenance (PM) can be performed. Often it is presumed that PM is necessary, in certain cases, when in fact break down maintenance (BDM) may be a better option. Secondly, when we search for optimal schedule for preventive maintenance the analytical tools normally fail due to the involvement of the transcendental expressions, randomness in the system and the stochastic behavior of the situation. The conventional search processes also face a risk of getting stuck in local optima. Simulated Annealing technique has been found to be suitable in such cases.

The present work derives its motivation from the need to address the issues of low availability of deteriorating systems. The work already done and reported in literature in this area uses algorithm based integrated graphical model which faces a risk of getting stuck in local optima. Thus, there is a need to look out for solutions that have minimal local optima issues. One such technique widely known is Simulated Annealing. Therefore Simulated Annealing in conjunction with already tested integrated graphical model evolves as a hybrid tool to offer an integrated solution in maintenance policy decision making for deteriorating systems in order to maximize availability.

Notation

A : Availability in case of BDM
A_s : Availability in case of PM
BDM : Break Down Maintenance

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β : Shape parameter of two parameter Weibull distribution  
M : Mean Time between Failures (MTBF)  
m : Mean maintenance time for Break Down Maintenance (BDM)  
ms : Mean time for Preventive Maintenance (PM)  
PM : Preventive Maintenance  
R(t) : Reliability function  
SA : Simulated Annealing  
T : Scheduled period for PM  
T* : Optimal schedule for PM  
T̅ : Actual mean time for which the machine is in operation  
α : Actual mean time of operation due to PM schedule as a fraction of MTBF  
γ : Ratio of mean PM time to mean time for BDM  
k : Decision parameter = 1 - γ  
µ : Down time in case of BDM as a fraction of MTBF

1.1 Literature Review

Kay [1] proposed a decision model which can be used to calculate approximate optimal maintenance schedule for degraded systems. Satoh and Nara [2] addressed thermal power plant generator maintenance scheduling problem. Authors formulated the problem as a mixed-integer programming problem, and it was solved by using Simulated Annealing. Authors presented numerical results on a real-scale test system, and demonstrated the effectiveness of the proposed method.

Kim et al. [3] presented a new Genetic Algorithm for the large scale and long term scheduling problems, the target study of which was to reduce the computing time of Simulated Annealing based method and make the solution more accurate than that of the simple Genetic Algorithm. Suman and Kumar [4] developed SA-based algorithms to solve single and multi-objective optimization problems, where a desired global minimum/maximum is hidden among many local minima/maxima. The authors have presented three single objective optimization algorithms (SA, SA with Tabu search and CSA) and five multi-objective optimization algorithms (SMOSA, UMOSA, PSA, WDMOSA and PDMOSA) based on SA. Dahal and Chakpita [5] presented the application of metaheuristic approaches, such as genetic algorithm (GA) and simulated annealing (SA) and their hybrid for generator maintenance scheduling (GMS) in a power system using an integer representation. The results show that the hybrid approaches are less sensitive to the variation of technique parameters and offer an effective alternative for solving generator maintenance scheduling problem. Mohanta et al. [6] presented a comparison of results for optimization of captive power plant maintenance using genetic algorithm (GA) as well as hybrid GA/Simulated Annealing (SA) techniques. Lamberti [7] presented an optimization algorithm based on Simulated Annealing. The algorithm denoted as CMLPSA (Corrected Multi-Level & Multi-Point Simulated Annealing) implements an advanced search mechanism where each candidate design is selected from a population of trial points randomly generated. Furthermore, CMLPSA includes a multi-level annealing. Global or local search is performed based on the current trend seen in the optimization process. CMLPSA is compared with other methods.

Ahmadi and Kumar [8] developed a cost rate function to identify the optimal frequency and interval for inspection of repairable components in aircraft undergoing aging. Saraiva et al. [9] formulated the scheduling problem of generator maintenance actions as a mixed integer optimization problem in which it was aimed at minimizing the
operation cost along the scheduling period plus a penalty on energy not supplied. This optimization problem was solved using Simulated Annealing. Mariappan et al. [10] developed an integrated graphical model to arrive at a quick decision on whether preventive maintenance is required to be performed on a degradable system. The model returns the optimal preventive maintenance schedule, in case if PM is applicable. Schlunz and Vuuren [11] presented a new version of Simulated Annealing method for solving the generator maintenance scheduling problem (GMS). The hybrid SA algorithm performs very well compared to other methods on the benchmark test system from the literature. The authors have presented an improved lower bound on the objective function value for the test system. Doostparast et al. [12] considered the problem of reliability based periodic preventive maintenance planning for system with deteriorating components with the objective of maintaining a certain level of reliability with minimal total maintenance related cost. Since the problem under study is combinatorial in nature involving several non-linear decision variables, the authors employed Simulated Annealing algorithm to give a good solution within reasonable search time.

1.2 Problem at Hand

From the literature reviewed, the authors have selected Simulated Annealing effectively for specific applications of optimization, but there seems to be a need to establish the suitability of Simulated Annealing as a tool to cover wide range of deteriorating systems. These systems can be defined by various combinations of parameters which include $\beta$, $\mu$ and $k$. The shape parameter of Weibull distribution $\beta$, primarily characterizes the failure process that the system undergoes. The parameter $\mu$, is the mean down time of performing BDM as a fraction of MTBF and characterizes the involvement of BDM. The parameter $k$ involves PM and is given by $1 - \gamma$, where $\gamma$ is the ratio of mean down time of performing PM to mean down time to carry out BDM. It is not uncommon that organizations go for PM without checking the feasibility of PM over BDM for the system under consideration. Often it is presumed that PM is always better than BDM when in fact there are situations where BDM is a superior choice as compared to PM.

Therefore, the problem can be solved using a hybrid tool for optimal preventive maintenance schedule for deteriorating systems which uses a conventional method to check for the feasibility of PM over BDM and hence check for the feasibility of using SA to arrive at global optimal PM schedules for maximizing availability. This has to be established to cover the wide range of deteriorating systems in which case various combinations of parameters $\beta$, $\mu$ and $k$ have to be considered.

Thus the present work is focused at providing a solution to optimize availability by proposing a hybrid tool which uses the integrated graphical model, assisted by SA. This hybrid (integrated) approach is proposed to serve the requirements for deriving optimal PM schedules for any and every deteriorating system. Thus in essence, the methodology proposed will primarily check for applicability of PM over BDM using conventional approach and on confirming the applicability of PM, use Simulated Annealing technique coded in MATLAB which will offer global optimal schedule for PM for maximizing availability. Thus the tool becomes hybrid.

2. Research Methodology

The aim of this work is to establish the feasibility for using Simulated Annealing as a tool to obtain the optimal schedule for Preventive Maintenance with an objective of maximizing availability. In this attempt, the technique of Simulated Annealing is compared with Integrated Graphical Model [10] for arriving at optimal preventive
maintenance schedules covering a wide range and combinations of $\beta$, $\mu$ and $k$. Further, statistical model adequacy is employed to compare results of Simulated Annealing with those of the Integrated Graphical Model. The work then proposes a combination of Integrated Graphical Model and Simulated Annealing technique as a hybrid tool to check for the feasibility of PM over BDM and then provide a global optimal PM schedule for maximizing the availability of any deteriorating system.

2.1 Baseline Model for Selection of Maintenance Policy

The model developed by Kay [1] offers considerable scope to derive collaborative maintenance decisions using single parameter Weibull distribution. The scheduled maintenance is to mitigate the failure of machinery, during its assigned operating time by means of scheduled overhauls. It has long been accepted that a reasonable criterion by which the effectiveness of PM can be addressed is via availability.

Equations for availability have been derived in respect of preventive and corrective maintenance. Availability under corrective maintenance is:

$$A = \frac{M}{M + m} = \frac{1}{1 + \mu}$$

And under preventive maintenance is:

$$A_s = \frac{T}{T + m_s R(T) + m[1 - R(T)]}$$

where

$$T = \int_{0}^{T} R(t) \, dt$$

For availability of PM to be greater than that of BDM:

$$A_s - A > 0$$

However, we have

$$\alpha = \frac{T}{M} < 1$$

Substituting the equations we get:

$$\alpha > 1 - k[1 - F(T)] = (1 - k) + kF(T)$$

The above equations provide two components, one is $\alpha$ and the other is $1 - kR(T)$. These two components play a very important role in making maintenance policy decisions. When $t = 0$, $\alpha = 0$ and $t = \infty$, $\alpha = 1$. Thus $\alpha$ is a curve passing through $(0, 0)$. Whereas $[1-kR(T)]$ is an increasing line with an intercept of $(1-k)$. Superimposing these two components the scenario will have $\alpha$ curve and decision line $[1-kR(T)]$ intersecting each other, which forms the base for the development of integrated graphical model proposed by Mariappan et al. [10]. This scenario is advantageously used to develop an appropriate objective function in establishing SA algorithm to obtain optimal preventive maintenance schedule for maximizing availability.

2.2 Optimal Schedule for Preventive Maintenance

Mariappan et al. [10] suggested a modified Kay’s model using 2 parameter Weibull distributions which addresses the basic failure process more effectively. This work gives insights to selection of maintenance policies between PM and BDM using an Integrated Graphical Model thereby making the task of the user simple. The integrated graphical model has a family of curves, each one for a value of $\beta$ ranging from 1 to 8 covering
failure processes modeled by exponential distribution to beyond lognormal distribution. It has three phases based on which the decision on PM policy can be arrived at. On obtaining the values of $k$ and $\beta$ for the case under consideration, the model can be used to select maintenance policy amongst PM and BDM. In the present work, all the applicable values of $\beta$, $k$, $\mu$ to cover all possible deteriorating systems are considered. Thus for any system under study, evaluating the parameters $\beta$, $k$ and $\mu$, decision on applicability of PM can be evaluated and if PM is applicable, the optimal schedule can be obtained from the integrated graphical model. The availability values for various combinations of $\beta$, $k$ and $\mu$ were calculated using the Integrated Graphical Model.

3. Algorithm for Optimization using Simulated Annealing

Algorithm for Simulated Annealing to arrive at global optimal preventive maintenance schedule for maximization of availability is developed and coded in MATLAB.

The expression of availability which is given at (2) can also be expressed as given below:

$$A_v = \frac{1}{M} \left[ \int_0^T e^{-\left(\frac{t}{\theta}\right)^\beta} \, dt \right]$$

where $\theta$ is the scale parameter of two parameter Weibull distribution. Equation (7) is used for the purpose of calculating the availability values.

The objective is to minimize the function $f=\left[1-kR(T)\right]-\alpha$ which is expected to give optimal PM schedule $T^*$ for maximizing availability.

Step 1. Choose the Initial Solution $T_{old}$ (Random Number) to evaluate the function $f_{old}=\left[1-kR(T)\right]-\alpha$, initial temperature $t'$, terminating temperature $t'_\text{min}$, fraction sigma, number of iterations to be performed at each temperature $n$ and cooling rate $\psi$.

Step 2. Evaluate the Function $f(T_{old})=f_{old}$ at initial solution.

Step 3. Move to the feasible neighboring point $T_{new}=T_{old}+\sigma \times \text{normal random number between 0 and 1}$.

Step 4. Evaluate the Function $f(T_{new})=f_{new}$ at this new point.

Step 5. Check if $\delta = f(T_{new}) - f(T_{old}) < 0$,

5.1. If $\delta < 0$, accept the new point and move to the neighboring point.

5.2. Check if number of iterations at this temperature = $n$. If yes, lower the temperature $t'$ according to the cooling schedule $t'=\psi \times t'$.

Step 6: Terminate the algorithm. Output the optimum value of time $T^*=T_{old}$.

Calculate optimum value of availability for $T^*$ using the availability function (equation 7).
The availability values for various combinations of $\beta$, $k$ and $\mu$ as done in § 2.2 were calculated using Simulated Annealing.

4. Model Adequacy

For various combinations of the parameters $\beta$, $k$ and $\mu$, which any deteriorating system under study will possess, corresponding availability values obtained as discussed in § 2.2 and § 3 are necessarily to undergo a comparative study to ascertain the effectiveness, that too statistically involving inferential statistics. This section presents such a comparison between integrated graphical model (conventional method) and SA. A failure phenomenon characterized by bathtub profile, on Weibull analysis, will indicate regions corresponding to $\beta < 1$, $\beta = 1$ and $\beta > 1$. Preventive maintenance is required only in the wear out region wherein the value of $\beta$ is greater than 1. Hence $\beta$ varying from 1.4 to 8 is considered. When $\beta$ assumes 4 it is closer to Gaussian distribution and for 7 it resembles lognormal distribution. Similarly it is required to split the decision parameter $k$ into number of segments from 0 to 1. The availability values for various combinations of $\beta$, $k$ and $\mu$ were calculated using Graphical method and Simulated Annealing. As the combinations of $\beta$, $k$ and $\mu$ considered in this work cover the entire spectrum of deteriorating systems, the model proposed assumes generic nature.

Using the expression (7), availability values were obtained for various values of $k$, $\beta$ and $\mu$. An appropriate code was developed in MATLAB to compute the same. For every combination of $k$, $\beta$ and $\mu$, SA algorithm was run and the availability values obtained were compared with those obtained using the Integrated Graphical Model proposed by Mariappan et al. [10]. The results obtained were put under statistical adequacy. It is observed that the availability values corresponding to optimal schedule ($T^*$) from SA are closer to that of Integrated Graphical model for various combinations of $\beta$, $\mu$ and $k$. SA technique simply demands annealing temperature along with initial solution and rate of cooling. Thus it becomes amazingly easier and simple. However, to evaluate the closeness and superiority of the methods it needs further investigations using inferential statistics.

5. Results and Discussion

For comparing the performance of Simulated Annealing with the Integrated Graphical Model, testing of hypothesis is carried out with the following hypothesis. This is the case of testing two population means which will be classified into population with same variances or different variances. The broader test will be having the following format.

$$H_0: A_1 = A_2$$
$$H_1: A_1 \neq A_2$$

Where $A_1$ is mean availability due to Simulated Annealing and $A_2$ is mean availability due to Integrated Graphical Model.

Values of $t_{\text{critical}} = t_{\alpha/2, \text{dof}}$ are obtained from ‘$t$’ distribution table at a specific significance level of say, 5% and then compared with the calculated values ($t_0$). The Null Hypothesis cannot be rejected if $-t_{\text{critical}} < t_0 < t_{\text{critical}}$.

5.1 Sample Case: for $\mu = 0.05$ & $\beta = 4$

A sample case for $\mu = 0.05$ & $\beta = 4$ is presented with following notation.

$$n_1, \bar{X}_1, S_1^2, \sigma_1^2 = \text{no. of observations, sample average, sample variance of availability values and variance using Simulated Annealing.}$$
$$n_2, \bar{X}_2, S_2^2, \sigma_2^2 = \text{no. of observations, sample average, sample variance of availability values and variance using Integrated Graphical Model.}$$
Sample variance \( S_1^2 = 0.00011 \) & \( S_2^2 = 0.000148 \)

\[ F = \frac{S_2^2}{S_1^2} = 1.347105 \]

From F table, for 5% significance level \( F_0 \) is given as

\[ F_0 = F_{0.05, 14, 14} = F_{0.05, n_2 - 1, n_1 - 1} = F_{0.05, 14, 14} = 2.46 \]

Since \( F < F_0 \), we conclude that \( \sigma_1^2 = \sigma_2^2 \).

When \( \sigma_1^2 = \sigma_2^2 \), Pooled sample variance is calculated as shown below:

\[ S_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2} = \frac{0.00011 + 0.000148}{21} = 0.000129 \]

\[ S_p = 0.01134 \]

\[ t_\alpha = \frac{X_1 - X_2}{S_p \sqrt{1/n_1 + 1/n_2}} = 0.523237 \]

From 't' distribution table, \( t_{n_2/2, n_1 = n_2 - 2} = t_{0.025, 28} = 2.048 \)

As \( t_\alpha \) lies within the limits of -2.048 and +2.048, we fail to reject the Null Hypothesis \( H_0: A_1 = A_2 \).

Therefore from the t test it is inferred that the mean availability due to Simulated Annealing is same as that of Integrated Graphical Model.

Combinations of \( k, \mu \) and \( \beta \) were taken, for \( k \) taking values from 0.25 to 0.95, \( \mu \) taking values from 0.05 to 0.5 and \( \beta \) taking values from 1.4 to 8. It is observed that for all above combinations the same result has been obtained. This leads to the inference that the mean availability using Simulated Annealing technique is as effective as that of Integrated Graphical Model. Range of parameters \( \beta, \mu \) and \( k \) discussed above cover the deteriorating system characteristics of almost all the combinations encountered in deteriorating systems. Thus it can be inferred from foregoing discussions that Simulated Annealing as a technique can be effectively used to optimize the availability function for the entire range of deteriorating systems.

Having established the suitability of Simulated Annealing for deciding optimal PM schedules for maximizing availability, the following methodology is proposed to give a hybrid tool for optimal preventive maintenance schedules to cover the entire range of deteriorating systems.

For any given deteriorating system, parameters \( \beta, k \) and \( \mu \) are determined based on analysis of failure and cost data. Integrated Graphical Model is then used to decide the choice between PM and BDM. If PM is suitable as compared to BDM, global optimal PM schedule for maximizing availability is obtained using the algorithm for Simulated Annealing, coded in MATLAB. This hybrid tool can be used to decide the feasibility of PM over BDM and hence arrive at close to global optimal PM schedule for maximizing availability of any deteriorating system.

6. Conclusions

It can be concluded from the discussions that the hybrid tool of Simulated Annealing assisted integrated graphical model is a feasible alternative in arriving at decisions regarding the feasibility of PM over BDM and hence providing close to global optimal schedules for PM of deteriorating systems for maximizing availability. This model does not get trapped in local optima and has ability to deal with chaotic and noisy data. Thus it has an edge over the traditional methods. This tool has been developed by taking a wide range of combinations of \( k, \mu \) and \( \beta \) so as to cover the entire spectrum of the deteriorating system characteristics. The proposed hybrid tool therefore is a generic tool for deriving optimal PM schedules for entire range of deteriorating systems and can be considered as a
powerful and potential candidate to replace the traditional methods which do not guarantee global optimal closed bound solutions.

References


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