Machinery Condition Monitoring System Selection – A Multi-Objective Decision Approach using GA

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Abstract

In this paper, a framework for Condition Based Maintenance (CBM) of large engineering systems has been suggested to address the need to optimize the characteristics of both the condition monitoring system and the plant that is being maintained at a macro level. CBM for large engineering systems has been modeled using Markov process. The issues which are critical to CBM, namely, predictability, detectability as well as implications of availability and cost have been considered in the framework to provide effective decision support. The application of the framework has been demonstrated using a numerical example. The trade offs between the Pareto optimal solutions of various objectives have been studied and the effects of variation of the maintenance objective function values with detectability and predictability have been brought out.

1. Introduction

Maintenance has an essential role in ensuring that engineering systems perform at expected levels of reliability, availability and safety in a cost effective manner and in keeping with the corporate demands. In the case of Maintenance of Large Engineering Plants (LEP) like, aircraft, shipboard machinery, power plants and nuclear installations, owing to their peculiarities, Time Based Maintenance (TBM) is preferred as an effective strategy [1]. But TBM is based on the assumption that failures are age related which is contrary to a study where it is shown that about 80% to 85% of equipment failures are caused due to the effects of random events that happen in the system [2]. Therefore it is necessary to augment TBM of large engineering plants with Condition Based Maintenance (CBM) so as to optimally realize the objectives of maintenance. Features of condition monitoring, diagnostic and prognostic systems have been discussed in literature[3-5]. There has been a widespread use of Markov and semi-Markov processes for studying maintenance effects[6-8]. Soft computing techniques and Genetic algorithms are increasingly being used in maintenance decision problems as they provide an efficient platform for both modeling and solution phases of the problem[9-13]. Most models in literature use deterioration levels of machinery systems to schedule inspection or condition monitoring. But, in many cases, particularly for large engineering plants, it is not possible to precisely identify the level of deterioration since there are several components in the plant and each of them has several modes of deterioration. Further, there are interdependencies between the components. Therefore, for a maintenance decision maker on site, it is preferable to identify the state of the sub-system by means of the level of repairs that are necessary to restore the prevailing state to a “as-good-as-new” state. There is also a need to optimize the characteristics of the condition monitoring system at a macro level. This will enable decisions regarding the area and extent of effective applicability of CBM for a large plant consisting of several sub-systems arranged in a complex way.

This paper presents a framework for providing decision support to select condition monitoring systems based on their detectability and predictability and provide for them at appropriate locations of the system. In section 2 the CBM model is described as a discrete space, continuous time Markov process. In sections 3 and 4, objective and constraint functions are developed. This is followed by formulation of expressions for detectability and predictability of the condition monitoring system in section 5. A numerical example is presented in section 6. Results and Conclusions are discussed in sections 7 and 8 respectively.

2. Model description

Consider a Large Engineering Plant (LEP) in which n modules are subjected to Condition Based Maintenance (CBM). Each of the n modules of the plant is subjected to a particular condition monitoring
arrangement. The condition monitoring arrangements comprise of one or more techniques, including manual inspection and assessment of condition of the module. Each of the \( n \) modules is essential for the plant to be in the operational state.

In respect of each of the \( n \) modules, initially, periodic monitoring of its condition is done at a particular monitoring rate. When an exceeding of the threshold values of one or more of those parameters indicating the healthy condition of the module (Relevant Condition Indicators, RCI [16]) is detected by the condition monitoring system, the module is subjected to a more detailed condition monitoring strategy. In this strategy, prediction of time to carry out preventive maintenance so as to prevent a catastrophic failure is done using the monitored parameters (Relevant Condition Predictor, RCP[16]). Again, when crossing of threshold value of the RCP of the module is detected by the condition monitoring system, the module is subjected to an appropriate level of preventive maintenance (PM). If the RCP or RCI is detected but the instant of failure is not detected by the monitoring system sufficiently in advance, the PM of the module is delayed for necessary logistic preparation. On the other hand, if the exceeding of an RCI or an RCP is not detected, the module fails catastrophically, necessitating Corrective Maintenance (CM). Both PM and CM restore the module to “as good as new” condition.

The model provides for the ability to enable regression to a previous operationally better state in case the measured deterioration value reduces due to state changes or cessation of some external disturbing factors [14]. The model is shown schematically in Figure 1. The above CBM problem is modeled as a discrete space, continuous time Markov process as shown in Figure 2. In constructing the model and formulating the objective functions, the discussions in reference [15] have been taken forward to include logistic delay and a detailed analysis of detectability and predictability features of condition monitoring system on the maintenance objectives of LEP.

3. Notation

The condition of the module in each state of the Markov model is determined by the extent or level of repairs or maintenance required to restore it to as good as new condition. It is required to minimize the Unavailability, overall cost of Condition Based

| \( i \) | Number of the module, \( i = 1, 2, \ldots, n \) |
| \( A_{i,a} \) | Operational state ‘\( a \)’ of module, ‘\( i \)’ |

Further, if \( \delta_{i,a} \in [0,1] \) is the detectability feature of the relevant condition monitoring arrangement \( \pi \) of module \( i \), and \( \alpha_{i,a} \) and \( \beta_{i,a} \) are the failure rates of the module \( i \) while undergoing condition monitoring of

![Figure 1. Schematic diagram showing CBM of LEP](image)

![Figure 2. Markov model of CBM of a LEP](image)
strategy π, then the transition rates to the states of higher levels of condition monitoring and various categories of logistic delays are respectively,
\[ \hat{\lambda}_{i,a} = \delta_{i,a} \hat{\alpha}_{i,x} \]
\[ \hat{\lambda}_{i,a} = \delta_{i,a} \hat{\beta}_{i,x} \]

Where, \( \hat{\lambda}_{i,a} \) is the probability of the module i undergoing level ‘h’ of PM. Also, the corresponding transition rates to the states of catastrophic failure are
\[ \lambda_{i,a} = (1-\delta_{i,a}) \hat{\alpha}_{i,x} \]
\[ \lambda_{i,a} = (1-\delta_{i,a}) \hat{\beta}_{i,x} \]

The transition from the states of logistic delays will depend on the predictability. Higher the predictability, faster will be the rate of transition from the state of logistic delay to that of PM. If \( \rho \in [0,1] \) is the predictability feature of the condition monitoring system of an impending failure, then,
\[ \hat{\lambda}_{i,a} = (1-\rho) \hat{\beta}_{i,x} \]

4. Formulation of objective and constraint functions

4.1 Objective functions

4.1.1 Unavailability. The steady state unavailability of the plant is given in respect of the probabilities of catastrophic failures of the constituent modules and the down time of the plant due to logistic delay. Since all modules are necessary for the operation of the plant, the steady state unavailability of the module is given by:
\[ U_{\text{Module}} = P(F_i) + \sum_{a=1}^{n} P(D_{l,a}) \]
And, for the entire plant,
\[ U_{\text{plant}} = 1 - \prod_{i=1}^{n} \left[ 1 - P(F_i) - \sum_{a=1}^{n} P(D_{l,a}) \right] \]

4.1.2 Cost. The cost of CBM is dependent on the initial and operational cost of the condition monitoring system as represented in this model by their detectability and predictability. Higher detectability and predictability imply higher cost. Cost is incurred when the plant is down for CM owing to not only the lost operational time, but also the secondary damages suffered and the safety compromised. Cost is also incurred due to the logistic delay, again due to the lost operational time as well as the extra effort and resources required for emergency arrangements for repairs and maintenance. A short logistic delay is possible if adequate warning of failure is given by the condition monitoring system, which in turn depends on its predictability. Further, the cost of CBM is proposed as a time rate which will be the rate of cost over an operational window of duration T. As per the CBM policy, replacement or repair or maintenance is done preventively when the condition demands or when the component of module fails. This can be given by
\[ T = \min \left[ \sum_{i=1}^{n} \frac{1}{P(A_{i,p})} \left( \sum_{a=1}^{n} \lambda_{i,a}^{(r)} \right) ; i = 1, 2, ..., n \right] \]

where \( \lambda_{i,a}^{(r)} \) is the rth transition rate out of state \( P_{i,p} \) and \( \lambda_{i,a}^{(f)} \) is the fth transition out of state \( F_1 \) (\( f = 1, 2, ..., F \)).
\[ C_{\text{plant}} = \frac{1}{T} \sum_{i=1}^{n} \sum_{a=1}^{n} \left[ C_{i,a} \delta_{i,a} + C_{i,p} P_{i,p} + C_{i,P} P(F_i) + \sum_{p=1}^{n} C_{i,p} P(P_{i,p}) + \sum_{d=1}^{n} C_{i,d} P(D_{l,d}) \right] \]

Where \( C_{i,a} \), \( C_{i,p} \), \( C_{i,P} \) and \( C_{i,d} \) are the cost related to the detectability of the condition monitoring system, predictability of the condition monitoring system, cost of catastrophic failure, cost of PM and the cost due to logistic delay respectively.

4.1.3 The ratio, \( \frac{\text{Prob(CM)}}{\text{Prob(PM)}} \) Plant

The ratio of the sum of the probabilities of CM and the sum of probabilities of PM in respect of all the modules of the plant is proposed an indicator towards the efficacy of the condition monitoring system.
\[ \left( \frac{\text{CM}}{\text{PM}} \right) = \frac{\sum_{i=1}^{n} P(F_i)}{\sum_{i=1}^{n} P(P_{i,p})} \]

4.2 Constraint Function

The CBM model for the plant has to integrate with the Time Based Maintenance or Scheduled Preventive Maintenance (SPM) Model. One of the approaches proposed for the same is by trying to ensure that the Mean Time Between Failures (MTBF) derived from the CBM model is greater or equal to the SPM interval, \( t_{SPM} \). The least MTBF of all the modules must be greater than or equal to the SPM interval and this is proposed as a constraint to the optimization problem.
\[ \min \left[ \sum_{i=1}^{n} \frac{1}{P(A_{i,p})} \left( \sum_{a=1}^{n} \lambda_{i,a}^{(r)} \right) ; i = 1, 2, ..., n \right] \geq t_{SPM} \]

4.3 Constrained Multi-Objective Optimisation Problem

The CBM problem modeled above is solved as a Constrained Multi-Objective Optimisation Problem.
5. Detectability and predictability

The overall outputs of the condition monitoring arrangements can be divided into detectability (representing RCI) and predictability (RCP) factors. Detectability is further divided into effectiveness and accuracy. Effectiveness $e_a$ is the proportion of the expected number of failures avoidable by technique $\pi$ relative to the total expected number of failures under Failure Replacement Policy (FRP). Accuracy $a_a$ of the same strategy is defined as the proportion of total expected number of failures under Failure Replacement Policy to the expected number of total removals. For the long run they are defined as [17]:

$$e_a = 1 - \frac{\mu_i P(\xi \leq T_{i,\pi})}{E[\min(\xi_i, T_{i,\pi})]}$$  \hspace{1cm} (14)$$

$$a_a = \frac{E[\min(\xi_i, T_{i,\pi})]}{\mu_i}$$  \hspace{1cm} (15)$$

where $\mu_i = E[\xi_i]$, $\xi_i$ is the failure time random variable of module $i$ and $T_{i,\pi}$ is the preventive replacement time.

Predictability is proposed to be further divided into prognostic ability $\rho_i^{d,a}$ and diagnose-ability. Both of these are essential for the predicting system to provide maximum lead time for preparation for maintenance and thereby reducing logistic delays and enabling better planning of maintenance. Following quantitative measures are proposed for determining Predictability:

(a) Prognostic ability:

$$\rho_i^{d,a} = 1 - \{1 - P(\xi_i \leq t_{i,\pi}^d)\} \cdot P(t_{i,\pi} \leq LDT; T_{i,\pi} < t_{SM})$$  \hspace{1cm} (16)$$

where, $\xi$ is a small positive number $t_{i,\pi}^d$ is the time of detection of the impending fault or failure of module $i$ using the technique $\pi$ and LDT is the logistic delay time.

(b) Diagnostic Ability

Let the set of parametric and non-parametric symptoms gathered by the condition predicting system be $P_{i,\pi} = \{P_{i,\pi,1}, P_{i,\pi,2}, \ldots, P_{i,\pi,n}\}$ \hspace{1cm} (17)$$

The set of diagnosis leading to preventive maintenance be $D_i = \{D_{i,1}, D_{i,2}, \ldots, D_{i,m}\}$ \hspace{1cm} (18)$$

$$S_{i,\pi} = \{ \text{All possible combinations of symptoms that are found to occur together to yield meaningful diagnosis}\}$$

Define $f : S_{i,\pi} \rightarrow D_i$ \hspace{1cm} (19)$$

Also, $A_{i,\pi} \subseteq S_{i,\pi} \hspace{1cm} (20)$$

Thus, diagnostic ability is given by

$$\rho_i^{d,a} = \sum_{A_{i,\pi} \subseteq S_{i,\pi}} P(A_{i,\pi}) P(f(A_{i,\pi}) \text{given} A_{i,\pi})$$  \hspace{1cm} (21)$$

Further, it is proposed that both the detectability and predictability be given as the weighted sum of their constituent parts.

Detectability: $\delta_{i,\pi} = \sigma_{i,\pi}^{d,a} + \sigma_{i,\pi}^{d,a} \hspace{1cm} (22)$$

Predictability: $\rho_{i,\pi} = \sigma_{i,\pi}^{d,a} \rho_i^{d,a} + \sigma_{i,\pi}^{d,a} \rho_i^{p} \hspace{1cm} (22)$

where, $\sigma_{i,\pi}^{d,a} + \sigma_{i,\pi}^{d,a} = 1 \hspace{1cm} (23)$

6. Numerical Example

A plant consists of two modules, both of which are required for the functioning of the plant. The CBM decision model proposed above is applied to the plant, appropriately adopting the Markov diagram in Figure 2. The values of the constants used in the problem are $\alpha_i = 0.033$; $\beta_i = 0.05$; $\lambda_{B_i,i,a,b,e} = 1 & 0.166$; $\lambda_{B_i,B_i,a,c} = 1 & 4$; $\lambda_{P_i,A_{i,d}} = 0.06$; $\lambda_{P_i,B_{i,b},a} = 1$. For simplicity, the failure rates are assumed to be identical for both the modules. The constrained multi-objective optimization problem was solved using Non-Dominated Sorting Genetic Algorithm (NSGA-II) [18]. The parameters for the GA are based on experimental/conservative values.

The steady state Probabilities and other terms in the objective and constraint functions are obtained by solving the matrix equation, 24 [19].

7. Results

The result of multi-objective optimisation using the GA is a set of optimal solutions which form Pareto optimal fronts in the objective spaces. Each solution corresponds to a set of values for the objectives, which in turn correspond to a set of decision variables. All
solutions are optimal, one differing from the other due to the trade off between the objectives. The trade offs between the relative cost rate of CBM and the ratio of probabilities of CM/PM is shown in Figure 3. It can be seen that the cost of CBM increases along with greater demand for PM in preference to CM. This result is on expected lines. However, the results give more precise decision support in respect of the two objectives to the decision maker. Likewise, Figure 4 shows the variation of cost with unavailability. Figure 5 gives the relation between the ratio of probabilities CM/PM and unavailability. It can be seen from Figure 6 that the variation of average predictability is more rapid than that of average of detectability with respect to unavailability. In other words, availability is relatively more sensitive to predictability. Extending this observation, detectability is more important in the early stages of monitoring which will improve reliability and safety of the plant and predictability is more important in the later stages, which will improve steady state availability.

Finally, the decision maker can select the most acceptable solution from among the Pareto optimal solutions using the decision statements for

Figure 5. Unavailability of the plant vs. the ratio of the probabilities of CM and PM

Figure 6. Averages of detectability and predictability of both modules compared against Unavailability
predictability and detectability (equations 14-23), which in turn can be ascertained based on statistical data or expert opinion or both.

8. Conclusions

CBM is aimed at preventing catastrophic failures of equipment and providing sufficient lead time for planning, preparing and undertaking preventive maintenance. Selection of a condition monitoring system would require decisions regarding the adequacy of detectability and predictability which would provide the necessary reliability and availability of the plant at affordable cost. In this paper, a framework for the above purpose has been provided by modeling CBM as a Markov process where detectability and predictability features of the condition monitoring system are incorporated as decision variables. The objectives of minimizing unreliability, cost and the extent of corrective maintenance compared to preventive maintenance have been simultaneously optimized using GA. The trade offs between the objectives as well as sensitivity of detectability and predictability to the objectives were studied. The decision maker can select that optimum solution in the light of the corresponding detectability and predictability.

9. References


