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Optimization of Preventive Maintenance Scheduling in Processing Plants

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Abstract

A new methodology designed to optimize both the planning of preventive maintenance and the amount of resources needed to perform maintenance in a process plant is presented. The methodology is based on the use of a Montecarlo simulation to evaluate the expected cost of maintenance as well as the expected economic loss, an economical indicator for maintenance performance. The Montecarlo simulation describes different failure modes of equipment and uses the prioritization of maintenance supplied, the availability of labour and spare parts. A Genetic algorithm is used for optimisation. The well-known Tennessee Eastman Plant problem is used to illustrate the results.

Keywords: Preventive maintenance, Maintenance optimization, Montecarlo simulation

1. Introduction

Maintenance can be defined as all actions appropriate for retaining an item/part/equipment in, or restoring it to a given condition (Dhillon, 2002). More specifically, maintenance is used to repair broken equipments, preserve equipment conditions and prevent their failure, which ultimately reduces production loss and downtime as well as the environmental and the associated safety hazards. It is estimated that a typical refinery experiences about 10 days downtime per year due to equipment failures, with an estimated economic lost of $20,000-$30,000 per hour (Tan and Kramer, 1997). In the age of high competition and stringent environmental and safety regulations, the perception for maintenance has been shifted from a "necessary evil" to an effective tool to increase profit, from a supporting part to an integrated part of the production process. Effective and optimum maintenance has been the subject of research both in academy and in industry for a long time.

There is a very large literature on maintenance methods, philosophies and strategies. In addition, there is a large number of Computerized Maintenance Management Systems (CMMS) software packages devoted to help managing / organizing the maintenance activities. Despite this abundance, the optimization of decision variables in maintenance planning like preventive maintenance frequency or spare parts inventory policy, is usually not discussed in textbooks nor included as a capability of the software packages. Nonetheless, it has been extensively studied in academic research: Many models were discussed and summarized in the excellent textbook by Wang and Pham (2006)] and various review papers, e.g. Wang (2002). Most of the models are deterministic models obtained by making use of simplified assumptions, which allow the use of mathematical programming techniques to solve. The most common optimization criterion is minimum cost and the constraints are requirements on system reliability measures: availability, average uptime or downtime. More complex maintenance models that consider simultaneously many decision variables like preventive maintenance (PM) time interval, labor workforce size, resources allocation are usually solved by Genetic algorithm (e.g. Sum and Gong, 2006; Saranga, 2004). Monte Carlo simulation is usually used to estimate reliability parameters in the model. Tan and Kramer (1997) utilized both Monte Carlo simulation and GA.

None of preventive maintenance planning models considers constraints on resources available in process plants, which include labor and materials (spare parts). For example, the maintenance work force, which is usually limited, cannot perform scheduled PM tasks for some equipments at scheduled PM time because of the need to repair other failed equipments. Such dynamic situations can not be handled by deterministic maintenance planning models or are not considered in published maintenance planning models that use Monte Carlo simulation tools.

To ameliorate all the aforementioned shortcomings, we developed a new maintenance model based on the use of Monte Carlo simulation. The model incorporates three practical issues that have not been considered in previous work: i) different failure modes of equipment, ii) ranking of equipments according to the consequences of failure, iii) labor resource constraints and material resource constraints. The maintenance model, which was developed by Nguyen et al. (2008) is integrated here with a GA optimization to optimize the PM frequency.

2. Monte Carlo simulation – based maintenance model

2.1. The objective value

The objective value is the total maintenance cost plus economic loss (to be minimized). The economic loss is the loss caused by equipment failures that lead to reduced production rate or downtime. It is the economic indicator for maintenance performance, i.e. the better the maintenance plan the smaller the economic loss. Thus by minimizing the maintenance cost plus the economic loss, one simultaneously optimizes the cost and the performance of maintenance.

The cost term includes four types of cost: the *PM cost* and *CM cost*, which are the costs associated with preventive maintenance and corrective maintenance activities, respectively, the *Labor cost* (the salary paid to employees) and the *inventory cost* (the cost associated with storing spare parts of equipments).

The economic loss term includes two types of losses: i) economic loss associated with failed equipments that have not been repaired (for example, a fouled heat exchanger can continue operating but at reduced heat transfer rate, ii) economic loss due to unavailability of equipment during repair time. The economic loss is calculated as a loss rate ($ per day) multiplied by the duration of the period within which the loss is realized. To determine economic loss rates, an analysis is carried out on each piece of equipment to determine the economical effects of equipment failure, which include reduced production rate or even shutdown, the deterioration of product quality, etc.

2.2. Input data

The following data are needed in the model: i) reliability data for equipment, ii) the time and the associated material cost to perform corrective maintenance (CM) and preventive maintenance, iii) economic data: labor paid rate, inventory cost rate and economic loss rate, iv) other data like the waiting time for an emergently ordered spare part to arrive.

We assume that the failure distribution is exponential, thus, only one parameter is needed to describe the reliability of equipment: the mean time between failures (MTBF). Other distributions can be used but they require at least two parameters.

2.3. Ranking of repairs

The equipments to be repaired are ranked according to the consequences of failures: 1 is emergent and 5 is affordable to go unrepaired. The maintenance of equipments with higher ranking takes precedence over the lower ranked ones. This is shown in Table 1.

Table 1: Ranking of equipments for Maintenance purpose (following Tischuk, 2002)

	Consequence of Failure		
Probability of subsequent catastrophic Failure	High	Medium	Low
High	1	2	3
Medium	2	3	4
Low	3	4	5

2.4. Failure modes of equipments

An equipment may have different failure modes involving different parts of the equipment. It can fail because of deterioration of mechanic parts (possible consequence is complete failure that requires equipment replacement) or electronic parts malfunction (partial failure that can be repaired). Different failure modes need different repair costs and repair times and induce different economic losses. The sampling of different failure modes of equipment is done as follows: i) assign a probability of occurrence for each type of failure mode using information on how common a failure mode is, ii) at the simulated failure time of the equipment, the type of failure mode that actually occurred is sampled in accordance with the failure modes' probability of occurrence.

2.5. Decision variables

Three decision variables are considered in the model: i) the PM time schedule that involves two parameters: the time to perform the first PM (called PM starting time) and the PM time interval, ii) the inventory policy, which is the decision whether to keep inventory for a specific spare part necessary for repairing a specific equipment, iii) the number of maintenance employees. The PM starting time and PM time interval are expressed as a fraction of MTBF (e.g. PM time interval = a*MTBF), the fraction a is to be optimized (for each equipment).

3. Monte Carlo simulation procedure

Most of the material in this section is taken from a recent paper (Nguyen et al, 2008) that has explored the use of Monte Carlo simulation for evaluation purposes.

3.1. Maintenance rules

- No delay in performing maintenance once the resources are available
- If equipment has undergone corrective maintenance a predetermined period of time prior to the scheduled PM (current value = 7 days), the PM is suspended so that resources can be used elsewhere

- If, due to unavailability of resources, repair of an equipment has been delayed more than a predetermined threshold value (current value = 21 days), the priority for repair of that equipment is upgraded one level

3.2. Simulation details

This technique is based on repeated sampling of the equipment failure and evaluation of the cost of maintenance activities as well as the economic losses associated to the failed states of equipments. The method continues sampling and computing an average until the average converges to a finite value.

The sampling procedure is as follows:

- Failure times of equipments are sampled using reliability function (failure rate) of equipments
- At failure times of equipment, the type of failure modes that caused equipment failure is sampled in accordance with the probability of occurrence.
- The cost of corrective maintenance, the repair time and the economic losses are determined corresponding to the type of failure modes identified.
- Preventive maintenance requests for equipments are generated in accordance with the predetermined preventive maintenance schedule (predetermined PM policy)
- The planning time horizon is divided into time intervals of weeks.
- In each week:
    i) All the CM requests (when equipments failed) and all the scheduled PM requests are identified.
    ii) CM request and PM requests for equipment with highest priority will be fulfilled. Continuing with CM requests and PM requests for equipments with lower priority until the (labor and materials) resource available is used up. If resources are not available, the requested maintenance action has to be delayed until the resources become available again (e.g. the needed spare part is available through emergent purchasing).
- When a maintenance action is performed on an equipment at time *t*, that equipment is assumed to be as good as brand new and failure events for that equipment will be re-sampled (updated) starting from time *t*.

4. Genetic algorithm

We used a standard binary GA whose detail can be found in various textbooks on GA. We describe only the step of coding from true values of decision variables into binary variables in the chromosome as follows:

- The PM time frequency is given by *a**MTBF (*for each equipment*). The fraction *a*, to be optimized by GA, is confined to take one of the following 16 values: [0.025, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2] (vector *A*). The value of *a* is indicated by the index *i* (the location) of the elements in vector *A*, e.g. if $i = 2$, then $a = A[2] = 0.05$
- A gene consisting of 4 binary variables *klmn* is used to represent the index *i*.
- Genes for spare parts inventory and labor are similar (these variables are fixed in this paper).

The GA parameters are as follows: population size = 20; fraction of population to keep = 0.5; mutation rate = 0.3; Roulette wheel selection and two point crossover method.

5. Example

The new framework for maintenance analysis and optimization is demonstrated using the well-known Tennessee Eastman (TE) plant. The description and the process flowsheet for the TE process can be found in the literature, e.g. in Ricker and Lee (1995). The list of equipments in the process is given in table 2.

Table 2. List of equipment of the TE process

Equipments	Qua-ntity	MTBF (days)	Time for CM (hrs)	Time for PM (hrs)	Prior-ity	PM interferes with production ?
Valves	11	1000	2-5	2	3	
Compressors	1	381	12-18	6	1	
Pumps	2	381	4-12	4	4	
Heat Exchanger	2	1193	12-14	8	2	x
Flash drum	1	2208	24-72	12	1	x
Stripper	1	2582	48-96	12	1	x
Reactor	1	1660	12-72	12	1	x

The MTBF and maintenance time are either obtained from literature (CCPS, 1989; Bloch and Geitner, 2006) or estimated if the information is not available. Our example shows the results when the PM time intervals are optimized. Other variables are fixed: ten employees, keeping inventory for all spare parts and reasonable numbers for the PM starting time. The maintenance model and the GA are implemented in Fortran running on a 2.8 GHz CPU, 1028 MB RAM PC. The final results for the fraction *a* (PM time interval = *a**MTBF) are shown in table 3.

Table 3. Optimal PM frequency

Equipments	11 Valves	2 Compresors	2 Pumps	Flash drum
Fraction *a*	0.1 (6 valves) & 0.25 (5 valves)	0.1	0.2	1.2
Equipments	Heat Exchangers	Stripper	Reactor	
Fraction *a*	1.2	1.0	1.0	

These results are consistent with the results obtained by Nguyen et al.(2008): for the group of equipments whose PM does not interfere with production (e.g. valves & pumps), high PM frequency is obtained: fraction *a* ranges from 0.1 to 0.25 (Nguyen et al., 2008 obtained 0.1 by inspection). In turn, for group of equipments whose PM interferes with production (e.g. the reactor) such that PM causes economic loss during maintenance time, frequent use of PM is not recommended (fraction *a* = 1.0, 1.2). The evolution of the current best value of objective function is shown in figure 1, which shows that the objective value converges to a finite value only after 7 iterations. The computation time (after 57 iterations) is 1 hr 24 min.

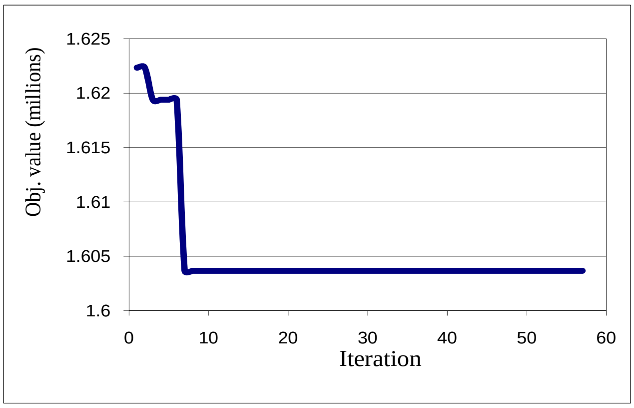

Figure 1. Evolution of the current best objective value in GA iterations

6. Conclusions

A new maintenance model based on the use of Monte Carlo simulation and integrated with GA optimization is presented in this article. The model incorporates three practical issues not considered in previous work and is capable of analyzing and optimizing complex maintenance operations.

References

Bloch H.P and Geitner F.K. (2006). *Maximizing Machinery Uptime*, Elsevier, MA, USA.

Center for Chemical Process Safety, AIChE (1989). *Guidelines for Process Equipment Reliability Data with Data Tables*, ISBN 0816904227

Dhillon B.S. 2002. *Engineering Maintenance*, CRC Press, Boca Raton, USA.

Nguyen D.Q, C. Brammer and M. Bagajewicz. (2008). *A New Tool for the Evaluation of the Scheduling of Preventive Maintenance for Chemical Process Plant*s. Industrial and Engineering Chemistry Research, To appear.

Ricker N.L and Lee J.H. (1995). *Nonlinear Modeling and State Estimation for the Tennessee Eastman Challenge Process*. Comput. Chem. Eng., 19(9), 983-1005.

Shum, Y.S and Gong, D.C. (2006). *The Application of Genetic Algorithm in the Development of Preventive Maintenance Analytic Model*. The International Journal of Advanced Manufacturing Technology. Vol. 32, pp.169-183.

Saranga. H. (2004). *Opportunistic Maintenance Using Genetic Algorithms*. Journal of Quality in Maintenance Engineering, 10(1), pp. 66-74.

Tan J.S. and Kramer M.A. (1997). *A General Framework For Preventive Maintenance Optimization In Chemical Process Operations*. Computers and Chemical Engineering, 21(12), pp. 1451-1469.

Tischuk, John L. (2002). *The Application of Risk Based Approaches to Inspection Planning*. Tischuk Enterprises (UK).

Wang H. and Pham H. (2006). *Reliability and Optimal Maintenance*, Springer Series in Reliability Engineering, Springer-Verlag, London.

Wang H. (2002). *A survey of maintenance policies of deteriorating systems*. European Journal of Operational Research, 139(3), pp. 469-489.