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Preventive Maintenance Optimization of Critical Equipments in Process Plant using Heuristic Algorithms

Mahadevan ML, Poorana Kumar S, and Vinodh R
Department of Mechanical Engineering
Thiagarajar College of Engineering, Madurai, Tamilnadu, India

Paul Robert T
Department of Industrial Engineering
Anna University, Chennai, Tamilnadu, India

Abstract

The rapid growth of industries has complicated the functioning system and has intensified the maintenance process emphasizing the need for effective maintenance planning. Maintenance planning is complex and inherently stochastic, indicating the need for heuristic techniques. In this paper, maintenance planning problem for a process industry is addressed. The problem is formulated to predict which of the two possible actions (viz. imperfect maintenance or component replacement) is to be carried out for each of the components during the planning period. The net present cost for the entire design out period is minimized and furthermore, improvement possibilities during the preventive maintenance action are analyzed in terms of Mean Time Between Failures (MTBF) & Mean Time To Repair (MTTR). Two search techniques, Simulated Annealing (SA) and Genetic Algorithms (GAs), are used to solve the problem.

Keywords
Maintenance planning, Simulated Annealing technique, Genetic Algorithms, Simulation.

1. Introduction
Maintenance Management is a key function used by industrial systems that deteriorate and wear with usage and age. The primary objective of maintenance management is to increase equipment availability and overall effectiveness. Since the cost of maintenance is very high, modern industry requires not only the theoretical basis to express the experience of operators, but also the identification of proper techniques to optimize the maintenance action. Maintenance Scheduling grows importance as the maintenance cost accounts for a significant portion of the total production cost in capital intensive industries. Scheduling is a crucial component of maintenance management. Effective use of scheduling is a major factor of workforce productivity.

The maintenance scheduling problem is a combinatorial optimization problem. Many traditional techniques have proved to be fruitful in maintenance optimization problems. The use of Max to Min and Min to Max heuristics has been proposed for solving preventive maintenance problems and their performances are compared [1]. The use of dynamic Lipschitz optimization algorithm has outperformed heuristic techniques for solving the Maintenance Scheduling Problem for a Family of Machines [2]. However, non traditional modeling techniques have typically been used in Maintenance planning. Non traditional techniques such as SA and GA overcome many of the limitations of the traditional optimization techniques and are well suited to solve generator maintenance scheduling problems [3]. A methodology based on GA and Monte Carlo simulation has been designed to optimize the preventive maintenance planning by evaluating the expected cost of maintenance and the expected economic loss [4]. An Ant Colony Optimization approach to solve Thermal Generator Maintenance Scheduling Problem has pointed out not only the good solutions to be adopted but also the bad solutions to be neglected [5]. A method for preventive maintenance scheduling optimization of standby systems based on genetic algorithm and probabilistic safety analysis with an approach to improve the average availability of the system has been proposed [6].

Hybrid models are known to include the positive aspects of two or more techniques to reach an optimal solution. A tabu-based GA prevents inbreeding and supplies moderate selection pressure so that the selection efficiency is improved and the population diversity is maintained [7]. A combined use of SA and GA considering reliability and operation expense provides a compromising solution for unit maintenance scheduling problems [8]. A hybrid approach based on combined use of SA and GA is more effective than approach based on GA for complex multidimensional maintenance scheduling problems [9]. The use of SA in a GA framework for solving generator maintenance scheduling in power systems has proved to be more effective than approaches based only on GA or SA [10]. A hybrid algorithm of SA and TS method is found to improve the computation time and the convergence property [11]. A combination of SA, GA and Tabu Search (TS) method has proved to be effective in solving large scale long-term thermal generating unit maintenance scheduling problems [12].

2. The Maintenance Model

Raw-mill process is one of the critical processes in a cement industry. In this process, lime ore is pulverized in different stages and is supplied to the clinkerization process. A schematic diagram of a raw-mill process system for a cement process industry including the subsystems is shown in figure1. The accurate failure and repair data required for a realistic system performance study are obtained from the in-house plant records maintained for the company's own use. The problem considers the choice of two possible actions (viz. imperfect maintenance or component replacement) for each of the components during the planning period. The study proposes various corrective maintenance actions on the critical components during the preventive maintenance to maximize the system performance at minimal costs.

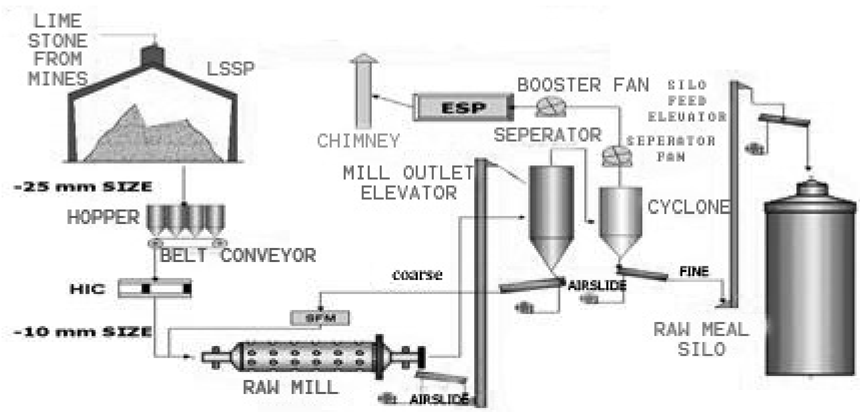

Figure 1: Raw-mill system of the cement industry

In practice, the two corrective maintenance policies namely increase in MTBF and/or decrease in MTTR can be implemented. The improvements to the MTBF and MTTR at 5%, 10% and 15 % levels in the critical components are considered for maintenance action. Hence, the objective is to determine the most cost effective maintenance policy. The identified critical subsystems are: (1) Booster fan (2) Conveyor roller assembly (3) Air slide (4) Silo feed elevator (5) Separator system (6) Impact crusher - rotor system (7) Raw-mill gear system – NWCS bearing and countershaft.

3. Objective Function

The problem considered is a maintenance scheduling problem for a process industry. There are seven subsystems connected in series configuration. Maintenance or replacement activity in any of these subsystems results in cessation of the entire process. In this problem, the combination of maintenance or replacement activities for the components during the entire design out period is obtained and for each period maintenance and replacement costs, time to repair, downtime cost, failure cost and standby costs are all included. The historical failure data of the raw-mill system are well fit into 2-P weibull distribution and the parameters β, η are estimated.

$$\text{Total cost: } Z = \sum_{j=1}^{n} \frac{(C_j + (d_{jp} * C_{sd}))}{(1+k)^j} \quad \forall j = 1, 2, \ldots 15 \tag{1}$$

Where, $C_j = \sum_{i=1}^{m}\{X_{ij}M_{ij} + Y_{ij}R_{ij} + X_{ij}(B_{ij} + MR_{ij}) + F_{ij}\}\ \forall i = 1,2,...7; \forall j = 1,2,...15$ (2)

$$F_{ij} = \left[R_{ij} + \left(TTR_i * Csd\right)\right] * V(t)_{ij} \quad (3)$$

$$V(t)_{ij} = \frac{\beta_i}{\eta_i}\left[\frac{t_{ij}}{\eta_i}\right]^{\beta_i - 1} \quad (4)$$

$$M_{ij} = M1_i(1+m)^j \quad (5)$$

$$R_{ij} = R1_i(1+r)^j \quad (6)$$

$$B_{ij} = \sum_{n=1}^{s} k1(1+P_n)^n \text{ Where s = 1,2,3} \quad (7)$$

$$MR_{ij} = k1 * Sc \text{ Where s = 1} \quad (8)$$

$$MR_{ijs} = MR_{ijs-1} + MR_{ijs-1}(1+Q_n) \text{ Where s = 2,3} \quad (9)$$

P, Q	Improvement percentage in MTBF and MTTR respectively
$X_{i,j}$	0 represents no maintenance & 1 represents maintenance for component 'i' at period 'j'
$Y_{i,j}$	0 represents no replacement & 1 represents replacement for components 'i' at period 'j'
$M_{i,j}$	Maintenance cost for component 'i' at period 'j'
$R_{i,j}$	Replacement cost for component 'i' at period 'j'
TTR_i	Time to repair the component 'i'
C_{sd}	Downtime cost of the system per hour
$V(t)$	Failure rate (Failure/period)
$F_{i,j}$	Failure cost per period for component 'i' at period 'j'
B_i	Cost of increasing MTBF of a component 'i'
MR_i	Cost of decreasing MTTR of a component 'i'
d_j	Downtime during the 'j' period in hours
$T_{i,j}$	Age of the component at the end of the period 'j'
α	Maintenance improvement factor ($0 \leq \alpha \leq 1$)
β_i , η_i	Weibull parameters for component 'i'
K	Discount factor per period

4. Genetic Algorithm

4.1 Principle

Genetic algorithms are stochastic search techniques based on the mechanism of natural selection and natural genetics [13]. GAs start with an initial set of random solutions called a population. Each individual in the population is called a chromosome. A chromosome is a string that is usually – but not always – a binary bit string. The chromosomes evolve through successive iterations called generations. During each generation, the chromosomes are evaluated using some measures of fitness. To create the next generation, crossover and mutation operations are carried out. Exceptional elements in the new generation are replaced by new chromosomes so as to keep the population size constant. After several generations, the solution converges into the best optimum value.

4.2 Fitness function

GA is naturally suited to solve maximization problems. Minimization problems are usually converted into maximization problems using an appropriate conversion. In general, a fitness function F(x) is first derived from the objective function f(x) and then used in successive genetic operations. The following fitness function is often used for minimization problem: F(x) = 1/(1+f(x))

4.3 Reproduction

The reproduction operator is applied to emphasize good solutions and to eliminate bad solutions in a population while keeping the population size constant. There are a wide number of reproduction operators. Rank order selection is one of the popular methods where the best fitness chromosomes are selected for the mating pool.

4.4 Crossover

Crossover operates on two chromosomes at a time and generates offspring by combining both chromosomes' features. In single point crossover of two chromosomes, a cross over point is selected (Random) in both chromosomes and the part of the chromosome before or after this point is replaced by the similar part from the other chromosome. A higher crossover rate (p_c) allows the exploration of large solution space and reduces the chances of a false optimum.

4.5 Mutation

Mutation involves flipping a bit in the chromosome. It replaces the genes lost from the population during the selection process or provides the genes that were absent in the initial population. The mutation rate (p_m) controls the rates at which new genes are introduced into the population. Very low mutation rate would neglect many useful genes and a very high value would result in large number of random perturbations, loss of parent-offspring resemblance and the algorithm will finally lose the ability to learn from the history of search.

4.6 GA procedure

```
begin
            g = 0
            initialize P(g)
            evaluate P(g) using fitness function
            termination_condition = false
            while (NOT termination_condition) do
      begin
            g = g+1; select parents from P(g)
            crossover
            mutation
            evaluate P(g+1) using fitness function
      end
end
```

5. Simulated Annealing Technique

5.1 Principle

The technique simulates the process of cooling of molten metal to achieve the minimum function value in a minimization problem [14]. Since a system at a low temperature has a small probability of being at a high energy state, the temperature is lowered from the initially set value to the terminating temperature where the convergence is achieved. The cooling factor reduces the temperature which in turn confines the search area towards the optimal solution.

5.2 Temperature

The initial temperature (T) and the number of iterations for a particular temperature determine the effective performance of this technique. When the T value is large, it takes a number of iterations for convergence while a small T value does not provide an adequate investigation of the search space before a true optimum solution is achieved. There is no proper strategy to set the initial temperature value and hence a trial and error approach is to be adopted. Unlike many traditional algorithms, the SA technique does not simply reject the less probable solutions but uses the Metropolis Algorithm to determine their acceptability. The algorithm generates a probability value which when compared with a random number generated from 0 to 1 says whether the solution is to be accepted or not. The common equation used to find the probability value is $P = \min[1, \exp(-\Delta E/kT)]$.

5.3 SA procedure

```
begin
initialize (T,x)
```

```
termination_condition = false
while (NOT termination_condition) do
        begin
        for i = 1 to L do
                begin
                generate y from x
                     if (f(y) – f(x) ≤ 0)
                         then x = y; else if (exp[-(f(y) – f(x))/T] >random[0,1]) then x = y
               end
           lower T
       end
end
```

6. GA Implementation

In this problem, the genotype encodes the possible combinations for all the subsystems. In the following canonical GA paradigm, a chromosome of 21 bits is considered. Among the first 7 bits (Binary) of the genotype, ones represent the maintenance activity and zeros represent the replacement activity. Among the next 14 bits (Real), the first seven bits represent the percentage increase in MTBF and the next seven bits represent the reduction in MTTR of the corresponding components. Chromosome: (Decision bits) (Improvement bits)

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The process starts with a random selection of 40 chromosomes. A random choice of a pair of chromosomes is made from these 40 chromosomes, crossover probability (p_c) is checked and the single point crossover is carried out to generate the offspring. A random choice of chromosomes is made and is checked with the mutation probability (p_m). The mutation location is chosen in random and single point mutation is carried out. Exceptional chromosomes are replaced by new ones during the evaluation process. This is repeated for 50 generations. F(x) value is calculated for each chromosome and the best one is selected. The same procedure is repeated for all the periods. Each period yields one best chromosome. Using these best chromosomes, the total cost and the combination of activities for each period are calculated.

7. SA implementation

The initial temperature and the number of iterations are fixed as 700 and 20 respectively. A string is generated in random and is considered as the global optimum value. Two strings are generated in random and compared. If the fitness of the second string is better than that of the first, then perturbation takes place. Or else, Metropolis algorithm is used to determine the acceptability of the string. The same procedure is repeated for 20 iterations. The global best is replaced at the end of each generation. The temperature is then lowered with a cooling factor of 0.04 and the entire process said above is repeated. A minimum temperature of 30 is set as a termination factor at which the process terminates. Using the final result, the total cost and the combination of maintenance activities for each period are decoded.

8. Numerical Analysis

The formulated maintenance model is validated using the following data collected from a cement industry.

Table 1: Input values for the critical components

Critical subsystem	M1 (Rs.)	R1 (Rs.)	Sc(Rs.)	β	η	TTR (min)
Booster fan	5000	18000	23000	2.14	22687	90
Conveyor roller assembly	4000	22000	27000	1.83	18647	40
Air slide	6000	15000	20000	1.98	18263	120
Elevator	6000	22000	27000	1.59	18170	150
Separator system	8000	20000	25000	1.45	28459	60
Impact crusher	12000	35000	40000	1.14	32477	200
Raw-mill gearbox	15000	38000	43000	2.29	11788	80

α=0.8; C_{sd}=Rs.1666/min; k = 0.1; m = 0.05; r = 0.04

The parameters are tuned using sensitivity analysis and are shown below:

GA parameters: No. of generations = 50; P_c = 0.8; P_m= 0.05; Population size = 40.

SA parameters: Initial temperature=700; Final temperature=30; Cooling factor=0.04; No. of iterations=20

9. Conclusion

The maintenance optimization in a cement industry has always been a critical issue. This paper effectively utilizes non-traditional optimization techniques to obtain optimal solution. The obtained results imply that GA and SA have capably solved the combinatorial maintenance optimization problem. The strategy of maintenance and replacement activities obtained during the PM action for all machines gives the minimum cost for the entire design out period. From figure 2, it is seen that GA exhibits a quick convergence to the optimal than SA. A continuation of this work intends to investigate the impact of component reliability on the decision making process. The work can be extended to solve the maintenance problem of any process industries.

Table 2: Typical outcome by GA or SA for each period

Maintenance Strategy
M(0.15,0.05), M(0,0.05), M(0.05,0.05), M(0,0.1), R, M(0.1,0.1), M(0,0.1)

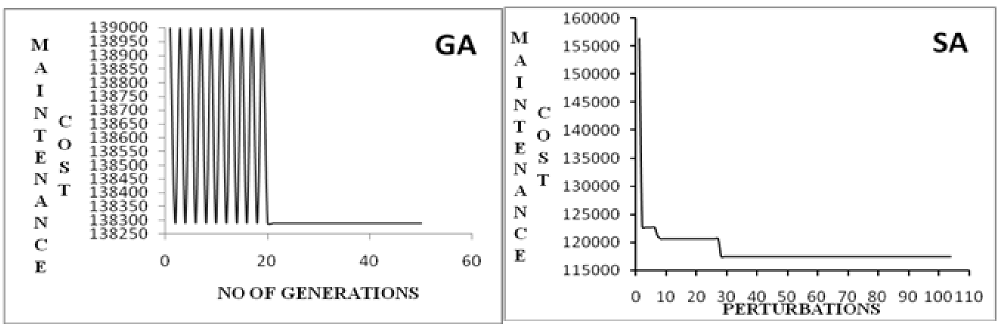

Figure 2: Convergence graph – GA, SA

References

1. Gabriella Budai, Dennis Huisman, Rommert Dekker, 2006,” Scheduling Preventive Railway Maintenance Activities,” Journal of the Operational Research Society.
2. Ming-Jong Yao, Jia-Yen Huang, 2007, “A Global-Optimization Algorithm for Solving the Maintenance Scheduling Problem for a Family of Machines,” Information and Management Sciences, 365-386.
3. K. P. Dahal, J. R. McDonald, G. M. Burt, 2000, “Modern heuristic techniques for scheduling generator maintenance in power systems,” Transactions of the Institute of Measurement and Control, 22(2), 179-194.
4. DuyQuang Nguyen and Miguel Bagajewicz, 2008, “Optimization of Preventive Maintenance Scheduling in Processing Plants,” 18th European Symposium on Computer Aided Process Engineering.
5. Triantafyllos Mytakidis, Aristidis Vlachos, 2008, “Maintenance Scheduling by using the Bi-Criterion Algorithm of Preferential Anti-Pheromone,” Leonardo Journal of Sciences, 143-164.
6. Celso M. F. Lapa, Cláudio M. N. A. Pereira, Antônio Carlos de A. Mol, 2000, “Maximization of a nuclear system availability through maintenance scheduling optimization using a genetic algorithm,” Nuclear Engineering and Design, 196(2), 219-231.
7. Sheng-Tun Li, Chuan-Kang Ting, Chungnan Lee, Shu-Ching Chen, 2006, “Maintenance Scheduling of Oil Storage Tanks using Tabu-based Genetic Algorithm,” 14th IEEE International Conference on Tools with Artificial Intelligence.
8. Rong-Ceng Leou, 2006, “A new method for unit maintenance scheduling considering reliability and operation expense,” International Journal of Electric Power and Energy Systems, 28(7), 471-481.
9. D K Mohanta, Dr P K Sadhu, Dr R N Chakrabarti, 2006,” Captive Power Plant Maintenance Scheduling using Genetic Algorithm and Simulated Annealing based Hybrid Techniques for Safety and Reliability Optimization,” Journal of the Institution of Engineers (India), 319-326.
10. Dahal, K.P. Burt, G.M. McDonald, J.R. Galloway, S.J., 2000, “GA/SA-based hybrid techniques for the scheduling of generator maintenance in power systems,” Proceedings of the 2000 Congress on Evolutionary computation, 567-574.
11. Young-Jae Jeon, Jae-Chul Kim, 2004, “Application of simulated annealing and tabu search for loss minimization in distribution systems,” International Journal of Electric Power and Energy Systems.

12. Kim, H. Hayashi, Y. Nara, K., 1997, “An algorithm for thermal unit maintenance scheduling through combined use of GA, SA and TS,” IEEE Transactions of Power Systems, 329-335.
13. Goldberg DE (1989) Genetic algorithms in search, optimization and machine learning, Pearson education Inc., Delhi.
14. Kalyanmoy Deb (2005) Optimization for Engineering Design: Algorithms and examples, PHI Pvt. Ltd, New Delhi.