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An Intelligent Opportunistic Maintenance (OM) System: A Genetic Algorithm Approach

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Abstract

Complex systems like aircrafts, space shuttles, nuclear power stations, and some complicated process industries operate under high reliability and safety requirements due to the complicated technology involved and hazardous consequences to the larger community in case of failures. The maintenance regime of complex systems most often consists of a variety of maintenance strategies, like preventive maintenance, corrective maintenance, condition-based maintenance and so on. Opportunistic or opportunity-based maintenance (OM) gives the maintenance staff an opportunity to replace or repair those items, which are found to be defective or need replacement in the immediate future, during the maintenance of a machine or component. This work presents an intelligent method of how to decide whether a particular item requires opportunistic maintenance or not, and if so how cost effective this opportunity-based maintenance will be when compared to a probable future grounding. This maintenance strategy is considered important when dealing with complex systems that contain expensive items with hard lives with condition-based maintenance (CBM) strategies. Genetic algorithms (GA) are employed to decide whether opportunistic maintenance is cost effective or not. An example of applying opportunistic maintenance strategy in process industry is used to describe the methodology for genetic algorithms.

Keywords: Keywords-Opportunistic Maintenance; Genetic Algorithms.

1. Introduction

Modern engineering systems, like process and energy systems, transport systems, offshore structures, bridges, pipelines are designed to ensure successful operation throughout the anticipated service life, in compliance with given safety requirements related to the risk posed to the personnel, the public and the environment. Unfortunately, the threat of deteriorating processes is always present, so that it is necessary to install proper maintenance measures to control the development of deterioration and ensure the performance of the system throughout its service life. This requires decisions on what to inspect and maintain, how to inspect and maintain, and when to inspect and maintain. These decisions are to be taken so as to achieve the maximum benefit from the control of the degradation process while minimizing the impact on the operation of the system and other economical and safety consequences.

Engineers are always on the look out for ways of reducing system down time and increasing availability, without compromising on required level of system reliability. The ultimate objective of any maintenance regime is to maintain the system functionality to the maximum extent possible with optimum tradeoffs between the down times and cost of maintenance, avoiding any hazardous failures. Opportunistic maintenance works out to be the perfect remedy, which utilizes the opportunity of system shutdown or module dismantle to perform any maintenance required in the immediate future and saves a substantial amount of system down-time.

In [1], the use of a genetic algorithm program for analyzing the optimal opportunity-based maintenance problem for real-sized systems, was investigated. They analyzed the performance of the genetic operators with a generation replacement genetic algorithm, using a hypothetical system consisting of 50 maintenance-significant parts, and they paid special attention to the sensitivity of solutions to the maximum number of maintenance groups considered by the genetic algorithm. They also found that better solutions were identified for larger numbers of groups but increasing complexity costs more in terms of the computer time required.

A simulation model for opportunistic maintenance strategies was presented in [2]. They proved that this automated model has a considerable improvement on the performance of the opportunistic maintenance strategies. In [3], a new approach to reliability-centered maintenance (RCM) using the concepts of soft life and hard life to optimize the total maintenance cost, was proposed. The proposed model was applied to find the optimal maintenance policies in the case of military aero-engines using Monte Carlo simulation. This case study showed a potential benefit from setting soft lives on relatively cheap

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components that can cause expensive, unplanned engine rejections.

An opportunistic maintenance policy for a continuously-monitored multi-unit series system with integrating imperfect effect into maintenance activities was developed in [4]. The simulation results implied that the proposed policy was better than the policy to maintain the system units separately. In [5], an opportunistic maintenance policy for a multi-component damage shock model with stochastically dependent components, was proposed. They utilized the coupling method to obtain stochastic maintenance comparisons on failure occurrences under different model parameters. In [6], An opportunistic preventive maintenance (PM) scheduling algorithm for the multi-unit series system based on dynamic programming, was introduced.

Opportunistic maintenance is a systematic method of collecting, investigating, preplanning, and publishing a set of proposed maintenance tasks and acting on them when there is an unscheduled failure or repair "opportunity". In this strategy, preventive maintenance activities are combined with corrective ones as soon as a certain technical and economical conditions are satisfied. Opportunity-based maintenance strategy involves several nonlinear variables which affect the total cost of maintenance that should be optimized to result in a cost-effective decision on maintenance actions. Genetic algorithms (GA) are particularly well-suited to solving problems where the space of all potential solutions is truly huge and too vast to search exhaustively in any reasonable amount of time. A genetic algorithm is a search technique used in computing to find exact or approximate solutions to optimization and search problem. It is categorized as a global search heuristics. It is a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology, such as inheritance, mutation, selection, and crossover.

This work is based on a real problem of improper maintenance strategy of a process industry (potash production). Actually the exploitation of the equipment maintenance records is often a weak point within an operations management organization. Inexistence of proper computerized maintenance system, lack of competences to properly handle maintenance data, or reduced knowledge in advanced maintenance processing techniques, are common problems to solve in order to benefit from the historical record of failures and maintenance operations carried out at certain equipment. In this work, the maintenance records analysis is used to provide critical information from past experience to improve current maintenance process in this Potash processing industry. Genetic algorithms techniques of time and cost analysis are used to build an intelligent maintenance system to predict whether the opportunity-based maintenance strategy is cost effective or not. GA-based opportunistic maintenance technique was applied on one of the critical production units which is the dryer.

This paper is organized as follows: section II will define the main concept of opportunity-based maintenance strategy. Genetic algorithms (GA) technique will be described in section III. The problem formulation of GA-based opportunity maintenance strategy will be presented in section IV. A hypothetical example on GA-based opportunistic maintenance system will be given in section V, and the last section is to conclude.

2. Opportunistic Maintenance (OM) Strategy

Opportunistic maintenance can be defined as a systematic method of collecting, investigating, preplanning, and publishing a set of proposed maintenance tasks and acting on them when there is an unscheduled failure or repair "opportunity" [1]. Opportunistic maintenance can be thought of as a modification of the run-to-fail maintenance management philosophy. An opportunistic maintenance strategy is proposed to maintain a production line consisting of *k* non identical processors and without intermediary stocks. Operational characteristics of processors are degraded with usage. In this strategy, preventive maintenance activities are combined with corrective ones as soon as a certain technical and economical conditions are satisfied.

Generally, there are two main purposes for applying opportunistic maintenance: 1. to extend equipment lifetime or at least the mean time to the next failure whose repair may be costly. It is expected that this maintenance policy can reduce the frequency of service interruption and the many undesirable consequences of such interruption, and 2. to take advantage of the resources, efforts and time already dedicated to the maintenance of other parts in the system in order to cut cost.

Opportunistic maintenance consists of opportunistic replacement policies and opportunistic build policies. Replacement policies specify which parts to remove when an opportunity arises. Build policies specify which parts should be taken from the spares inventory to replace the parts removed according to the opportunistic replacement policies. Both policies should be used to reduce future maintenance requirements [3]. The opportunistic maintenance may be divided into two categories: 1. Age related, and 2. Non-age related. Fig. 1 shows the main categories of opportunistic maintenance.

- Non–age related opportunistic maintenance: the maintenance of those items, which failed before, but went undetected until the module's strip. These are the items, which are inaccessible unless the modules containing them are completely dismantled and whose failures do not cause system failure.
- Age–related opportunistic maintenance: this category contains three sub-categories as follows: 1. Hard life, 2. Soft life, and 3. Degradation.

1. Hard life: is defined as the age of the component, at or by which the component has to be replaced.
2. Soft life: is the age of the component after which it will be rejected the next time one of the modules containing it is recovered.

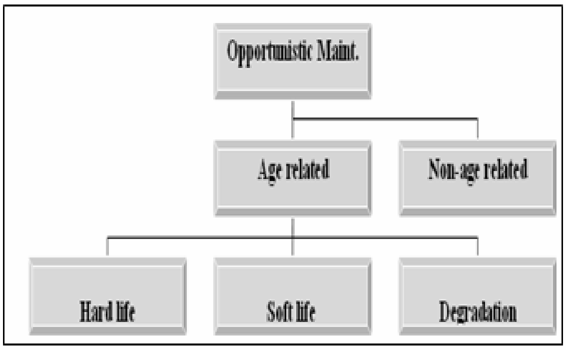

Figure 1. Categories of opportunistic maintenance strategy.

3. Degradation: failure mechanisms are monitored through condition monitoring devices and components are repaired or replaced once the condition deteriorates to a critical level.

In opportunity-based maintenance of a certain component, three important variables need to be collected and analyzed as follows:

- The remaining life of component or sub-module under consideration.
- The cost of down time that will occur if one decides to wait until the component has exhausted its useful life.
- The cost of risk involved or the probability of failure.

In such cases, an optimization model that carries out a comparative analysis of cost of remaining useful life and cost of down time for a group of components that will reach their hard lives within a small period of time will result in a list of components that should be replaced or repaired through opportunistic maintenance. Genetic algorithms (GA) are well-suited to carry out such an optimization task.

3. Genetic Algorithms (GA) Technique

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search [7]. GA are considered one of the most powerful searches and optimization algorithms because GA are conducted from a population of points rather than a single point, thus increasing the exploratory capability of GA. In addition, GA lend themselves naturally to implementation in parallel processing environments leading to the ability to exploit newer technologies in this domain, thus achieving faster computational times. Moreover, GA work with a direct coding of the parameter set rather than the parameters themselves, so, it is suitable for discontinuous, high dimensional and multi-nodal problems. The mechanics of a simple genetic algorithm are surprisingly simple, involving nothing more complex than copying strings and swapping partial strings. A simple GA that yields good results in many practical problems is composed of three operators: 1. Reproduction, 2. Cross-over, and 3. Mutation.

The reproduction operator may be implemented in algorithmic form in a number of ways. Perhaps the easiest is to create a biased roulette wheel, where each current string in the population has a roulette wheel slot sized in proportion to its fitness.

Crossover is the process of combining information from two parents of strings, such that two children strings have a resemblance to each parent.

Mutation operator plays a secondary role in the simple GA. The frequency of mutation to obtain good results in empirical GA studies is on the order of one mutation per thousand position transfer. In the simple GA, mutation is the occasional random alteration of the value of a string position. Fig. 2 shows the flow diagram of the GA process.

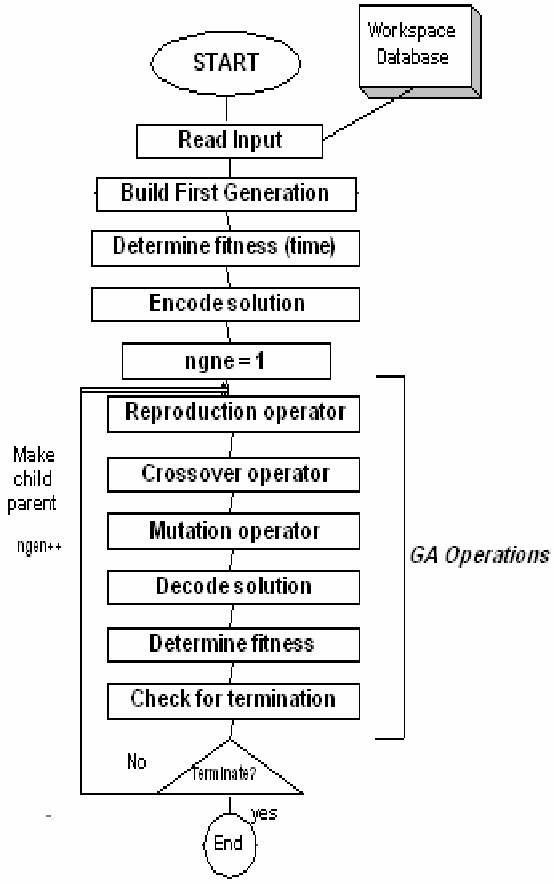

Figure 2. Genetic algorithms (GA) flowchart.

4. GA-based Opportunistic Maintenance: (Problem Formulation)

Using opportunistic maintenance where complex systems require periodic replacements of expensive parts is beneficial and considerably important. But, there are numerous factors to be considered while deciding on whether a particular component should be replaced or repaired when an opportunity arises. Genetic algorithms are used, as an optimization tool to compare the cost of premature replacement with the cost of downtime if grounded for the sole purpose of replacement.

The main factors or variables that may affect the final decision about the application of opportunistic maintenance could be described as follows:

- Remaining life cost (*RLC*): For an item, it is the product of number of hours or cycles remaining (*RL*) and the cost of item (*CI*) per hour/cycle as given in (1).

$$RLC = (RL).(CI) \tag{1}$$

- Down time cost (DTC): This is a very tricky component and completely depends on the complexity of the system, whether the downtime is planned or unplanned, and a lot of other similar factors which are specific to the environment under consideration.
- Unplanned down time cost (UDTC): It is the cost due to unplanned failure and it includes the direct and the indirect costs.
- Risk cost (RC): This is the risk involved in letting the components function until their complete useful life is utilized. The risk cost is given in (2), where (HF) is the hazard function, and (SDC) is the secondary damage cost.

$$RC = HF.(UDTC + SDC) \tag{2}$$

- Hazard function (HF): this is known as the failure rate, hazard rate, or force of mortality. Hazard function h(x) is the ratio of the probability function p(x) to the survival function s(x). Hazard function (HF) is given in (3).

$$HF = \frac{p(x)}{s(x)} \tag{3}$$

- Secondary damage cost due to failure (*SDC*): the cost which can be obtained with the help of failure modes and critical analysis.
- Unit price: It is the price per finished product unit or service unit.

In this study, the genetic algorithms (GA) toolbox of Matlab 7.0 was used in order to take the right decision whether to repair or replace the components under study. A scattered crossover function and a uniform mutation was adopted A fitness function (i.e., objective function) was formulated in order to quantify the optimality of a solution (i.e., chromosome in genetic algorithms) so that a particular chromosome may be ranked against all the other chromosomes. Optimal chromosomes, or at least chromosomes which are more optimal, are allowed to breed and mix their datasets by any of several techniques, producing a new generation that will (hopefully) be even better. Also, the fitness function is a way to describe the dynamics of gene frequencies in populations of reproducing individuals. The fitness function measures the potential for reproductive success of any individual in a given environment. The objective function was formulated for this problem and given in (4), where (*CLR*) is cost of lost revenue, (*DT*) is the downtime in hours, (*RC*) is the risk cost, (*RLC*) is the remaining life cost, and (*Z*) is the fitness value (i.e., total cost of maintenance in Dollars).

$$Z = (CLR).(DT) + (RC) - (RLC) \tag{4}$$

The value of *Z* in (4) gives an indication of the decision; whether to perform the opportunistic maintenance on the studied components or not. In this work, if the fitness function (*Z*) yields a positive value, it will be represented by number one and the decision will be "perform opportunistic maintenance on the component", otherwise if the value of *Z* is negative, it will be represented by number zero, and the decision will be "do not perform opportunistic maintenance on the component".

Since the final decisions; whether to do opportunistic maintenance or not; depend on the value of *Z*, it was computed by first evaluating the total losses if the component continues running until failure occur (i.e., *(CLR).(DT)+(RC)* as in (4)). Then, the remaining life cost *(RLC*) was subtracted from the total losses in order to compare which is bigger, the total losses or the cost of remaining life. If the losses were bigger than the (*RLC*), then *Z* is positive and the decision is to perform opportunistic maintenance, because having positive value for *Z* means that repairing or replacing the component during the scheduled maintenance for the other components is better than replacing or repairing it when it fails .Otherwise, if the losses were smaller than the (*RLC*), then *Z* will give a negative value, and the decision is not to perform opportunistic maintenance.

One may notice that the down time (*DT*) and (*RLC*) for all items or components in the same group (as shown in section V), are the same. Therefore, the only independent variables in (4) are the (*CLR*) and (*RC*). These two variables will be the main GA fitness function variables, and will be denoted as follows: *X1*: Cost of lost revenue (*CLR*), and *X2*: Risk cost (*RC*). Therefore, the final GA fitness function will be as shown in (5).

$$Z = (DT).X1 + X2 - (RLC) \tag{5}$$

5. GA-Based Opportunistic Maintenance System: (A Hypothetical Example)

The final fitness function (i.e., objective function) as formulated in (5) contains two constants (i.e., *DT* and *RLC*). These two parameters remain constant for all components in the same group. In (5), *X1* and *X2* are the variables which will enter the GA computational loop, as shown in Fig. (2), in order to optimize the total cost of maintenance (i.e., fitness value *Z*).

In this work, the final formulated GA-based system was applied to an example from process industry (i.e., potash production plants). The data which was collected from the potash plant is given in Table I, and contains values for the following variables: i) the down time (*DT*) in hours, ii) production loss in tons (as an indicator of the cost of revenue lost), and iii) the remaining life cost (*RLC*) in dollars, for 17 components of a rotary dryer machine, for years 2004, 2005, and 2006. Fig. 3 shows an inside view of a normal rotary dryer, whereas Fig.4 shows an inside view of a faulty rotary dryer.

Table I shows the ungrouped data for years 2004 – 2006. These data points were then grouped into seven different groups depending on the downtime (*DT*) and remaining life cost (*RLC*) which both remain constant for all components in the same group. The final grouped data for years 2004 to 2006 is shown in Table II.

Figure 3. The inside view of a normal rotary dryer.

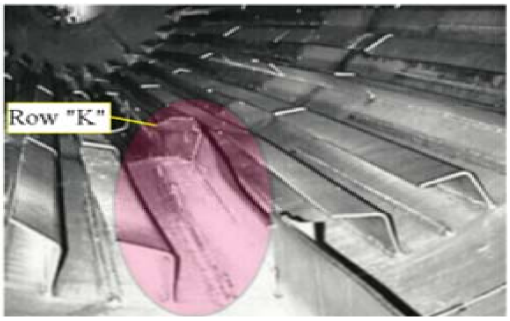

Figure 4.The inside view of a faulty rotary dryer.

Table1. Ungrouped Data for Years (2004 – 2006).

Year	***Downtime (DT) (Hours)***	***Production Loss (tons)***	***Remaining life Cost (RLC) ($)***
2004	6	988.2	592920
2004	16	2635.2	4216320
2004	18	2964.6	5336280
2004	18	2964.6	5336280
2004	12	1976.4	2371680
2004	24	3952.8	9486720
2004	50	8235	4117500
2005	6	988.2	592920
2005	8	1317.6	1054080
2005	8	1317.6	1054080
2005	24	3952.8	9486720
2005	50	8235	4117500
2006	6	988.2	592920
2006	8	1317.6	1054080
2006	16	2635.2	4216320
2006	24	3952.8	9486720
2006	24	3952.8	9486720

Table 2. Grouped Data Based on Downtime (*DT*).

Group Number	***Downtime (DT) (Hours)***	***Production Loss (tons)***	***Remaining life Cost (RLC) ($)***
1	6	988.2	592920
	6	988.2	592920
	6	988.2	592920
2	8	1317.6	1054080
	8	1317.6	1054080
	8	1317.6	1054080
3	12	1976.4	2371680
4	16	2635.2	4216320
	16	2635.2	4216320
5	18	2964.6	5336280
	18	2964.6	5336280
6	24	3952.8	9486720
	24	3952.8	9486720
	24	3952.8	9486720
	24	3952.8	9486720
7	50	8235	4117500
	50	8235	4117500
	50	8235	4117500

The grouped data of Table II was then fed into the genetic algorithms (GA) process in order to identify the desired outputs of this model which are represented by the fitness values (*Z*). As described earlier, the equation of the fitness function differs from group to group. For example, the fitness function for (group 1) is given in (6).

$$Z = 6X1 + X2 - 592920 \quad (6)$$

Different groups have different fitness functions depending on their downtimes (*DT*). Each fitness function (*Z*) was then given to the GA operators with initial population of 130, and terminates at 100 generations with a uniform crossover technique. The final outputs from the GA process are the best fitness values for each group, which could be negative or positive values. If the best (*Z*) from GA is negative, the decision is (zero) or not to perform opportunistic maintenance for this group of components. Otherwise, the decision is (one) and opportunistic maintenance strategy should be applied. Fig. 5 and Fig 6 are samples of the GA outputs for groups 4 and 7, respectively. As shown in Fig. 5 and Fig. 6, the points at the bottom of the plot denote the best fitness values, while the points above them denote the averages of the fitness values in each generation.

In Fig. 5, the best fitness value (*Z*) is (-4.2167×10^6), which indicates a negative total cost of opportunistic maintenance, and the decision is "not to perform opportunistic maintenance. As noticed in Fig. 5 and Fig. 6, the first generation's fitness value was very low, and while the number of generation increases, the fitness value improves, which means that when the generation increases, the fitness value converges into the optimal value. The best fitness value improves more slowly in later generations whose populations are closer to the optimal point.

The final fitness values and decisions generated by the GA are given in Table III. As indicated by Table III, the components of groups 1 and 2 are the only components which have positive best fitness values, therefore; the decision is "to perform opportunistic maintenance" on group 1 and 2, but "not to perform opportunistic maintenance" on group 3, 4, 5, 6, and 7.

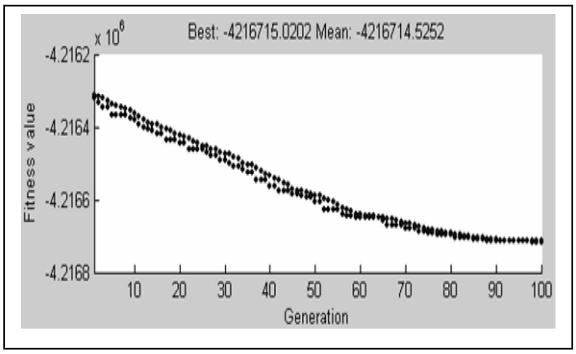

Figure 5.The best and average fitness values Vs. GA generation for group 4.

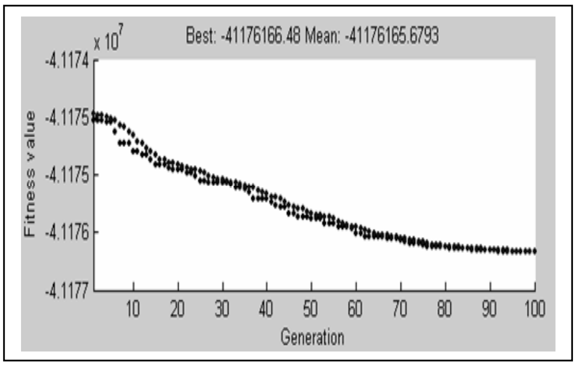

Figure 6.The best and average fitness values Vs. GA generation for group 7.

Table 3. The Final GA-Generated Fitness Values and Descisions

Group Number	***Downtime (DT) (Hours)***	***Best Fitness Value (Z)***	***Decision***
1	6	+ 0.593 X 10^6	1
	6		
	6		
2	8	+ 1.054 X 10^6	1
	8		
	8		
3	12	- 2.372 X 10^6	0
4	16	- 4.217 X 10^6	0
	16		
5	18	- 5.336 X 10^6	0
	18		
6	24	- 9.487 X 10^6	0
	24		
	24		
	24		
7	50	- 41.176 X 10^6	0
	50		
	50		

6. Conclusions

In this work, genetic algorithms (GA) were adopted as an optimization tool to identify the maintenance cost variables that optimize the total cost of maintenance in order to decide if opportunistic maintenance is favorable or not. The main conclusions of this work could be summarized as follow:

- based approach to opportunistic maintenance is a necessary procedure before deciding on whether to perform opportunistic maintenance strategy or not. This approach optimized the total cost of maintenance and gave an accurate indication about the economic of repairing or replacing a certain component under opportunistic maintenance strategy.
- Genetic algorithms for opportunistic maintenance are a novel application. GA technique is very suitable for the problem of opportunistic maintenance where the variables interactions complicate the problem. The final decision on whether to perform opportunistic maintenance or not depending on a minimum total cost gives the maintenance department an opportunity for considerable savings on the total maintenance expenses.
- The success of genetic algorithms in optimizing the cost of opportunistic maintenance suggests the use of this intelligent technique in many other industrial fields, particularly in maintenance and safety.
- It is recommended to improve the accuracy of the GA fitness function by considering more maintenance variables like the direct and indirect costs of maintenance tasks. This will guarantee GA convergence into better optimal solution.

References

[1] A. Savic, G. Walters, J. Knezevic, "Optimal, opportunistic maintenance policy using genetic algorithms, 2: analysis". Journal of Quality in Maintenance Engineering, Vol. 1, No. 3, 1995, 25-34.

[2] J. Crocker, U. Kumar, "Age related maintenance versus reliability centered maintenance: a case study on aero-engines". Journal of Reliability Engineering and Systems Safety, Vol. 67, No. 2, 2000, 113-118.

[3] O. Mohamed-Salah, A-K. Daoud, G. Ali, "A simulation model for opportunistic maintenance strategies". 7th IEEE International Conference on Energy Technologies and Factory Automation, Vol. 1, 1999, Barcelona, Spain, 703 – 708.

[4] X. Zhaou, L. Xi, J. Lee, "A dynamic opportunistic maintenance policy for continuously monitored systems". Trans. J. of Quality Management Engineering, Vol. 12, No. 3, 2006, 294 – 305.

[5] L. Cui, H. Li, "Opportunistic maintenance for multi-component shock models". Journal of Mathematical Methods of Operations Research, Vol. 63, No. 3, 2006, 180 – 191.

[6] X. Zhaou, L. Xi, J. Lee, "Opportunistic preventive maintenance scheduling for a multi-unit Series system based on dynamic programming". Internatonal Journal of Production Economies, 2008, In Press.

[7] Goldberg D. Genetic algorithms in search, optimization, and machine learning. New York: Addison Wesley; 1994.