



Optimal Policy of Condition-based Maintenance Considering Probabilistic Logistic Times and Environmental Contamination Issues

H. Rahimi Komijania^a, M. Shahin^b, A. Jabbarzadeh^{*b}

^a Department of Industrial Engineering, K.N. Toosi University, Tehran, Iran

^b Department of Industrial Engineering, Science and Technology University, Tehran, Iran

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ABSTRACT

This article proposes a preventive maintenance policy for equipment that - by their very nature - can cause some forms of contamination and destruction in the environment. The purpose is to reduce overhead costs related to environmental degradation and pollution as well as other costs (e.g., inspection and replacement) by minimizing the function of the average total cost. The condition of equipment should be determined through inspection, and its operating cycle just ends in the event of a failure or precautionary repair. Maintenance services include complete repair or replacement. However, equipment conditions can cause environmental pollution, as the variables for such monitoring go beyond warning limit. After an item has been inspected in unfavorable operating conditions, complete preventive maintenance tasks should be included, in which preparation times and logistics are random variables. A mathematical model and a genetic algorithm are developed to find the optimal inspection strategy for the defined sets of parameters. Moreover, a numerical example is presented and the results are discussed.

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1. INTRODUCTION

Much of the equipment shows a gradual erosion or sudden failures due to its function and life. Beside quality problems, the equipment results in multiple effects, which can be referred as the degradation of the environment by Chouikhi et al. [1]. Meanwhile, standards and special environmental regulations have been set for the companies, whose operations impose damages on the environment as to control their operation. Many countries have developed various arrangements to control adverse impacts of systems. Environment degradation is considered as one of the ten official threats that have been warned in the UN high level panel on threats. Furthermore, the prevention of producing contaminants is another serious issue that can include management of chemicals as to reduce their risk, detection and estimating the emission of pollutants, and minimization of wastes. Environmental pollution resulting from industrial operations is very obvious. All manufacturing processes, for example, employed in

cement factories are major cause for the environmental pollution. Also, much of the manufacturing equipment leads in the production of harmful gases in the atmosphere. Moreover, many other items including the use of coolers in some industries, such as petrochemical platforms and nuclear power plants, are among the causes of environmental pollution. As a result, there is a need for a policy that can achieve proper strategy to reduce the maintenance cost.

The main idea of condition-based maintenance is based on this assumption that the process of equipment failures can be observed about 99% through certain symptoms by Bloch and Geitner [2]. Perez-Ocon and Montoro-Cazorla [3] examined a repairable system with a fuzzy probability distribution for the lifetime and its repair times. Simulation approaches are also employed for analyzing the general maintenance models based on incomplete repair by Cassady et al. [4]. Also, a study was calculated the average time until its failure in a steady state for repairable systems by Wang and Trivedi [5]. In this policy, the failure probability depends on the number of shocks occurred due to the last alternative.

*Corresponding Author's Email: arminj@iust.ac.ir (A. Jabbarzadeh)

The Markov and quasi-Markov decision-making models are powerful instruments for sequential decision-making processes by Chen and Trivedi [6]. Wu and Clements-Croome [7] evaluated the optimized maintenance policy under different operational schedules and developed three models for cost functions. The examination of single-unit Markov repairable system is other issue that came up in the condition-based maintenance by Zheng et al. [8].

Tang and Lam [9] presented a shock maintenance model- δ for dismantled systems, in which shocks enter the system through a renewable process and the periods between shock arrivals show a viable distribution. Here, the amount of tolerance follows an increasing geometric process. The presented model focuses on the frequency or the number of shocks and this distinguishes the model. For many condition-based maintenance policies, equipment monitoring is a continuous process by Liao et al. [10]. Further, the optimal replacement policy and minor repairing services under minor maintenance operation have been measured considering shocks by Chien and Sheu [11] and Chien et al. [12]. This approach was first introduced to maximize the effectiveness in the decision-making process of preventive maintenance. Condition-Based maintenance is principally a maintenance and repair plan that makes all decisions based on the data collected from monitoring system conditions of or components. This information covers a wide range of variables, such as vibration, temperature, noise and other pollutions by Jardine et al. [13]. Wang and Pham [14] investigated availability and maintenance operations for series systems under incomplete maintenance operations. A geometric process consisting of two and three steps is used to display a repairable system deterioration by Zhang [15]. Finally, the optimal policy is developed by minimizing the average cost. Other activities implemented to reduce the effects of environmental destruction includes the development of a comprehensive structure for quality environmental management that it is a combination of quality management systems with the prevention of resource pollution and wasting by Deltas [16]. Rabbani et al. [17] introduce a model to make a decision on the maintenance of a mechanical component subject to condition monitoring. A stochastic model is used to determine what maintenance actions should be taken at a monitoring check and the follow up inspection times. The condition of component has a stochastic relation with measurements. A new state space model is developed and used, to predict the hazard rate and condition monitoring measurements, to indirectly assess the hazard rate of the system.

The process of equipment degradation can be affected by the environment, in which the equipment is placed. Multi-objective evolutionary algorithms are

used in maintenance scheduling policies by Quan et al. [18]. Also, maintenance policies have been explained according to exhaustion process of a system subject to deterioration by Crowder and Lawless [19]. In this line, it is crucial the usage of a policy that can meet the requirements of such standards on the one hand, and gain the maximum efficiency for companies on the other hand. Condition-Based maintenance is a well-known technique in maintenance recently considered by Peng et al. [20]. It was introduced by Tian et al. [21] for the power generation systems using the wind turbines, in which two thresholds of possible failure were used for displaying conditions. The study of collective effects of all variables involved in status monitoring with simultaneously using the information of several variables and providing control charts obtained from Bays equations were mentioned by Wang [22]. Mishra and Jain [23] proposed a condition-based maintenance and corrective maintenance policy for a continuously operating system. The condition of the system is assumed to deteriorate with time. Their model incorporates both deterioration and random common cause failures. The deterioration stages are modeled as discrete state processes. Condition-Based maintenance significantly depends on the health status of the system. There are two general methods for estimating the system status: inspection in discrete times and continuous condition monitoring. Many studies are just relied on one of these methods; however, the application of one could not be trustable, and thus structures of discrete inspection and continuous monitoring have also been introduced by Le and Tan [24]. As technologies of sensors developed, the system status can be monitored with high reliability; however, continuous monitoring is not impossible in many cases, and discrete inspection plays a significance role.

Considerable research has been done in the field of status monitoring. From recent research, a study investigated the proper maintenance policy in terms of environmental degradation under a condition variable with the definitive preparation time and using the Nelder-Mead's optimization method by Chouikhi et al. [1]. Do et al. [25] proposed a proactive condition-based maintenance (CBM) considering both perfect and imperfect maintenance actions for a deteriorating system. Perfect maintenance actions restore completely the system to the 'as good as new' state. Their related cost are however often high. The first objective was to investigate the impacts of imperfect maintenance actions and the second objective was to propose an adaptive maintenance policy which can help to select optimally maintenance actions (perfect or imperfect actions). Chen et al. [26] considered an optimal condition-based replacement policy with an optimal inspection interval when the degradation conforms to an inverse Gaussian process with random effects. The

random effects parameter is used to account for heterogeneities commonly observed among a product population. Mokhtari et al. [27] proposed a realistic variant of flow shop scheduling that integrates flow shop batch processing machines (FBPM) and preventive maintenance for minimizing the makespan. In order to tackle the given problem, they employ reliability concept, and develop an electromagnetism-like (EM) algorithm, as an evolutionary technique, and proposed an enhanced EM algorithm, in which the EM is hybridized with a diversification mechanism, and an effective local search to enhance the efficiency of the algorithm. Sarker and Faiz [28] presented an opportunistic multi-level preventive maintenance strategy for offshore wind turbines. In their strategy, maintenance activities were initiated by the failure of any component and the maintenance team took the opportunity to preventively replace or perform maintenance on functioning components when replacing a failed component.

Despite the rigorous modeling efforts on condition-based maintenance planning, the environmental issues have been rarely addressed by the existing optimization models. While, in real world applications, maintenance activities can drastically impact environment. For instance, maintenance actions on cranes, industrial machineries, transportation vehicles (e.g., boats) and equipment (e.g., crushers) used in the cement industry can have enormous negative effects on environment. More specifically, cement production includes many chemical and physical processes that produce air pollutants (e.g., carbon dioxide, sulfur dioxide, and nitrogen oxide), noise pollution, and hazardous wastes. It should be noted that sulfur dioxide, nitrogen oxide and dust emissions are major environmental risk factors to human health. In particular, the relation between many respiratory diseases and pulmonary function abnormalities with sulfur dioxide has been proved. This indicates the significant importance of considering environmental factors in maintenance planning.

Given this research gap, the present paper contributes to the literature by accounting for environmental issues in condition-based maintenance. Here, the equipment under study can cause environmental degradation and pollution after passing its warning limit. The purpose is to reduce overhead costs related to environmental degradation and pollution plus other costs (i.e., inspection and replacement), through minimizing the function of the average total cost. The condition of equipment should be determined through inspection, and its operating cycle just ends in the event of a failure or precautionary repair. Maintenance services include complete repair or replacement. However, when an item has been inspected in unfavorable operating conditions, complete preventive maintenance tasks must be included. Unlike

Chouikhi et al. [1], preparation times and logistics are considered as random variables. A mathematical model and a genetic algorithm are developed to find the optimal inspection strategy for the defined sets of parameters. Moreover, a numerical example is presented and the results are discussed.

2. MODEL DESCRIPTION

The system investigated has two condition variables that show the operation and device performance. Different types of equipment, such as turbines and gas turbines, are examples of systems that can be used with two or more condition variables that will be monitored, like monitoring temperature and vibration at the same time. Monitoring vibration and noise of the electronic equipment is another related example. Reaching beyond the warning levels leads to the environmental degradation. The cycle defined for the system covers only two operation mode under normal and failure conditions. The variables of the condition monitoring in many systems are interdependent and independent of each other. For example, the status structure for shock and erosion can mutually influence on each other, but at the same time, oil and vibration analysis usually has no effect on each other and their distribution functions can be considered independent. Each condition variable after passing its warning level plays a different role in the environmental degradation. All variables are assumed to be independent. When one scheduled inspections shows that one of the conditional variables has reached beyond the warning level, a preventive maintenance plan is developed. The cycle or period in the system is equal to the amount of time taken for the system start up until its end, in which one of either preventive maintenance or failure events exists. Time between inspections of the proposed system has different intervals. In the early life of equipment, the components are in good condition. As a result, fewer inspections are required and the inspection intervals are large. However, over time the condition of equipment deteriorates and it requires a higher number of inspections. As a result, the inspection intervals are reduced.

Figure 1 presents a scheme of the system when the first condition variable passed its warning limit. Having found that one variable reached beyond the warning level, all inspections would be stopped and then the time elapsed includes the preparation and logistic times or the equipment failure.

2. 1. Parameters, Variables and Model Assumptions

Meanwhile, the following variables are used to introduce the model structure:

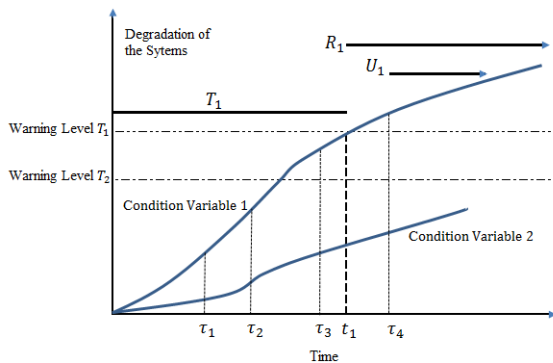


Figure 1. System status based on monitoring variables

T_1 : Random variable of time status until the first warning level.

T_2 : The random variable of time status until the second warning level.

R_1 : The random variable of time elapsed from the moment t_1 until the failure event (i.e., remaining life of the system from the moment that the first status variable is passed its warning level).

R_2 : The random variable of time elapsed from the moment t_2 until the failure event (i.e., remaining life of the system from the moment that the second status variable is passed its warning level).

U_1 : Random variable from the time period of preparation and logistics for first status variable.

U_2 : Random variable from the time period of preparation and logistics for the second status variable.

N : Random variable showing the number of inspections.

C_t : Random variable of total cost.

T_e : Random variable of the time period for environmental degradation.

T_c : Random variable of the time that one cycle finishes with corrective or preventive maintenance.

f_1 : Probability density distribution function of random variable T_1 .

f_2 : Probability density distribution function of random variable T_2 .

g_1 : Probability density distribution function from random variable R_1 .

g_2 : Probability density distribution function from random variable R_2 .

h_1 : Probability density distribution function of random variable U_1 .

h_2 : Probability density distribution function of random variable U_2 .

C_f : Cost of one corrective maintenance.

$$E(C_t) = C_c P_c + C_p P_p + C_i E(N) + C_e E(T_e), E(T_c) = E(T) + E(T_e) \tag{2}$$

$$P_c = P(T_1 < T_2) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int G_1(\tau_i + u_1 - t_1) h_1(u_1) f_1(t_1) du_1 dt_1 \right] + P(T_2 < T_1) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int G_2(\tau_i + u_2 - t_2) h_2(u_2) f_2(t_2) du_2 dt_2 \right] \tag{3}$$

C_p : Cost of one preventive maintenance.

C_i : Inspection cost.

C_e : Price in unit of time because of degradation or erosion of environment, penalty cost.

τ_i : Inspection time in turn i

$\underline{\tau}$: Vector of inspection time.

$\vartheta = \frac{E(T_e)}{E(T_c)}$: Time rate of environment degradation per cycle time (i.e., The average time that equipment pollutes or destroys the environment per cycle time).

P_p : Finishing probability of one cycle with the beginning of preventive maintenance.

P_c : Finishing probability of one cycle with beginning of corrective maintenance.

During the interval time a condition variables passed its warning level, all further inspections would be stopped and then the focus will be on the preparation and repairing operations. In many circumstances condition monitoring only means of warning. In other words, equipment must at the time designated for inspection completely overhaul (dismantling and assembling equipment), and thus the model after passing alert level status variable from the value that is determined through inspection. Given the known costs of C_f , C_p , C_i and C_e , all probability density distributions are also assumed as known values.

2. 2. Model Structure

As the model aims to reduce overhead costs caused by the environmental degradation plus other costs (e.g., inspection and replacement), the function of the average total cost per the unit time is widely used in optimization problems. According to the definition of cycle or period, an infinite time horizon can be considered for the process so that the cycle is repeated. Based on Choukhi et al. [1], the function of the cost rate can be estimated with the expected total cost on the expected cycle time.

$$J(\bar{\tau}) = \frac{E(C_t)}{E(T_c)} \tag{1}$$

where $E(C_t)$ is the average total cost and $E(T_c)$ is the average cycle time (2).

The probability that one cycle finishes with an equipment failure is equal to (3). Since one cycle finishes with one of two corrective or preventive maintenance actions, it is obvious that: $P_p + P_c = 1$

The average number of inspections $E(N)$ is achieved by (4):

$$E(N) = \sum_{i=1}^{\infty} i \left[\left[P(T_1 < T_2) \left(\int_0^{\tau_{i+1}} G_1(\tau_{i+1} - t_1) f_1(t_1) dt_1 \right) + P(T_2 < T_1) \left(\int_0^{\tau_{i+1}} G_2(\tau_{i+1} - t_2) f_2(t_2) dt_2 \right) \right] - \left[P(T_1 < T_2) \left(\int_0^{\tau_i} G_1(\tau_i - t_1) f_1(t_1) dt_1 \right) + P(T_2 < T_1) \left(\int_0^{\tau_i} G_2(\tau_i - t_2) f_2(t_2) dt_2 \right) \right] \right] \quad (4)$$

$$E(T_e) = P(T_2 < T_1) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int_{u_2}^{\infty} \left(\int_0^{\tau_i+u_2-t_2} [1 - G_2(r_2)] dr_2 \right) h_2(u_2) f_2(t_2) du_2 dt_2 \right] + P(T_1 < T_2) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int_{u_1}^{\infty} \left(\int_0^{\tau_i+u_1-t_1} [1 - G_1(r_1)] dr_1 \right) h_1(u_1) f_1(t_1) du_1 dt_1 \right] \quad (5)$$

$$E(T_c) = E(T) + E(T_e) \quad (6)$$

$$E(T) = E(T = T_1 | T_1 < T_2) + E(T = T_2 | T_2 < T_1) = E(T_1)P(T_1 < T_2) + E(T_2)P(T_2 < T_1) = P(T_2 < T_1) \sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} t_2 f_2(t_2) dt_2 + P(T_1 < T_2) \sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} t_1 f_1(t_1) dt_1 \quad (7)$$

$$E(T_c) = \left[P(T_1 < T_2) \sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} t_1 f_1(t_1) dt_1 + P(T_2 < T_1) \sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} t_2 f_2(t_2) dt_2 \right] + P(T_2 < T_1) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int_{u_2}^{\infty} \left(\int_0^{\tau_i+u_2-t_2} [1 - G_2(r_2)] dr_2 \right) h_2(u_2) f_2(t_2) du_2 dt_2 \right] + P(T_1 < T_2) \left[\sum_{i=1}^{\infty} \int_{\tau_{i-1}}^{\tau_i} \int_{u_1}^{\infty} \left(\int_0^{\tau_i+u_1-t_1} [1 - G_1(r_1)] dr_1 \right) h_1(u_1) f_1(t_1) du_1 dt_1 \right] \quad (8)$$

The average time from the environment degradation is given by (5). The average cycle time $E(T_c)$ is calculated in (6). $E(T_e)$ is calculated by using (5); as a result, $E(T)$ equal to the average life time until the time for reaching the warning level is achieved. According to (5) and (7), the average cycle time $E(T_c)$ can be calculated by (8).

3. SOLUTION PROCEDURE

Since the model (1) has an NP-hard complexity, an efficient solution is needed. A genetic algorithm is a random search algorithm inspired from the nature. Dealing just with functions is one of its advantages, which overcomes the need for knowing the exact equation to choose a function. For classical approaches, this algorithm is successful to solve linear and convex optimization problems, and more efficient for discrete and non-linear problems. The genetic code is written in MATLAB. Figure 2 shows the solution process for the algorithm. The stopping condition in the above algorithm is the end of the occurrence of repetitions or a distance of less than 0.0001 between two successive solutions.

4. NUMERICAL EXAMPLE AND ALGORITHM VALIDATION

Table 1 shows the optimal values for various costs of environment degradation (the inspection costs equals to 500 unit price). Moreover, Table 2 presents the optimal values for the objective function according to changes in the inspection cost (the cost rate of environment degradation is equal to 500 unit price). There is a direct relationship between the total cost rate and the

degradation cost rate. According to the values of degradation cost, Figure 4 shows the changes in ϑ . As seen, when the penalty cost increases, the time proportion decreases when the equipment continues to degrade the environment. Also, Figures 5 and 6 show this situation according to the variables of the inspection cost. In Figure 7, the convergence of the algorithm is shown for two of the solutions.

5. CONCLUSION AND RECOMMENDATION

The present study investigated a production system described by two variables. The model proposed here was extended from the approach in Chouikhi et al. [1], in which probabilistic logistic and preparation times were considered.

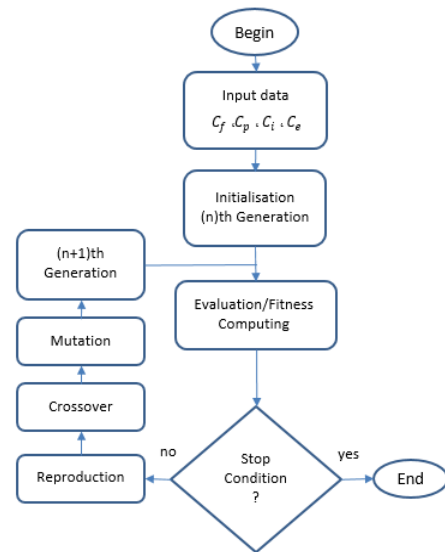


Figure 2. Structure of the genetic algorithm

TABLE 1. Optimal inspection dates and total cost rate according to changes in environment degradation cost

C_e	$\bar{\tau}^*$	$J(\bar{\tau})^*$	$100\vartheta[\%]$
2000	[473.8 3248.8 3735.5 3705.8 4142.1 4047.6 4605.9 5250 5494.9 5726.8 6172.3 6653.3]	32.7739	11.57
1500	[468.7 3393.1 3472.5 3704.3 3965.3 4369.2 4637.6 4892.7 5182.4 5467.9 6249.0]	32.1934	11.63
1000	[459.3 4207.3 4394.7 5049.2 5624.3 6323.9 6637.4]	31.6075	11.74
750	[455.1 4517.4 5638.5 6949.2]	31.3133	11.79
500	[450.9 6947.1]	31.0179	11.84
100	[445.2 6674.6]	30.5429	11.9

TABLE 2. Optimal inspection dates and total cost rate according to changes in inspection cost

C_i	$\bar{\tau}^*$	$J(\bar{\tau})^*$	$100\vartheta[\%]$
2000	[473.6 6656.1 6991.3]	32.7008	11.57
1500	[467.1 3801.5 4299.6 5498.5]	32.1448	11.65
1000	[459.1 5865.5 6379.6 6647.5]	31.5832	11.74
750	[455.3 3905.8 4831 5062 5332.2 6465.9]	31.3013	11.79
500	[448.8 3760.1 4154.3 5984.6 6066.4 6159.5 6545.4]	31.0182	11.86
100	[446 3116.5 3133.9 3592.1 3850.9 4682.3 5205 5234.1 6397.3 6708.8]	30.5628	11.9

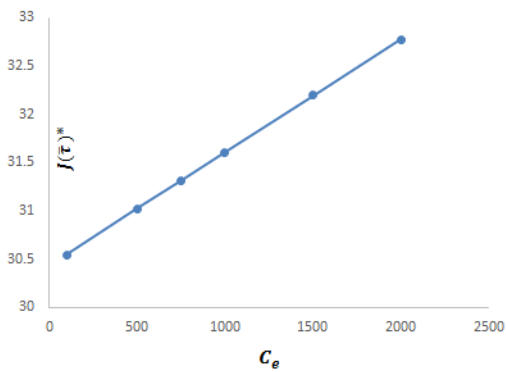


Figure 3. Changes in total cost rate and degradation cost

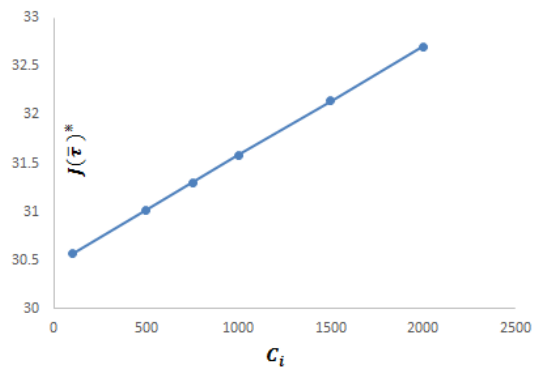


Figure 5. Changes in total cost rate and inspection cost

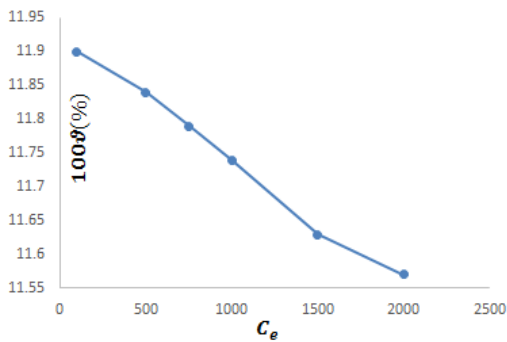


Figure 4. Changes in ϑ and degradation cost

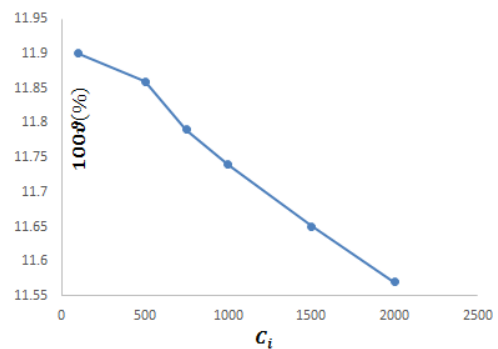


Figure 6. Changes in ϑ and inspection cost

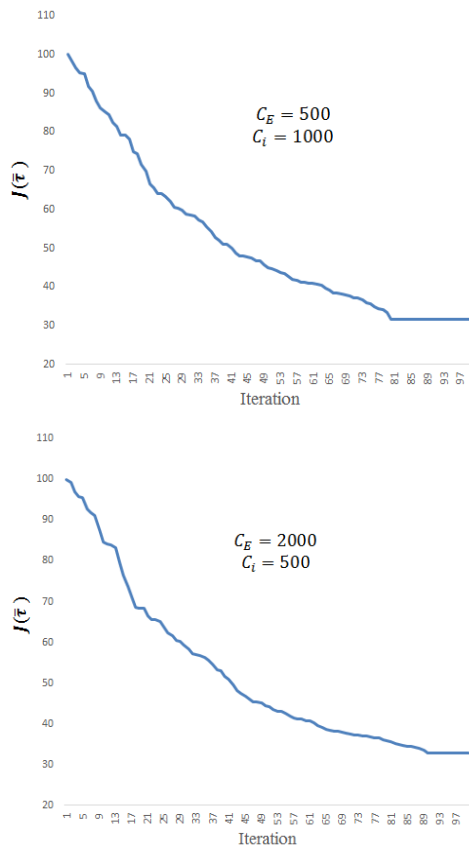


Figure 7. Convergence of two of the solutions

Furthermore, the optimization method was based on the genetic algorithm. The equipment condition was such described when a conditional variables passed its warning level, an additional cost was imposed on the system due to the environment degradation. The optimization criterion was the function of the average total cost per unit time. According to the optimization method, time restrictions could be introduced for inspection dates as certain constrains. Further studies are recommended to consider the association between condition variables (e.g., close relationship of the vibration and sound analysis) and the condition of updating the estimation by using the Biz theory after each inspection and observing the destruction process. However, the employment of some minor repairing in the equations is also suggested.

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Optimal Policy of Condition-based Maintenance Considering Probabilistic Logistic Times and the Environmental Contamination Issues

H. Rahimi Komijania^a, M. Shahin^b, A. Jabbarzadeh^b

^a *Departement of Industrial Engineering, K.N.Toosi University, Tehran, Iran*

^b *Departement of Industrial Engineering, Science and Technology University, Tehran, Iran*

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این مقاله به ارایه سیاست نگهداری و تعمیرات پیشگیرانه برای تجهیزاتی که با کارکرد خود می تواند موجب آلودگی و تخریب محیط زیست گردد می پردازد. هدف کاهش هزینه های سربار مرتبط با آلودگی و تخریب محیط به همراه هزینه های دیگر (بازرسی و تعویض)، از طریق کمینه کردن تابع متوسط کل هزینه است. وضعیت تجهیز از طریق بازرسی تعیین می گردد و دوره عملیاتی تجهیز با یک تعویض پیشگیرانه و یا خرابی تجهیز به اتمام می رسد. وضعیت تجهیز در هنگامی که متغیر وضعیت از سطح هشدار خود بگذرد سبب آلودگی محیط می گردد. پس از آنکه بازرسی وضعیت یک تجهیز را در شرایط نامطلوب نشان داد، یک عملیات نگهداری و تعمیرات پیشگیرانه کامل باید اجرا گردد، در جاییکه زمان های لجستیک آماده سازی برای انجام این عملیات نت متغیرهای تصادفی می باشد. یک مدل ریاضی به همراه الگوریتم ژنتیک با تنظیم پارامترهای معین برای یافتن سیاست بهینه بازرسی توسعه داده شده است. همچنین یک مثال عددی تشریح و نتایج تفسیر گردید.

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