Joint Optimization of Spare Parts Strategy and Maintenance Policies for Manufacturing Systems

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Abstract: Cost is the most important factor in engineering systems, thus cost reduction and producing components with a reasonable cost are mandatory for manufacturing engineers. Effective maintenance influences the total cost of manufacturing systems, and its efficiency depends on spare parts management. Therefore, maintenance and spare parts should be jointly managed and significant characters such as ordering, repair and replacement times, shortage, cost, quality, and storage condition of spare parts have to be considered. In this paper, intelligent manufacturing systems with the multi-component structure are considered, that three types of maintenance policies (condition-based maintenance, corrective maintenance, and preventive maintenance) simultaneously support these systems. A joint optimization method based on GA-PS and Monte Carlo simulation is proposed to achieve minimum cost and maximum availability. Also, the influence of spare parts degradation in storage to evaluate system performance is considered. A framework is proposed for this; it can successfully consider the manufacturing machines, maintenance policies and spare parts inventory to obtain the optimal system with the maximum availability and the minimum cost. Also, the results demonstrate that different factors impress the system, and these parameters must be jointly considered. The ordering and replacement times, storing conditions and suppliers' situation are the main factors considered to obtain an optimal system.

Keywords: Joint Optimization, Multi-Component Manufacturing System, Multi-Policy Maintenance, Spare Part Strategy, Supply Chain, Storage Condition

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1 INTRODUCTION

Manufacturing systems are very complex, and several techniques are used to increase production capacity and lead time reduction according to customer's requests. Industries need an intelligent and smart system to reduce human error and improve manufacturing system planning. Advanced devices and sophisticated technologies are applied for smart systems installation and increase utilization. Similar to the traditional system, smart systems should be maintained to hold their capabilities. Condition monitoring methods such as oil analysis, vibration measurement, thermography approach are applied to monitor and check a system. The collected data are used to diagnose and Remained Useful Lifetime (RUL) estimation. Then, spare parts are managed by this data analysis.

Several parameters must be considered to achieve a high level of system availability under cost constraints. Intelligent manufacturing system should be adopted to changing environments and varying process requirements. Also, this system should be adopted with variation in supply change and maintenance. Their modelling and controlling are very interesting subjects studied by different researchers to increase these systems performance; often they focused on system technology, process planning, and production planning to obtain the optimal production facilities [1-2].

Engineers tried to improve and develop maintenance strategies to decrease idle and shutdown times. Recent studies showed that an effective system needs jointed analysis manufacturing and maintenance program [3]. Also, we know that other aspects of the system should be considered too. Problems such as storage condition, spare parts management, procurement management, and market situation have to be investigated similar to production and maintenance policies because storage takes the large space in a factory and several valuable components are kept in this space.

Starting from the 1970s, the METRIC acquired relevant attention promptly in the field of spare parts management [4]. Different methods have been proposed to solve this problem and find the optimal level of spare parts to overcome the operation cost increasing. Spare parts strategy and managements strictly depend on maintenance method and system type. Several papers may be found about spare inventory management and maintenance plan. Armstrong and Atkins [5] developed a joint optimization order and replacement policy for a simple system with one component subject to random failure with space to only carry one spare. Chelbi and Kadi [6] suggested a jointly optimal periodic replacement and spare parts provisioning strategy that determines the replacement period, replenishment cycle, and reordering point. Alenka et al. investigated the joint optimization problem of periodic batch replacement and periodic spare procurement [7]. They studied the spare parts ordering strategy and planned maintenance. Chen et al. studied a manufacturing system under imperfect preventive maintenance [8]. They tried to maximize profit composed of production value, production cost, maintenance cost (including the preventive maintenance cost and replacement cost) and tardiness cost.

Condition-based Maintenance (CBM) is one of the newest method used to improve system utilization and research reports about this method modeling and optimization are continually growing. In recent years, jointly study on CBM and spare inventory is increased. CBM considers system condition and spare parts are ordered according to the system condition.

Rausch tried to minimize the spare part inventory and the expected total operating cost of a manufacturing system [9]. He used a heuristic two-step approach, to find the optimal spare parts level, along with the preventive maintenance threshold. Elwany and Gebraeel [10] used a Bayesian approach for spare parts ordering for a single component system, whereas at least one spare part should be stored in the storage. Wang et al. [11] studied spare parts modeling when a system is monitored during its operation. They introduced the optimal threshold of preventive maintenance to satisfy spare parts to support requirements.

Chen et al. [12] proposed an algorithm to determine the best time for replacement and spare ordering. Their method includes three phases. At the first phase, they collect data from the desired system, and an ANN is trained. In the second phase, the system condition is monitored, and RUL is predicted via the trained ANN. Eventually, they determine replacement and spare ordering time based on the minimum system cost.

Nguyen et al. [13] studied a system with seven units as a series-parallel structure. They investigated the joint optimization of predictive maintenance and inventory strategy; an adaptive maintenance opportunity rule was also proposed. A cost model was used to assess and optimize the performance of the proposed joint strategy. Zahedi-Hosseini et al. [14] proposed a framework for studying the interaction of spare parts ordering with maintenance scheduling.

Sharma et al. [15] worked on army equipment and applied selective maintenance method to model this equipment for reducing the supply lead time. They propose a method based GA to select maintenance tasks and determine the optimal costs of spare parts replenishment yet achieving the desired mission reliability.

Kalinowska and Stachowiak [16] investigated spare parts management in the automotive industry. They briefly reviewed the spare parts management methods and described some of the parameters that influence the spare parts management as spare parts supplier, competitors, and user/customer.

Siddique et al. [17] worked on joint maintenance and spare parts inventory optimization. They assumed that the arrival time of failures follows the Poisson process with a constant rate, and machines are non-repairable. (*T*, *S*) Ordering policy was adopted in this research. Their simulation showed that the total cost per unit time decreases when the PM interval is increased, and a higher quantity should be ordered at each ordering epoch.

Israel et al. [18] investigated an intelligent maintenance system. They proposed a hybrid model along with mixed linear programming simulation and demand information. Their work focused on supply chain effects on spare parts management and the cost reduction of supply. Hellingrath et al. [19] described forecasting methods for spare parts and explained the state of the art of spare parts forecasting and condition monitoring. They proposed a draft conceptual approach for the spare parts planning for CBM systems.

Azadeh et al. [20] considered a power generation system and estimated reliability and cost of this system. They evaluated three stated maintenance policies (PM, CBM, and CM) by general Markovian discrete-event simulation. They showed that if CBM policy is implemented efficiently, not only it will reduce system cost, but also it will enhance the reliability of the system. Frank [21] reviewed the United States Air Force (USAF) aircraft parts forecasting techniques. The physics-based model as a robust CBM system was used to investigate the current forecasting method applied by the USAF. CBM could reduce forecasting error by 2.46% or $12.6 million worth of parts in those categories alone for the B-1 aircraft.

The lecture shows that the maintenance influence on the engineering systems performance, effectiveness and efficiency is very important, and for manufacturing systems this topic is more critical. The intelligent manufacturing system with different dependencies needs an effective plan for maintenance, also this plan should consider spare parts inventory. Although some of the relationships between them have been considered, more research in this area is necessary. For this, in this paper, spare parts management and maintenance are jointly modeled and optimized, and the main contributions of our paper to the existing literature are in the following areas:

a-Some factors such as supplier's effects and storage condition influence on the cost and availability of a system are investigated. These parameters have not considered in the literature of joint optimization of maintenance and spare part management.

b- In this paper, three types of maintenance policies as CBM, Corrective Maintenance (CM), and Preventive Maintenance are simultaneously considered, and optimum values for the significant parameters are computed to achieve high availability and minimum cost. c- Multi-component intelligent systems are considered, a single component is deeply investigated and work on multi-component systems is rare. In this study, a system is considered that the system includes multi-critical units monitored and each component can be provided by different suppliers.

2 SYSTEM DESCRIPTION

Manufacturing machines are complex and use different components to perform their mission. Some components need a particular program to keep their performance because they are sensitive and accurate, they are calibrated, and their error is compensated via a predefined program. Some units should be maintained based on a time table. For example, the gearboxes oil and lubricant are changed based on a specified plan to reduce a system failure rate. Some parts and accessories such as chip conveyor and tools changing devices help to increase machine's performance and reduce production time, but they are not as important as the critical units. These units are complex and include several components; thus we can assume that their failures occur as a random failure based on an exponential distribution, and they are usually repaired as run-to-failure policy. Finally, usually, a machine has a critical unit that impresses the system. When this unit is failed, the production performance becomes zero. Usually, this component is expensive and its repair and changing time are too long, and when it is replaced before failure, the total cost is decreased. Often, this unit is monitored, and critical data are collected and diagnosed. The main motor and the main shaft or spindle in a CNC machine can be categorized in this group. Therefore, we should perform three types of maintenance policies to increase utilization: CM, PM, and CBM. CM has used for secondary units that their failure is not critical and their failures are randomly occurred. PM or time table based maintenance is often proposed for general units fixing and changing consumables such as oil and lubricants. CBM is an intelligent method applied to control and predict the lifetime of the critical components to prevent the hazard and reduce repair time and cost.

In this study, an intelligent manufacturing system that can be adopted with variation in maintenance plan and supply change is considered, it is supported by all of the above-mentioned maintenance policies. It is assumed that the times of PM tasks can be accomplished based on other repair processes. Timetable flexibility helps us to decrease total system cost. In this study, we assume that the scheduled task can be varied to 20 percentages of the desired timetable for opportunistic maintenance. The critical components are monitored, and the collected data are used to estimate the remained useful lifetime (RUL).

RUL determination is one of the most critical steps in the maintenance policy and intelligent manufacturing systems management. A time-dependent Proportional Hazards Model (PHM), Hidden Markov Model (HMM), the P-F interval method, Bayesian approach, and so on can be applied in the survival analysis and replacement time/failure time estimation. The P-F interval is a conventional method combined with CBM [21]. This method application can be found in several papers and industry.

Moubray [22] formed a method known as the P-F interval method, which uses condition monitoring data to determine the probability of a component failure. In this approach, a P-F interval is a time between a potential failure (P) and a functional failure (F). This method was enhanced by Goode et al. by combining reliability data with condition monitoring data, to predict the time to failure of steel mill plant machinery [23]. In this study, we use the P-F interval method, and it is assumed that F indicates the time of spare parts ordering, and F defines repair and replacement time for the desired component. Ordering and replacement times are essential factors in achieving an effective maintenance program. These times have to proposed based on CBM method capability (since fault detection is an essential factor in spare parts provision), and survival analysis (since the RUL defines the replacement time). The RUL from reliability engineering view, can be defined by a specified statistical distribution function. Manufacturing machines consist of mechanical and electrical units that mechanical unit such as rotational components commonly follow a Weibull distribution. Therefore, we assume that the RUL can be determined by a specified Weibull distribution. The mean time to failure and reliability of a component based on Weibull distribution can be determined as follows [24]:

$$\text{MTTF}=\alpha \times \Gamma(1+\frac{1}{\beta}) \quad (1)$$

$$R = \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right) \quad (2)$$

Where, Alfa is the scale parameter, and beta is the shape parameter. These parameters are obtained based on the fields or defined by suppliers. The scale parameter defines approximately mean lifetime and the scale parameter depends on the component type and utilization conditions.

3 THE SYSTEM MODELING

Reliability and availability are the most characters of a system to evaluate the system performance and efficiency, that may be calculated by different methods such as the Markov process, Bayesian, and Monte Carlo Simulation (MCS). According to MCS capability and flexibility to systems reliability modeling, at this study, this method is applied. In this approach, we simulate system behavior randomly at the desired lifetime, for example 3000 hr, and operating time, repair time and shutdowns are determined. The spare parts delivery time and repair times are not constant, and their uncertainty is defined as a normal distribution.

The total cost is a vital factor in the market and production plant. Thus, a product must have the minimum cost. In this study, the total cost is calculated by shutdown, maintenance, and spare parts management costs. The following equation is proposed for the total cost calculation:

$$\begin{aligned} TC = \sum_{i=1}^{n} Cs_i + \sum_{i=1}^{n} CR_i + \sum\nolimits_{j=1}^{m} CPM_j + \sum_{h=1}^{l} Shc_h \\ + \sum\nolimits_{k=1}^{h} STC_k + \sum_{z=1}^{y} RNDC_z \end{aligned} \quad (3)$$

Where, TC is the total cost, m and n indicate the number of machines and spare parts. Cs_i denotes the spare part cost, and the CR_i is the replacement action cost for a spare part. Stopping or shutdown events add a system cost ShC, and when a k^{th} spare part needs to be stored, the STC_k cost is accounted. RND denotes random failure, and corrective maintenance cost and preventive maintenance cost are defined by CPM. This multi-component system has series structure, and when a component is failed the system is stopped.

Figure 1 shows the algorithm used in this study to determine system cost and availability. System modeling has three stages that simultaneously are accomplished. Firstly, CBM is used as a reference to evaluate system performance. Failure times and replace time during operation time are estimated by Weibull distribution. When the first failure happens, the second part is idle and its failure time is postponed to repair the first part. Before the component failure, the supplier should be selected randomly, and a request is sent to him/her. The delivery time has to mentioned to determine delay or storing cost and its effects on the quality. When the new spare part is delivered, the repair time is calculated, since repair time is a random variable as a normal distribution.

In the second stage, the time of the random failures is calculated by an exponential distribution, thus corrective maintenance is considered at this stage. In other words; It is assumed that failures are random events and their times are determined by random sampling from an exponential distribution. Repair duration is a normal random variable defined by the mean and variance.

In the third stage, PM times are calculated; these times are checked by other failures time to opportunity maintenance. The times should be updated simultaneously to concern the influence of each policy on others. We assume that the PM times can be varied by 20% of the time between two PM tasks. For example, if PM duration is equal to 20 hr, it can be performed between 16 to 24 hr since it might be accomplished with another repair task.

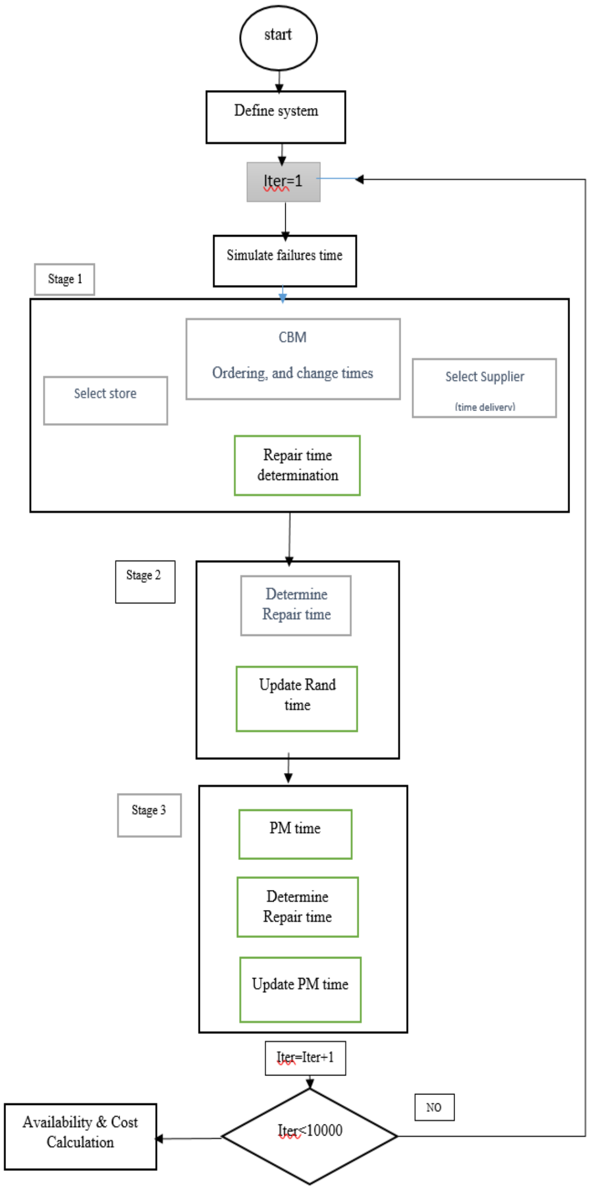

Fig. 1 System modeling flowchart.

Let us assume a manufacturing system that consists of two machines as serial structure, machines are monitored and spare parts can be purchased from two suppliers. Some random failures also occur during operation time. This layout of machines commonly is used in manufacturing factories for production or assembly lines. The important parameters are defined in Appendix. We would like to model and optimize the system cost and availability based on the mentioned method.

In this system, the new spare part is ordered when the components work until 75 percentages of expected life, and at 95 percentages of the lifetime and before the breakdown, it is replaced. Thus, total cost and availability for 3000 hr working time are calculated as follows:

Cost=63000, availability = 0.351

4 SENSITIVITY ANALYSIS

In the previous section, a manufacturing system was defined and modeled. Engineers try to improve system availability and decrease cost. In this section, the effects of the significant parameters are investigated.

4.1. Ordering Time

Ordering time is an essential factor in spare parts management and maintenance policy. The Fault and Failure Detection (FD) is applied to avoid an unexpected event during machine mission, and this is the goal of a CBM method; thus this is a vital parameter. Different methods may be implemented to FD; each method has a specified accuracy. Commonly industries use advanced and expensive instruments to detect a fault, but this decision should be combined with spare parts forecasting and management plan. It is suggested that ordering time be defined based on component reliability. On the other hand, it is a good idea that we detect a fault sooner and send a request for spare part provision, but ordering time should be selected according to delivery time, storage cost and store effect on the spare part quality. In this paper, three values for ordering time is investigated, and the results are shown in “Table 1”.

Table 1 Ordering time influence on the system performance

Reliability at ordering time	0.75	0.85	0.90
Cost	63000	18000	62113
Availability	0.351	0.823	0.640

This result shows that ordering time is very important and system performance depends on this factor. Also, the application of a detection device to fault detection and increase ordering time interval cannot help to improve the desired system performance when spare parts inventory aspects are ignored. For instance, when ordering is performed sooner than the optimum time, the storage cost is increased. On the other hands, spare parts quality may be decreased in storage duration. Therefore, the total cost is increased, and availability is reduced. If the ordering is performed with delay, the cost is increased, because of increasing the probability of failure for components and availability reduction.

4.2. Replacement Time

The repair/replacement time is another important factor that can influence system performance. Incorrect replace time leads to a dangerous state, or increase the total cost. Therefore, this time is critical and should be selected according to risk and cost. This time selection also depends on ordering and supplier delivery times. “Table 2” shows the influence of this factor on system performance. It is assumed that spare parts are ordered when the working time is equal to 0.85 percent of the lifetime, and spare parts are provided by the first supplier.

Table 2. The influence of the repair time on system performance

Reliability at changing time	0.95	0.90	0.85
Cost	17853	17847	19768
Availability	0.8257	0.8259	0.8197

The result shows that replacement time can impress the cost and system availability. When replacement is carried out sooner, the system cost due to the spare part cost is increased, and when it is replaced later, the system cost increased, and availability is decreased because failure probability is increased. The influence of replacement time on the system is less than ordering time influence.

4.3. Storage Condition

One of the most important parameters for spare parts management is storing and its management. Some parts are sensitive to storage condition when storage environment parameters such as temperature and humidity are out of the standard interval, the spare part is deteriorated, and the failure rate is increased. In this study, this effect is investigated, and three types of storage are considered. Modeling and definition of storage effect are very complicated, and it is performed based on the physics of failure. In this paper, it is assumed that storage condition impresses spare parts quality and the scale parameter of spare parts is changed. The scale parameter of Weibull distribution for a spare part in situation 1, situation 2 and situation 3 is decreased as 0.5, 0.55,0.6 percent per storage hour respectively. The result is shown in “Table 3”.

This result demonstrates the storage influence on the cost and availability of the system. In situation 3, the storage condition decreases spare parts quality, so failure probability is increased and the total cost is higher. In situations of 1 and 2, the quality reduction is less than situation 3; thus availability is increased. In situation 1, availability is the highest because spare parts have the best quality; but storage cost overcomes other aspects of total cost and cost is more than situation 2. Also, if spare parts quality during storing time are not decreased, the cost can be reduced to 11082, and availability is raised up to 0.8676.

Table 3 The influence of the storing condition on system performance

Storing factors	Situation 1	Situation 2	Situation 3	Whit out degradation
Cost	17853	17226	23800	11082
Availability	0.8257	0.8163	0.7363	0.867

4.4. Supplier Effect

A supplier capability and quality are vital to obtaining an optimal system. It is assumed that each spare part is provided by two suppliers, but their quality, delivery time and cost are not the same. It is assumed that the original component quality is same as the first supplier quality. “Table 4” shows the influence of supplier selection on system performance. According to management decisions, supply changes strategy or capacity of a supplier; sometimes, the factory uses a combination of different suppliers to spare parts provision. “Table 4” shows this situation too. In this condition, system availability is the highest, and the cost is reasonable. Thus, it is recommended that the supply chain management uses different suppliers to improve system performance.

Table 4 The influence of supplier selection on the system

	Only supplier 1	Only supplier 2	Supplier 1= 80%, supplier 2= 20%
Cost	17853	14500	15223
Availability	0.8257	0.836	0.86

4.5. Opportunity Maintenance Factor

Preventive maintenance defines the tasks and processes that they are accomplished to increase system lifetime. These tasks are necessary, but their time is not often strict and can be varied. This variation is limited in an interval and depends on the system and PM tasks. This interval can be proposed by expert engineers or determined by the system history. Nevertheless, it is reasonable that this timetable may be improved. Opportunity factor is defined as a time variation for a repair task that it is defined as a ratio of the time between two maintenance tasks. Sometimes this parameter is considered as the economic dependency between components. In this study, this dependence is considered as a repair time reduction. “Table 5” illustrates this parameter effect on system cost and availability. When this factor is ignored the cost is increased, and system availability is reduced, since some repair tasks can be performed together and the total time for repairs is decreased.

Table 5 The influence of the Opportunity factor on the system

Opportunity factor	0%	20%
Cost	18200	17853
Availability	0.825	0.8257

In this example, the results show that the influence of the parameters ordering time, replacement time, supplier selection and storage condition on the system performance is important. In the next section, the optimal state of the system is determined.

5 THE OPTIMAL STATE DETERMINATION

Spare parts inventory and maintenance jointly modeling are difficult because the relationships between their parameters are complex. On the other hand, a manufacturing system should be worked in the optimal state and the lowest cost. Thus, to better management, we should use the optimal plan for maintenance and spare parts management. According to the results of the previous section, different parameters should be considered; also repair times and spare parts provision time are not constant, and their uncertainty should be considered. Because human influence on repair time cannot be ignored, and the logistics problem, raw material conditions, and the supplier program can change the delivery time. Thus, these times are randomly sampled from a normal distribution.
When all of the covered parameters are considered in a model, the system behavior is complex, and we deal with an NP-hard problem. Thus, for optimal planning, we need a powerful tool to find the best parameters. In the next section, this tool is introduced.

5.1. The GA-PSO Algorithm for Optimization

Different algorithms and approaches have been developed by researchers to solve NP-hard problems. Commonly, these algorithms are inspired by nature and animal behavior. The Genetic Algorithm (GA), Particle Swarm (PS), Bat algorithm (BA), Ant Colony, and so on have been proposed to find the optimal parameters in real-world problems, especially for manufacturing systems [24-25]. In this paper, we combine two popular methods (GA and PS) to achieve better performance and increase convergence speed. We use PS moving relations to determine the cross over in GA. The next gene is created based on the best gene value and the average value of all of the gens. The average factor effect is two times of the best gen factor at the next situation creating. Also, ten percentage of genes (as the worse gens) are mutated in each epoch. In this study, nine parameters are investigated, and the optimal values are determined for cost reduction and satisfy the desired availability. Figure 2 shows a schematic of this optimization procedure.

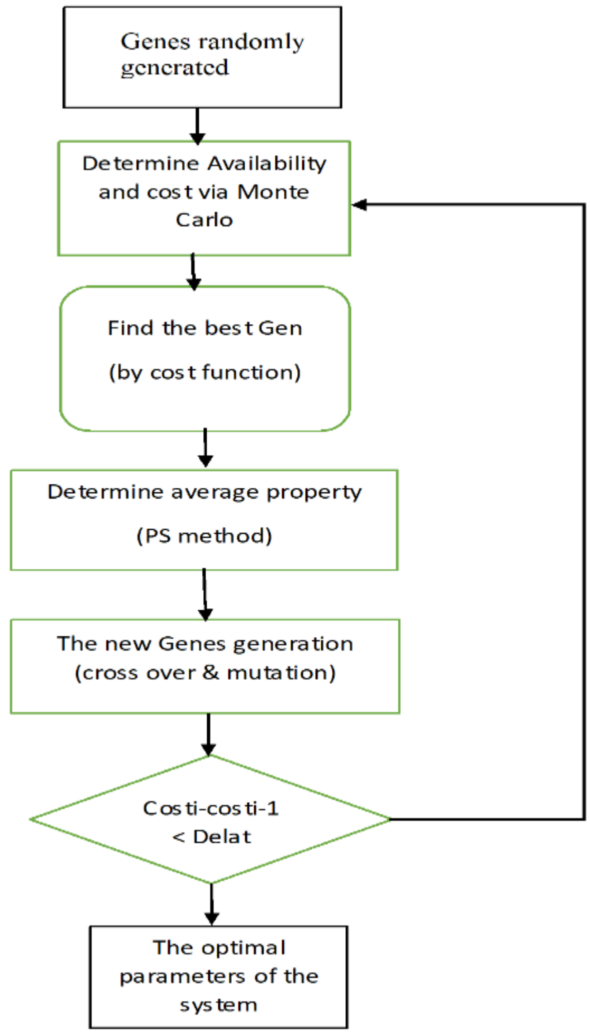

Fig. 2 The optimization procedure.

Also, the general form of this problem can be presented in Equation (4).

$$\begin{aligned} &\text{Min: Total Cost} \\ &A>=A_{min} \\ &S_{min} \leq S_i \leq S_{max}\ ,\ i=1,2,\ldots,9. \end{aligned} \tag{4}$$

Where, S_i denotes controllable parameters, these parameters have been introduced in the previous sections. For the problem described in the previous section, the best values are computed and shown in "Table 6"; the component parameters for the second machine are colored. In this example, the desired parameters can be chosen by intervals defined as "Table 7".

Table 6 The best values of the system parameters

Cost	Availability	Opp. factor	1st ordering time	1st repair time	1st support. Prob.	1st storing cond.	2nd ordering time	2nd repair time	1st supp. Prob.*	2nd storing cond.
9522	0.870	0.119	0.8553	0.86	0.595	1	0.8578	0.8796	0.4203	3

*- The first supplier probability to select as the provider of the second spare part.

Table 7 Parameters interval

Reliability at ordering time	Reliability at changing time	opportunity factor	supplier selection Prob.	storing cond.
(0.7-0.90) of Lifetime	(0.8-0.95) of Lifetime	(0-0.20)	(0.2-0.8)	3 situations

The result shows that the proposed algorithm is a powerful tool to determine the optimal values of system parameters. These parameters are defined based on the CBM and spare parts strategy. Thus to achieve effective maintenance and spare parts inventory to support manufacturing systems, maintenance, and spare parts inventory should be integrated.

6 CONCLUSION

According to the relationships among production plan, maintenance, and spare parts inventory, these subjects must jointly be considered. In this paper, we study a manufacturing system with multi-component as the serial structure maintained by three types of maintenance policies. Each maintenance policy has special requirements and constraints, thus, if one of them is ignored, the executive plan deals with defeat. Therefore, the maintenance policies and the spare parts management factors are investigated to obtain the optimal state of the system. This study shows the influence of the ordering time, repair/replacement time, supplier selection and storage on the maintenance cost and the system availability which are very important. If spare parts are sensitive to storage condition and their performance may be decreased at storing duration time, this parameter influence on the maintenance should be considered. Sometime, according to market policy, the second supplier should be applied to provide spare parts. The influence of these characters are not the same and maybe opposite, thus to determine the best state of the system, all of them should be considered and it needs to be determined by a powerful optimization tool. In this study, GA_PS optimization technique is developed to determine the optimal state of the system. This method is fast and powerful for determination of the optimum state of the system under three maintenance policies and joint maintenance and spare parts inventory consideration. A new manufacturing system and dependence among its components are very complex, although supply change and maintenance management are studied in this paper, more research in this area is necessary, and other types of dependence among components such as load sharing, functional dependence, and complex structure should be considered in the next studies. Also, the logistics problem, FD cost, and FD device selection could be recommended for the next researches.

7 APPENDIX

The system parameters are defined as below:

The random failure rate is: 0.002 hr^{-1}
The first supplier factors for the first spare part: Delivery time (100,22), cost=4000, Weibull distribution (Alfa=5000, beta=1.5)
The first supplier factors for the second spare part: delivery time (90,20), cost=5500, Weibull distribution (Alfa=6000, beta=1.4)
The second supplier factors for the first spare part: delivery time (70,5), cost=8000, Weibull distribution (Alfa=7000, beta=1.3)
The second supplier factors for the second spare part: delivery time (70,15), cost=3500, Weibull distribution (Alfa= 4000, beta=1.3)
Storing conditions: cost for the standard condition is 30 per hour for the first spare part, and 20 for the second spare part.
Maintenance policies factors: the duration of the PM repairs is 60 hr, the repair time is (8,1), and the repair cost is 200.
CBM repair time for the first part follows a normal distribution as (40,3), and for the second part is (40,3).
CBM repair cost for the first part is 2000, and for the second part is 1500.
The random failure repair cost is 1600, and repair time follows a normal distribution as (20,4).
Opportunity maintenance chance equals to 20% of the scheduled time.
The probability and chance to select the first supplier is 1.

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