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ORIGINAL ARTICLE

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Joint optimization of spare parts inventory and maintenance policies using genetic algorithms

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Abstract In general, the maintenance and spare parts inventory policies are treated either separately or sequentially in industry. However, since the stock level of spare parts is often dependent on the maintenance policies, it is a better practice to deal with these problems simultaneously. In this study, a simulation optimization approach using genetic algorithms (GAs) has been proposed for the joint optimization of preventive maintenance (PM) and spare provisioning policies of a manufacturing system operating in the automotive sector. A factorial experiment was carried out to identify the best values for the GA parameters, including the probabilities of crossover and mutation, the population size, and the number of generations. The computational experiments showed that the parameter settings given by the proposed approach achieves a significant cost reduction while increasing the throughput of the manufacturing system.

Keywords Genetic algorithms · Inventory · Maintenance · Simulation · Spare parts

1 Introduction

The reliability and availability of industrial plants represent a critical aspect in many modern manufacturing and service organizations. Increasing the efficiency of production plants requires the minimization of machine downtime. With widespread use of advanced manufacturing technologies, many modern companies are showing increasing attention to the development of maintenance management systems [1–3] so that their capital-intensive equipment can be utilized more efficiently. It must be noted that spare parts availability and its prompt accession are key to the success of maintenance management systems. Thus a logical approach to solving the issue of spare parts availability lies in preserving ample sizes of inventories of spare parts for immediate disposition whenever needed. However, a cost-effective solution to this problem requires a trade-off between overstocking and shortages of spare parts. For these reasons, designing the reserve of spare parts in an optimal way represents a critical and important task for production managers [4].

In the literature, the most commonly used approaches to develop a possible spare provisioning decision model are simulation and mathematical programming. Mathematical programming concerns the development of mathematical models based on linear programming, dynamic programming, goal programming, etc. Multi-echelon technique for recoverable item control model of Sherbrooke [5] is the first application of mathematical programming in spare parts inventory management problem. Following this study, several researchers studied different aspects of the spare parts management problem. The reader can refer to Kennedy et al. [6] for an overview of these studies. It is noted that all these studies entail the use of simplified plants' or systems' models whose predictions may be of questionable realism and reliability.

Another approach that is commonly used to solve the spare parts inventory management problem in the industrial world is simulation modeling [7, 8]. The main advantage of simulation modeling over mathematical modeling is its ability to describe multivariate non-linear relations, which can hardly be put in an explicit analytical form. However, simulation modeling is not an optimization technique. If the objective is to develop optimal spare parts inventory policies using simulation, then it is necessary to integrate the simulation model with an optimization technique. In simulation optimization, one or more discrete event simulation models replace the analytical objective function and constraints. The decision variables are the conditions the simulation is run under, and the performance measure becomes one (or a function of several) of the responses

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generated by a simulation model [9]. The classical methods used with simulation are response surface methodology [10], design of experiments [11], and stochastic approximation [12]. Kabir and Al-Olayan [7] proposed a jointly optimized age based replacement and ordering policy using simulation. They employed a 5-factor second-order rotatory design to select ranges for the replacement interval, stocking level and replenishment level over which the total cost of replacement is minimized. Sarker and Haque [8] extended Kabir and Al-Olayan [7] by considering replacement durations of the operating units with spare parts. In both of these studies, the authors specified all experimental design points prior to the experimentation process. In other words, they did not integrate the simulation model with any guided search method to decide on which factor levels to run in the next experiment so that the danger of falling in local optima can be avoided.

In recent years, metaheuristics such as genetic algorithms (GAs), simulated annealing [13, 14], and tabu search [15] have been extensively used along with simulation to enhance the efficiency of the search procedure. Among these guided search methods, simulation optimization via GAs is a quite active research area. There are successful applications of GA-based simulation optimization in scheduling [16–18], facility layout [19], assembly-line planning [20], supply-chain management [21], kanban systems [22], maintenance-policy selection [23–25], and spare parts inventory management [26, 27]. This study particularly deals with maintenance and spare parts inventory policy optimization using GAs.

Azadivar and Shu [23] investigated the performance of five different maintenance policies based on the desired service level of a production system. The authors applied a simulation optimization procedure based on GAs to four different problems ranging from a very simple to a very complex system. Robert and Shahabudeen [24] evaluated multiple corrective maintenance policies using simulation based GAs. Marsequerra et al. [25] considered a continuously monitored multi-component system and used a GA for determining the optimal degradation level beyond which preventive maintenance (PM) has to be performed. In these three studies, the optimal maintenance policies were developed under the assumption that the required spare parts will be immediately available.

During this literature survey, we also noted another group of studies which solely focused on the development of spare parts inventory policy by ignoring the effect of maintenance policies. Marsequerra et al. [26] proposed a GA-based simulation optimization approach for the determination of spare parts inventory levels required by a multi component system. They considered the net profit achievable during a given mission time as objective function and used simulation to determine the objective function values of various alternative spare part allocation schemes. The proposed approach was verified on a simple system. In a following study, the authors [27] extended their previous work [26] to a multi-objective optimization problem involving maximization of the net profit of the system and minimization of the total volume of the spare parts. The comparison of two alternative solutions with respect to these objectives is achieved through the use of the concepts of the pareto optimality and dominance. The authors gave a good example of GA-based simulation optimization in spare parts inventory management, but they did not take into consideration some practical aspects such as age-related failure processes and maintenance-driven spare demands.

The influence of maintenance policies on the spare provisioning policy cannot be ignored, since the need for spare parts is directly dictated by the maintenance policies. Considering the fact that the PM is scheduled, the demand for spare parts is predictable. For a machine breakdown, which requires unplanned repair, the stockouts of spare parts cause the production to stop, with significant costs. We noted only one study [28] that explicitly considers both maintenance and spare parts inventory management using GA. Shum and Gong [28] proposed a GA for the joint optimization of maintenance and spare part purchasing policies. The maintenance policy proposed in this study includes both frequency of PM and maintenance workforce level. The authors utilized an analytical objective function to evaluate the performance of alternative policies under some simplified assumptions. Namely, they ignored the replacement times of spare parts, the probabilistic nature of spare part demand, and the shortage and emergency ordering costs of spare parts.

Noting only one study for joint optimization of maintenance and spare parts inventory policies using GA, we can state that this area needs further attention. So, to fill the perceived gap in this area, we not only dealt with these problems simultaneously by proposing a GA but we also employed a detailed simulation model of the manufacturing line as a fitness function evaluator. A simulation-based fitness function evaluator enables us to capture all dynamic and stochastic aspects of the system such as age-related failure processes, maintenance-driven spare demand, spare part shortages, and emergency orders. Considering the decreasing profit margins in the automotive industry, it is very important to adopt a cost-effective maintenance system to be competitive in today's global markets. We hope that the joint optimization procedure suggested in this study will help to cut down on the operational costs and enhance the company's competitiveness in the long run.

In this study, we have illustrated the efficacy of simulation optimization based on GAs for identifying the optimal policies for spare parts inventory management by using a real-life case study in the automotive sector. The following section gives a short introduction to GAs. Simulation optimization via GAs is discussed in Section 3. In Section 4, the proposed approach for the joint optimization of spare parts provisioning and maintenance policies is presented. The concluding remarks are presented in Section 5.

2 Genetic algorithms

Genetic algorithms are biologically inspired search procedures that have been used to solve different NP-hard problems. Like other biologically inspired techniques (i.e., ant colony optimization, particle swarm optimization), they try to extract ideas from a natural system, in particular the natural evolution, in order to develop computational tools for solving engineering problems. They are used to search large, non-linear search spaces where expert knowledge is lacking or difficult to encode and where traditional optimization methods fall short [29].

A GA operates on a population of individuals (chromosomes) representing potential solutions to a given problem. Each chromosome is assigned a fitness value according to the result of the fitness (objective) function. The selection mechanism favors individuals with better objective function value to reproduce more often than worse ones when a new population is formed. Recombination allows for the mixing of parental information, and mutation introduces innovation in the population. Usually, the initial population is randomly initialized and the evolution process is stopped after a predefined number of iterations [17]. Supposing P (t) is the population of chromosomes at generation t; the structure of a simple GA consists of the following phases [21]:

- Procedure: Genetic algorithms
- begin
- t←0;
- initialize P(t);
- evaluate P(t);
- while (not termination condition) do

- select P(t+1) from P(t);
- crossover (recombine P(t+1));
- mutation (recombine P(t+1));
- evaluate P(t+1) ;
- t←t+1;
- end
- end

The initial population is usually generated randomly. There are also other alternatives to generate the initial population. One is to carry out a series of initializations for each chromosome and then pick the highest performing values. Another alternative is to locate approximate solutions by using other methods (i.e., simulated annealing, tabu search) and to start the algorithm from such points [30]. Besides these, neural networks were also applied to generate initial population [31].

The individuals in the initial population evolve through successive iterations, called generations. During each generation, the individuals are evaluated, using some measure of fitness. The fitness function, also called payback function, defines a fitness value for every chromosome in the population. On the basis of this value the selection operator decides which of the genomes will be chosen for reproduction. Selection is a process in which chromosomes are copied according to their fitness function value. There are many selection methods for selecting the best chromosome such as roulette wheel selection, Boltzman selection, tournament selection, rank selection, steady-state selection and so on [21]. The selected chromosomes are recombined to produce new offsprings. Recombination includes crossover and mutation to yield offspring.

Crossover is the primary genetic operator that permits new regions in the search space to be explored. Crossover combines the "fittest" chromosomes and passes superior genes to the next generation. It refers to the occasional crossing of two chromosomes in such a way that they exchange equivalent genes with one another.

Following the crossover operation, the mutation process is carried out in an effort to avoid local minima and to ensure that newly generated populations are not uniform and incapable of further evolution [32]. In this process, a random number is generated in the interval [0, 1] and compared with a specified threshold value P_m: if it is less than P_m then mutation is carried out for that gene; otherwise the gene is skipped.

3 Simulation optimization using genetic algorithms

A simulation optimization problem is an optimization problem where the objective function is a response evaluated by the simulation. In the context of simulation optimization, a simulation model can be thought of as a "mechanism that turns input parameters into output performance measures" [33]. In other words, the simulation model is a function (whose explicit form is unknown) that evaluates the merit of a set of specifications, typically represented as a set of values [34].

Using simulation in the optimization process includes several specific challenges. Some of these issues are those involved in optimization of any complex and highly nonlinear function. Others are more specifically related to the special nature of simulation modeling [35]. The major issues to address when comparing simulation optimization problems to generic non-linear programming problems are as follows [35, 36]:

There does not exist an analytical expression of the objective function or the constraints.

- The objective function(s) and constraints are stochastic functions of the deterministic decision variables.
- Performance measures could have many local extrema.
- The parameter space is not continuous. So there is often a need for discrete parameters such as integer, logical or linguistic.
- The search space is not compact. There could be zones of parameter values that are forbidden or impossible for the model.

The above list of features is a direct recommendation for the use of GAs, since they differ from conventional optimization and search procedures in several fundamental ways [21, 24, 37]:

GAs use only objective function information to guide themselves through the solution space. So, they do not have much mathematical requirements about the optimization problems. The search for solutions will be guided without considering the inner workings of the problem. GAs can handle any kind of objective functions and any kind of

Table 1 Machines subject to PM and associated spare parts

Machine (M) identification	Spare Part (SP) identification
M01	SP01, SP02, SP03
M03	SP02, SP03, SP04, SP05, SP06
M07	SP05, SP06, SP07, SP08, SP09, SP10, SP11, SP12
M08	SP08, SP13
M09	SP14, SP15, SP16
M12	SP17, SP18

constraints (linear or non-linear) defined on discrete, continuous, or mixed search spaces.

One of the most striking differences between GAs and most of the traditional optimization methods is that a GA works with a population of solutions instead of a single solution. Most classical optimization methods generate a deterministic sequence of optimization based on gradient or higher-order derivatives of the objective function. The methods are applied to a single point in the search space. The point is then improved along the deepest descending/ascending direction gradually through iterations. This point-to-point approach takes the danger of falling in local optima. GAs perform a multiple directional search by maintaining a population of potential solutions. The population-to-population approach attempts to make the search escape from local optima.

The other difference is that a GA uses an encoding of control variables, rather than the variables themselves. Encoding discretizes the search space and allows GAs to be applied to discrete and discontinuous problems. The other advantage is that GAs exploit the similarities in string-structures to create an effective search.

In addition to the above differences, GAs use probabilistic transition rules, as opposed to deterministic rules, to guide search. In early GA iterations, this randomness in GA operators makes the search unbiased toward any particular region in the search space. This avoids a hasty wrong decision and affects a directed search later in the optimization process. Use of stochastic transition rules also increases the chance of recovering from a mistake.

Table 2 Current reorder and maximum stock levels for spare parts

Spare part identification	s	S	Spare part identification	s	S	Spare part identification	s	S
SP01	2	5	SP07	1	3	SP13	2	6
SP02	1	2	SP08	3	6	SP14	1	2
SP03	1	2	SP09	2	4	SP15	2	4
SP04	2	4	SP10	3	5	SP16	2	5
SP05	3	5	SP11	3	5	SP17	2	5
SP06	1	2	SP12	1	2	SP18	1	2

Table 3 Current PM intervals for the machines

Machines	M01	M03	M07	M08	M09	M12
PM intervals	1350	1450	1350	1350	1450	1350

4 The proposed study for joint optimization of spare parts inventory and maintenance policies

This study aims at joint optimization of spare part provisioning and maintenance policies of an automotive factory by integrating simulation and GA. The proposed procedure has been implemented in three phases. The first phase involves the development of a discrete event simulation model, which represents the manufacturing system behaviour with its maintenance, and inventory related aspects. The development of a GA to optimize the control parameters of spare parts inventory management policy takes place in the second stage. The last stage involves the integration of the GA with the discrete event simulation model embedded in the optimization loop. In the following sections, the manufacturing system is first introduced. Then, the steps of the proposed procedure are presented in detail.

4.1 An overview of the manufacturing system

The proposed procedure has been applied in motor block manufacturing line of an automotive factory. The manufacturing process begins with the arrival of block castings from the foundry at a constant rate of 16 castings per day. Various machining operations (i.e., milling, drilling) are carried out on these castings and the completed motor blocks are sent to the motor assembly storage area. Information about these operations and the flow of manufacturing process can be found in (the Appendix see Table 10 and Fig. 8). It must be noted that the third column in Table 10 presents the machines employed in carrying out these operations.

Preventive maintenance (PM) is not applied to all the machines in this line, since the application of PM is not cost-effective for some machines. It must be noted that the replacement of an operating unit with a spare part is not necessary for all preventive or breakdown maintenance (BM) instances of the machines. In other words, sometimes, just cleaning the machine or fixing the failed operating units may be sufficient. When the replacement is required, the demand for a spare part may be more than one.

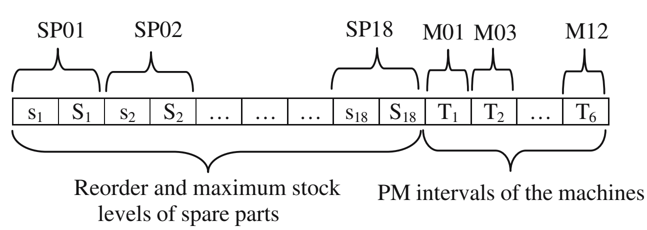

Fig. 1 Structure of a chromosome

Table 4 Ranges for reorder, maximum stock levels of critical spare parts

Spare part identification	s	S	Spare part identification	s	S	Spare part identification	s	S
SP01	1–2	3–5	SP07	1–2	2–4	SP13	1–2	3–5
SP02	2–4	5–8	SP08	1–2	3–5	SP14	1–3	5–8
SP03	1–3	5–8	SP09	1–2	3–6	SP15	1–2	3–5
SP04	1–2	3–5	SP10	1–2	3–5	SP16	1–3	4–6
SP05	1–3	4–6	SP11	1–3	4–8	SP17	1–2	3–4
SP06	2–4	5–8	SP12	1–3	5–7	SP18	1–3	4–6

The spare parts that do not cost much and common to all the machines are stocked according to the two-bin inventory system. Machine specific and more expensive spare parts are regarded as critical and provisioned according to minimum-maximum (s-S) version of the continuous review inventory system, where s is the reorder level and S is the maximum stock level. Currently, there are 18 critical spare parts associated with six machines and PM is applied to these six machines (see Table 1). The order lead times of critical spare parts are variable. Depending on the urgency of needs, the orders can be expedited at the expense of higher ordering costs.

To control the reorder and maximum inventory levels for these spare parts, the company just relies on the intuition and experience of the maintenance personnel. Table 2 and Table 3 list the spare parts inventory levels and PM intervals currently practiced in the company, respectively. It has been observed in the plant that this practice is leading to stock-out incidences for some spares and for others, unnecessary holding cost. So, this study aims at finding the optimal levels of inventory for the spare parts and periodic intervals for PM by simultaneously dealing with these problems.

4.2 Simulation model development

The simulation model was developed in a modular approach using Arena 3.0. The first module includes the operation of the motor block manufacturing line. The second module incorporates preventive maintenance, breakdown maintenance activities and the spare parts demand arising from these activities. The issues related to inventory control, ordering, and emergency ordering of the spare parts are included in the third module. Arena Input Analyzer was utilized to analyze spare part lead time and maintenance data which were gathered from the purchasing and maintenance departments of the firm, respectively. Based on this analysis, mean time between failures (MTBF), mean time to repair (MTTR), and PM durations are all found to follow Weibull distribution and order lead times are found to follow triangular distribution. Hence, in modeling all stochastic input data, we referred to the results of this analysis. Besides, we assumed that:

– A PM action is performed when the machine is free of the product. So, there are no interruptions due to PM.
– There are enough maintenance personnel to carry out the required maintenance activities.

We developed the simulation model in detail to realistically reflect the issues arising in case of BM or PM. The need for BM arises due to a machine breakdown whereas PM is carried out in pre-specified time intervals. Following the record of a need for a maintenance activity of any type based on the probabilities given in Table 11 in the Appendix, the necessity of operating unit replacement is checked. If the maintenance activity requires the replacement, the types of the spare parts required are determined by the simulation model based on the probabilities given in the Appendix, Table 12. As seen in this table, for each machine, one or more replacement types have been defined. Each replacement type of a machine requires the use of a different spare part or a combination of spare parts. The demand for a spare part under each replacement type is determined using the probabilities

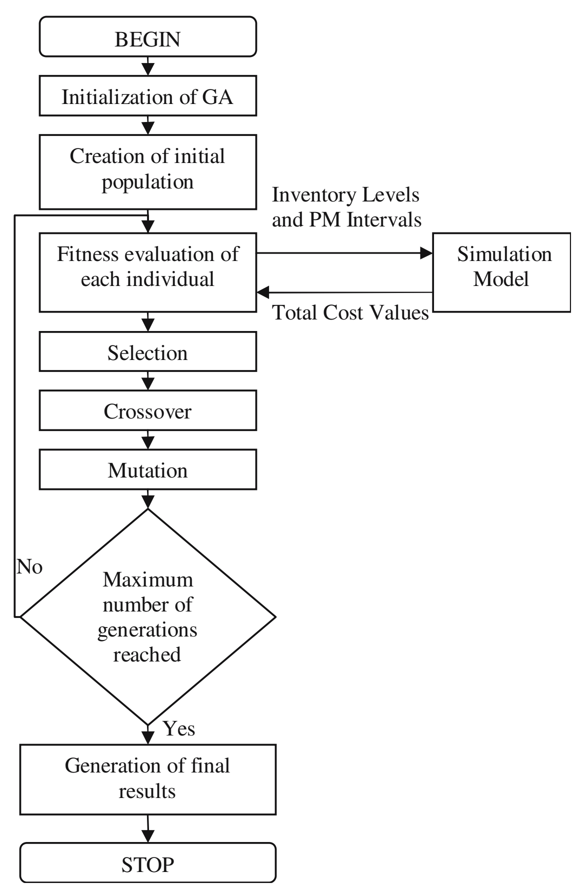

Fig. 2 Flow chart of the proposed approach

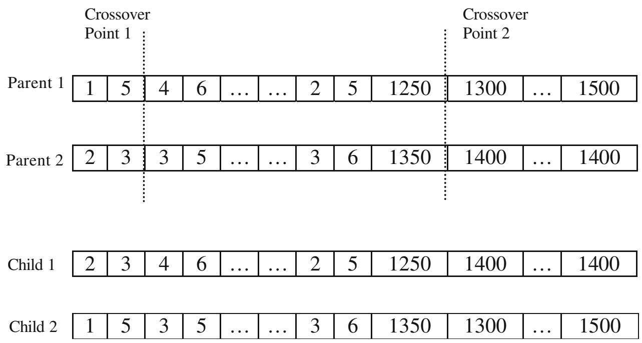

Fig. 3 Two-point crossover

given in the Appendix, Table 13. If there is sufficient amount of spare part(s), the maintenance activity is carried out. Otherwise, the necessity of order expediting is searched for.

The simulation model is of non-terminating type and has to be warmed up to a steady state before experimenting with each of the input data sets. The warm-up period has been found as 75,000 min and each simulation experiment has been carried out for 300 working days with three 8-h shifts.

4.3 Design of the genetic algorithm

While designing the GA, at first the reorder and maximum stock levels of critical spare parts and PM intervals of the machines were coded into chromosomes so as to perform the genetic operation. So, each chromosome represents a possible configuration of the reorder, maximum stock levels of critical spare parts and the PM intervals of the machines within the specified ranges. It must be noted that for each machine, the PM Interval range was accepted to change from 1,250 to 1,500 h. An example chromosome structure is given in Fig. 1. In this figure, s_j, S_j, T_k represent the reorder, maximum stock levels of the spare parts, and the PM intervals for the machines, respectively.

Table 4 shows the ranges of values for reorder and maximum stock levels of spare parts. The whole search space has a volume of $4.46*10^{30}$ solutions. The search for a globally optimum solution in such a large search space is very difficult. This necessitates the use of search heuristics such as GAs since traditional, local search methods require a large computational time to search for quality solutions.

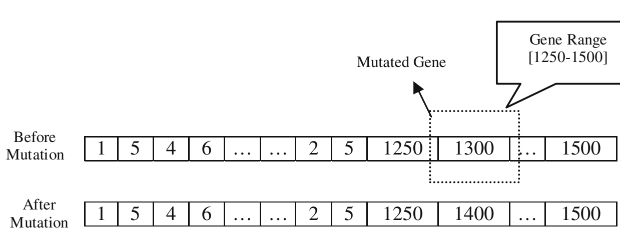

Fig. 4 Mutation

Table 5 Experimental factors

Quantitative input factors	Coded	Levels 1	2	3
Crossover probability (%C)	x_1	0.30	0.60	0.90
Mutation probability (%M)	x_2	0.02	0.06	0.10
Population/generation combination (P/G)	z_1	z_2		
20/60	1	0		
30/40	0	1		
60/20	0	0		

4.3.1 Fitness evaluation

The GA process involves searching for the optimum levels of PM intervals for the machines and the optimum inventory levels for the critical spare parts. During this search process, the following total annual cost (TAC) function is employed to evaluate the fitness of each alternative solution:

$$TAC = C_H + C_R + C_E + C_S + C_P \tag{1}$$

where:

$C_H = \sum_{j=1}^{N_{sp}} H_j$ is the cost associated with holding N_{sp} number of spare parts and H_j is the cost of managing spare part j throughout a year.

$C_R = \sum_{j=1}^{N_r} R_j$ is the cost associated with N_r number of regular orders given throughout a year and R_j is the cost of placing regular order j.

$C_E = \sum_{j=1}^{N_e} C_j$ is the cost associated with N_e number of emergency orders given throughout a year and E_j is the cost of placing emergency order j

$C_S = \sum_{j=1}^{N_{out}} D_j \cdot S$ is the cost associated with N_{out} number of stockouts of critical spare parts. D_j is the duration of stockout j. S is the cost of stockout per unit of time. In this

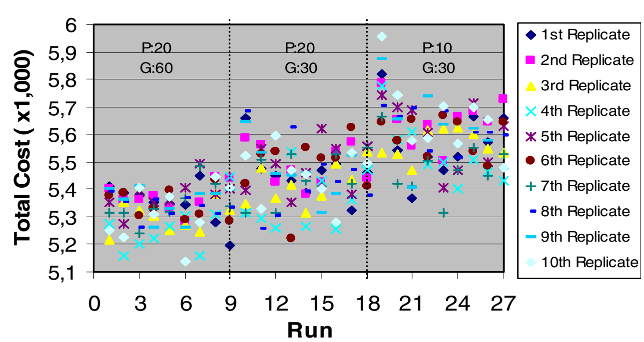

Fig. 5 Scatter-plot of responses from ten replications when the number of chromosomes generated is varied

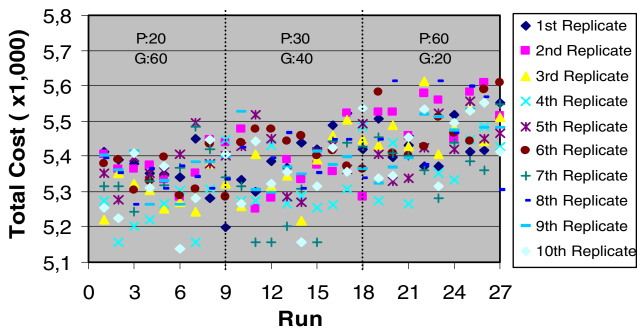

Fig. 6 Scatter-plot of responses from ten replications when the number of chromosomes generated is fixed

study, S is assumed to be equal to the gross revenue per minute [38].

$C_P = \sum_{j=1}^{N_p} T_j \cdot P$ is the cost associated with N_P number of PM instances. T_j is the duration of PM activity j. P is the cost of PM per unit of time.

There is an important trade-off that exists between the spare parts holding cost and the shortage cost. Unavailability of a spare part when it is needed by the maintenance department results in high shortage costs. On the other hand, if the spare part is overstocked to ensure availability, a substantial holding cost will occur. By varying the PM interval, the time of demand can be controlled and some reduction can be achieved in ordering and emergency ordering costs. However, this variation may result in increased PM cost.

Unless some simplifying assumptions are made, it is very difficult to evaluate the objective function (1)

Table 6 Regression analysis

Predictor	Coefficient	Standard deviation	p-value
Constant	5432	18.17	0.000
x_1	−14.06	21.08	0.506
x_2	579.4	158.1	0.000
z_1	−114.57	12.65	0.000
z_2	−88.79	12.65	0.000

analytically. If a more realistic modeling of the system is desired, the discrete event simulation modeling is the most feasible approach for the evaluation of the objective function (1). That's why, in the proposed approach, the fitness of each possible solution is evaluated by the simulation model. According to the fitness results, the GA creates new alternative solutions. So, there is a two-way communication between the GA and the simulation model. The flow chart depicting the computational procedure of the GA is shown in Fig. 2.

The initial population is constructed by randomly creating a set of chromosomes. Each chromosome of the initial population is then evaluated by the simulation model. The GA code automatically gets the fitness value of each alternative solution from the simulation model to create a new generation using genetic operators. When the maximum number of generations is reached, the solution is accepted as optimal.

The algorithm stores the fitness of each chromosome. If the chromosome appears in future generations, the stored fitness is directly assigned to the chromosome. This property speeds up the algorithm by avoiding the unnecessary simulation runs.

4.3.2 Selection, crossover, and mutation

The GA performs tournament selection. In tournament selection, two individuals are chosen at random from the population. The fittest of two individuals is selected to be a parent. The other is returned to the population and can be selected again. The GA also uses elitism to save and copy the fittest chromosomes into the next generation.

For each pair of selected parents, crossover and mutation operations are applied to generate a new pair of offspring. In the proposed algorithm, two-point crossover is performed [21, 39], and the crossover points are selected randomly. Two parent chromosomes between these points are then interchanged to produce two new offsprings. The process of crossover operation is demonstrated in Fig. 3. Since real-valued encoding is used in the GA, the mutation operator, which is applied to each gene, is implemented by

Fig. 7 Convergence graph of the genetic algorithm

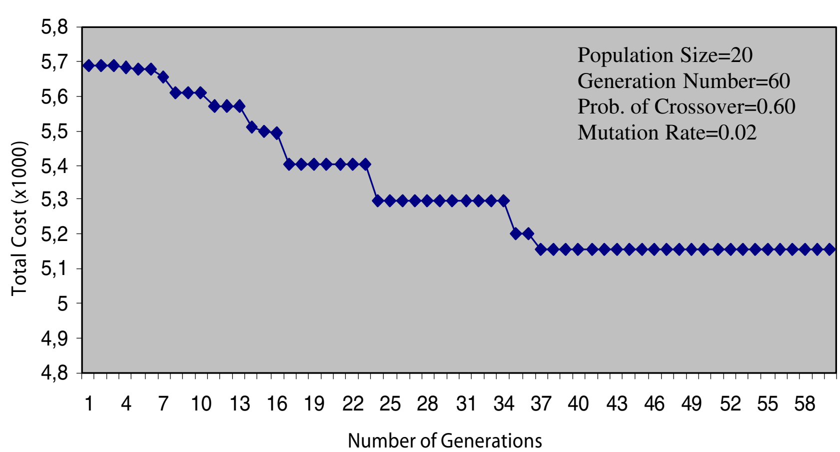

Table 7 Reorder, maximum stock levels of spare parts for the optimal solution

Spare part identification	s	S	Spare part identification	s	S	Spare part identification	s	S
SP01	1	3	SP07	1	2	SP13	1	3
SP02	3	5	SP08	1	3	SP14	1	5
SP03	2	5	SP09	1	3	SP15	1	3
SP04	1	4	SP10	1	3	SP16	1	4
SP05	1	4	SP11	1	4	SP17	1	3
SP06	2	5	SP12	2	5	SP18	1	4

random replacement [40]. So, if a gene is to be mutated, a new inventory level or PM interval is randomly picked and assigned to the gene (see Fig. 4).

4.3.3 Identification of efficient GA parameters

4.3.3.1 Design of experiments Design of experiments (DoE) provides a systematic approach to investigate the effects of some controllable factors on a pre-defined response variable. DoE involves specifying the number of runs and the level at which these controllable factors must be set on each run. In this study, we are particularly interested in control parameters of a GA, namely population size, number of generations, crossover and mutation probabilities. In order to determine the most efficient GA parameters that achieve minimum total costs and minimum spread, we carried out a set of experiments.

Using the data collected in the experiments, a multiple linear regression analysis was carried out. Regression analysis uses observed data to create a predictive equation based on the tendency of some dependent variable (i.e. total cost) to vary with a set of independent variables (i.e., population size, number of generations). The levels of the two quantitative input factors and the population size/ generation number combination are given in Table 5.

4.3.3.2 Experimental results Firstly, the performance of the algorithm searched for under three different levels of total number of chromosomes generated. As expected, the best results are obtained when the total number of chromosomes generated was large, 1,200 (see Fig. 5). Next, by fixing the total number of chromosomes at 1,200 (i.e., three different combinations of population size and the number of generations 20/60, 30/40 and 60/20 resulted in 1,200 chromosomes) the probability of crossover and mutation has been varied in three levels. As seen in Table 5, two indicator variables have been used to denote the three levels of population size / generation number combination in the regression model. A full factorial design replicated ten times has been used to carry out the experiments.

Figure 6 provides the scatter-plot that shows the value of objective function under each run. Based on this scatter-plot, we could state that the runs that use a population size of 20 with 60 generations achieve the lowest total cost with the smallest spread.

Table 6 summarizes the results of the regression analysis. In this table, p represents the descriptive level of significance. The factors with a p-value that is smaller than 0.05 are statistically significant with a 95% level of confidence. As seen in Table 6, except for probability of crossover, all input factors are significant. This regression model suggests that the total cost can be minimized with small values of mutation probability and a population size of 20 with 60 generations.

4.4 The search for the optimum policy

Based on the results of the regression analysis discussed above, this study presents the results of a GA optimization using a population size of 20, and 60 generations of evolution. The probability of crossover operation is set as 0.6. Mutation is performed immediately after the crossover with probability 0.02. To balance the disruptive nature of the chosen crossover and mutation, elitism is used with two elite chromosomes to preserve the best individuals.

The optimization process takes approximately 1 h and the best solution is obtained after evaluating no more than 1,200 alternatives. So, the ratio of search space investigated is very small when compared to the number of solution alternatives given in Section 4.3. This shows the efficiency of the proposed simulation-based GA approach in accurately examining only a limited portion of the search space.

The convergence graph of the algorithm is presented in Fig. 7. As shown in this figure, after 37 iterations the algorithm arrives at a solution that reduces the total cost from the initial value of 5,690 to 5,156 (a reduction of 9%). This recommended solution remains unchanged for the

Table 8 PM intervals of the machines for the optimum solution

Machines	M01	M03	M07	M08	M09	M12
PM intervals	1291	1348	1276	1304	1361	1406

Table 9 Actual monthly throughput and the simulation model's estimates

Replications	1	2	3	4	5	6	7	8	9	10	Average
Actual monthly throughput	340	325	325	380	362	380	325	343	370	362	351
Model's estimates	378	380	360	360	376	380	378	360	378	378	373

next 23 generations. The min-max inventory levels of spare parts and PM intervals of the machines proposed by GA are given in Tables 7 and 8, respectively. Based on the company records, the total annual maintenance cost for the past year was $10,968 accompanied by a average monthly throughput of 351 motor blocks. The optimum solution suggested by this integrated approach resulted in $5,156 total annual maintenance cost and average monthly production of 373 motor blocks (see Table 9). These results imply 53% reduction in total annual maintenance cost and 6% improvement in average monthly production.

5 Conclusions

The unavailability of spare parts at the time they are needed by the maintenance department is a major problem for many industrial organizations. The common approach to solve this problem is overstocking the spare parts at a substantial inventory-carrying cost. However, a cost-effective solution to this problem requires a trade-off between overstocking and shortages of spare parts. In order to deal with this trade-off, the problem should be solved by joint, rather than separate or sequential optimization of PM and spare parts inventory policies.

In this study, we have presented an approach that combines GAs and simulation for the joint optimization of spare part provisioning and PM policies for an automotive factory. A simulation model of the manufacturing system was developed and a GA was integrated with this model to optimize the parameters of the simulation model. Moreover, a set of designed experiments was carried out to determine the best combination of GA parameters.

The best solution proposed by the GA was compared to the current combination of control variables in terms of total annual cost and average monthly production. It was found that the total annual cost could be reduced by about 53% while achieving a larger amount of throughput.

Finally, it must be pointed out that there is usually more than one objective (low costs, low WIP, high revenue) when attempting to optimize a maintenance management system. This necessitates a multi-objective approach. Now, the authors are trying to develop a multi-objective simulation-based GA optimization procedure for the joint optimization of spare parts inventory and maintenance policies.

Appendix

Table 10

Information on manufacturing operations

Operation (OP) identification	Operation description	Machine identification	Standard time (min)
OP01	Volume control	–	11.98
OP02	Milling of reference surfaces	M01	4.95
OP03	Raw and finish milling of carter surface, drilling of oil gallery hole	M01	35.19
OP04	Raw milling of gasket surface	M02	9.32
OP05	Semi-finish milling of gasket surface, drilling and tapping of cover coupling	M03	29.16
OP06	Raw milling of front and back surfaces	M04	7.49
OP07	Raw boring of cylinder bores	M05	21.34
OP08	Raw milling of cap surface	M06	8.19
OP09	Drilling and tapping of cap coupling holes, milling of cap settling surface	M03	32.71
OP10	Finish milling of front and back side surfaces	M04	7.16
OP11	Drilling of front and back side surface holes	M07	31.35
OP12	Milling, drilling and tapping of right and left side surfaces	M08	29.19
OP13	Boring of front and back eccentric bearing	M07	31.87
OP14	Drilling of right and left side surface angular holes	M08	31.36
OP15	Drilling of main bearing oil hole	M09	7.56
OP16	Finish milling of cap surface	M06	6.33
OP17	First washing	–	10.05
OP18	Raw boring of main bearing and eccentric bearing	M10	12.23
OP19	Finish boring of main bearing and eccentric bearing	M11	25.65
OP20	Honing of main bearing	M12	8.70
OP21	Drilling of front and back side pin holes	M13	26.80
OP22	Finish milling of gasket surface	M14	9.13
OP23	Finish boring of cylinder bores	M09	15.28
OP24	Raw and finish honing of cylinder bores	M12	32.35
OP25	Vibrating	M14	12.34
OP26	Second washing	–	10.05
OP27	Water and oil gallery pressure test	–	40.68
OP28	Final control	–	13

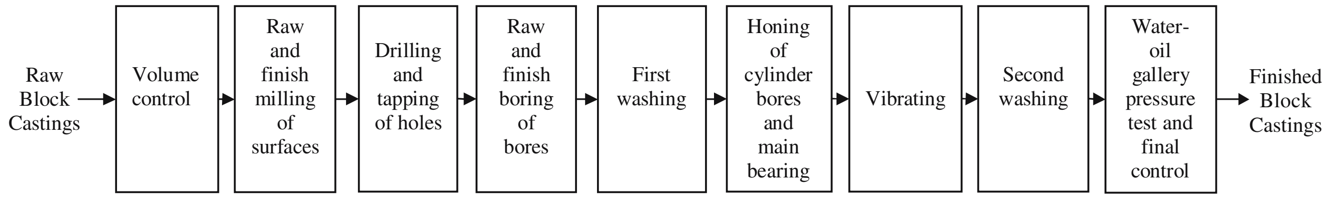

Fig. 8 Flow of the manufacturing process

Table 11

Replacement probabilities

Machine identification	Maintenance type	Probability of operating unit replacement
M01	BM	0.60
	PM	0.52
M03	BM	0.73
	PM	0.59
M07	BM	0.60
	PM	0.65
M08	BM	0.50
	PM	0.50
M09	BM	0.53
	PM	0.52
M12	BM	0.49
	PM	0.62

Table 12

Replacement types

Machine identification	Replacement type	Spare part identification	Probability of occurrence	
			BM	PM
M01	1	SP01	0.46	0.36
	2	SP02	0.27	0.28
	3	SP02 and SP03	0.27	0.36
M03	1	SP02	0.25	0.31
	2	SP04	0.13	0.23
	3	SP05	0.16	0.23
	4	SP06	0.21	0.15
	5	SP02 and SP03	0.25	0.08
M07	1	SP05	0.11	0.13
	2	SP06	0.14	0.13
	3	SP07	0.11	0.20
	4	SP09	0.14	0.20
	5	SP10	0.14	0.20
	6	SP11	0.18	0.07
	7	SP08 and SP12	0.18	0.07
M08	1	SP08 and SP13	1	1
M09	1	SP14	0.37	0.50
	2	SP15 and SP16	0.63	0.50
M12	1	SP17	0.32	0.38
	2	SP18	0.68	0.62

Table 13

Demand for spare parts

Machine identification	Replacement type	Spare part identification	Demand quantity	Probability of occurrence	
				BM	PM
M01	1	SP01	1	0.60	0.25
			2	0.40	0.75
	2	SP02	2	0.44	0.33
			3	0.56	0.67
	3	SP02	1	1	1
		SP03	1	1	1
M03	1	SP02	1	0.80	1
			2	0.20	–
	2	SP04	1	0.50	0.67
			2	0.50	0.33
	3	SP05	1	1	1
	4	SP06	1	0.25	1
			2	0.75	–
	5	SP02	1	1	1
		SP03	1	1	1
M07	1	SP05	1	0.75	0.50
			2	0.25	0.50
	2	SP06	1	1	1
	3	SP07	2	0.50	1
			3	0.50	–
	4	SP09	1	0.33	0.33
			2	0.67	0.67
	5	SP10	1	0.50	1
			2	0.50	–
	6	SP11	1	0.75	1
			2	0.25	–
	7	SP08	1	1	1
		SP12	1	1	1
M08	1	SP08	1	1	1
		SP13	1	1	1
M09	1	SP14	1	–	0.75
			2	0.50	0.25
			3	0.50	–
	2	SP15	1	1	1
		SP16	1	1	1
M12	1	SP17	1	0.33	0.40
			2	0.67	0.60
	2	SP18	1	0.62	0.50
			2	0.38	0.50

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