Improved Genetic Algorithm for Minimizing Periodic Preventive Maintenance Costs in Series-Parallel Systems

Chun-Ho Wang[1], Chao-Hui Huang[2]

[1]Department of Power Vehicle and Systems Engineering, Chung Cheng Institute of Technology, National Defense University, Taiwan
Email: chwang@ndu.edu.tw
[2]Department of Applied Science, R.O.C. Naval Academy, Taiwan
Email: a0970437433@gmail.com

Abstract**—*This work presents an improved genetic algorithm (IGA) for minimizing periodic preventive maintenance costs in series-parallel systems. The intrinsic properties of a repairable system, including the structure of reliability block diagrams and component maintenance priorities are considered by the proposed IGA. The proposed component importance measure considers these properties, identifies key components, and determines their maintenance priorities. The optimal maintenance periods of these important components are then determined to minimize total maintenance cost given the allowable worst reliability of a repairable system. An adjustment mechanism is established to solve the problem of chromosomes falling into infeasible areas. An elitist conservation strategy is applied to retain superior chromosomes in the iterative breeding process and to accelerate the approach toward the global optimum. A response surface methodology is further used to systematically determine crossover probability and mutation probability in the GA instead of using the conventional trial-and-error process. A case study demonstrates the effectiveness and practicality of the proposed IGA for optimizing the periodic preventive maintenance model in series-parallel systems.*

Keywords—genetic algorithms, importance measure, periodic preventive maintenance, reliability, response surface methodology.

I. INTRODUCTION

Maintenance and repair activities are essential for the safe and efficient operation of any equipment. Particularly, implementing appropriate maintenance to keep a system function properly is important during lifetime of equipment. Establishing a superior maintenance strategy for a complex repairable system requires that the maintenance priority of subsystems or components and their maintenance periods given limited maintenance resources be determined simultaneously. As preventive maintenance consumes human resources and time, and has associated costs, nonessential services or an inadequate maintenance schedule wastes the limited maintenance resources. Furthermore, to meet practical requirements, numerous studies have constructed maintenance models and optimization algorithms [13]. However, the complexity of optimizing a maintenance model in a series-parallel system increases significantly as the number of components in a system increases. In such situations, obtaining the exact global optimum using analytical approaches via mathematical inference is impractical. Therefore, meta-heuristic algorithms, such as a genetic algorithm [4] [15], ant colony optimization [19] and simulated annealing [13], are commonly employed to optimize these models and approach the global optimum.

Meta-heuristic algorithms have three impediments to efficiently solving complex optimization problems [2] becoming trapped in local optimum, a limited cycle, and an inability to escape from a specific search region. These hindrances must be overcome when optimizing complex problems. Additionally, past studies [1] demonstrated that a superior initial population structure can significantly benefit the ability of meta-heuristic algorithm to approach the global optimum. Hence, numerous studies [6] [20] have attempted to establish a superior initial population to enhance solving ability of current algorithms, particularly for solving complex problems. However, the idea regarding the establishment of the superior initial population in optimizing the preventive maintenance model for series-parallel systems has seldom been seen.

Holland developed genetic algorithm (GA) in 1975. The search mechanism in a GA relies on chromosome evolution, comprising reproduction, crossover, and mutation, during a simutated breeding process. Goldberg [9] summarized the attributes of GAs as follows: <1> Genetic algorithm calculations are based on coded parameters, rather than the parameter values. <2> Genetic algorithm posses highly parallel search capability, avoiding becoming trapped in a local optimum. <3> Genetic algorithm has no complex mathematical formulas – only the fitness function must be calculated. <4> Genetic algorithm has no specific rules for guiding the search direction for an optimum; rather, a random search mechanism uses the probability rule. Although capable of providing the above functions, GA is easily trapped in local areas when solving large and complex problems. Furthermore, a retrieval mechanism that prevents chromosomes from moving into infeasible areas of a constrained optimization model can benefit the optimized solutions for GA [7] [12] [18]. The limitations of conventional GA must be addressed to solve complex optimization problems.

This study aims to propose an improved genetic algorithm (IGA) that efficiently optimizes the periodic preventive maintenance (PM) model for series-parallel systems. The improved mechanisms mainly overcome the weaknesses in conventional GA. Since the structure of a repairable series-parallel system markedly impacts system reliability, the properties of a preventive maintenance model in series-parallel systems subjecting to the allowable worst system reliability are considered to create the improvement mechanisms. The proposed IGA has two stages. The first stage identifies important components for a repairable series-parallel system. A novel importance measure of components is developed to overcome the drawbacks of past importance measures of components [3] [11] [8] and appropriately assess the importance of components in a PM model during mission duration. The second stage determines the optimal maintenance periods of important components using the IGA search mechanism. An adjustment mechanism is established to make the chromosomes move back to feasible area in case the chromosomes fall into infeasible area. Doing so can enhance the exploring ability of conventional GA. Furthermore, an elitist conservation strategy is applied to retain superior chromosomes and facilitate search toward the global optimum. The response surface methodology (RSM) [16] from the design of experiments is employed to systematically determine the crossover probability and mutation probability—instead of using the trial-and-error approach—to enhance IGA search capability. A case from the study by Bris et al. [4], subsequently applied by Samrout et al. [19], demonstrates the effectiveness and practicality of the proposed IGA in optimizing the periodic preventive maintenance model in series-parallel systems.

II. LITERATURE

2.1 Maintenance strategy of a series-parallel system

Maintenance is defined as activities that retain or restore the operational status of a system. Normally, maintenance can be classified as e-maintenance [17], corrective maintenance (CM) and preventive maintenance [14]. E-maintenance is a new concept of maintenance. It contains predictive prognostics and condition-based monitor, and integrates existing telemaintenance principles with Web services and modern e-collaboration principles. CM includes minimal repairs and corrective replacement when a system fails. PM includes simple preventive maintenance and preventive replacement when a system is operating. The maintenance policies of a repairable deteriorating system are <1> age-dependent PM policy, <2> periodic PM policy, <3> failure limit policy, <4> sequential PM policy, <5> repair limit policy, and <6> repair number counting and reference time policy [23]. Periodic PM is widely used in practice simply because of its ease of implementation and management. This maintenance policy, applied in a series-parallel system with multiple components, received much attention. For example, Tsai, Wang, and Teng [21] developed a periodic PM schedule for a system with deteriorating electro-mechanical components and optimized it using a GA. Leou [13] proposed a novel algorithm for determining a maintenance schedule for a power plant. This algorithm combines the GA with simulated annealing to optimize maintenance periods and minimize maintenance and operational cost. Tsai, Wang, and Tsai [22] also proposed a preventive maintenance policy for a multi-component system. Maintenance activities for components in each stage of PM were determined by maximizing the availability of the system for maintenance. Busacca, Marseguerra, and Zio [5] focused on a high-pressure injection system at a nuclear power plant to establish a multi-objective optimization model to obtain a maintenance strategy using GA. Bris et al. [4] proposed a periodic PM model that minimizes maintenance costs under the reliability constraint. The optimal maintenance period of each components after the first maintenance task for that component was determined using a GA. Samrout et al. [19] optimized the Bris's case [4] using the same procedure, but the ant colony optimization was adopted to optimize the maintenance periods for all components.

2.2 Importance measures

The importance measures can be used for identifying design weaknesses, and evaluating the impact on proper functioning of a system in the case of the component failure. In general, most of the importance measures are based on specific time to evaluate the impact on system reliability at which whether the component is functioning properly or not. This section briefly describes the importance measures that are commonly used in practice, as follows.

2.2.1 Birnbaum importance measure

The Birnbaum importance measure [3] is defined to be the probability that the ith component is critical to the functioning of the system at time t. It can be expressed as

$$I_B^i(t) = \frac{\partial G(q(t))}{\partial q_i(t)} = G(1_i, q(t)) - G(0_i, q(t)) \tag{1}$$

where $I_B^i(t)$ is the Birnbaum's importance measure of component i at time t; $G(q(t))$ is the system unreliability at time t; $q_i(t)$ is the unreliability of component i at time t; $G(1_i, q(t))$ is the unreliability of a system when the ith component fails; $G(0_i, q(t))$ is the unreliability of a system when the ith component is operating; If $I_B^i(t)$ is large, a small change in the reliability of component i will result a large change in the system reliability at time t.

2.2.2 Criticality importance measure

The criticality importance measure [11] is based on the fact that it is more difficult to improve the more reliable components than to improve the less reliable components for enhancing system reliability. It is expressed as

$$I_{CR}^i(t) = \frac{\partial G(q(t))}{\partial q_i(t)} \times \frac{q_i(t)}{G(q(t))} \tag{2}$$

where $I_{CR}^i(t)$ is the criticality importance measure of component i at time t; $G(q(t))$ is the system unreliability at time t; $q_i(t)$ is the unreliability of component i at time t.

2.2.3 Fussell-Vesely importance measure

The Fussell-Vesely importance measure [8] is the probability that at least one minimal cut that contains component i is failed at time t, given that the system is failed at time t. It can be expressed as

$$I_{FV}^i(t) = \frac{G_i(q(t))}{G(q(t))} \tag{3}$$

where $I_{FV}^i(t)$ is the Fussell-Vesely importance measure of component i at time t; $G_i(q(t))$ is the probability of component i contributing to cut set failure; $G(q(t))$ is the system unreliability at time t.

2.2.4 Improvement potential

In some case it may be of interest to know how much the system reliability increases if component i is replaced by a perfect component. The difference is called the improvement potential with respect to component i [11]. It can be expressed as

$$I_{IP}^i(t) = I_B^i(t) \times q_i(t) \tag{4}$$

where $I_{IP}^i(t)$ is the improvement potential of component i at time t; $I_B^i(t)$ is the Birnbaum's importance measure of component i at time t; $q_i(t)$ is the unreliability of component i at time t.

2.2.5 Ratio-criterion

Bris et al. [4] proposed this index to prioritize components from both reliability and cost point of view. It can be expressed as

$$R_i(t) = \frac{C(i)}{I_B^i(t)} \tag{5}$$

where $R_i(t)$ is the ratio-criterion of component i at time t; $C(i)$ is cost of maintenance of i th component; $I_B^i(t)$ is the Birnbaum importance measure of component i at time t. The component with smallest value of index is determined the most important component.

These mentioned above measures hold some limitations or drawbacks in evaluation the effect of components on system reliability in the parallel system. The criticality importance measures and Fussell-Vesely importance measures yield value of 1 for evaluating the effect of each component on the parallel system. Similarly, the values of improvement potential of components are the same for identifying the effect of each component on a parallel system. Therefore, these three measures are inappropriately to determine the components importance in a series-parallel system. Although Birnbaum importance measure can discriminate the importance of components in a series-parallel system, the component with the highest reliability in a parallel system will be determined as the most importance component. This property makes this measure inappropriate use for optimizing a maintenance model of parallel system because the component with highest reliability will always be determined to conduct maintenance during the mission duration. The ratio-criterion is resulted from Birnbaum measure, and the maintenance cost is considered. Hence, its property is similar to Birnbaum measure when the differences of maintenance cost among the components are not extremely large. Additionally, these measures merely calculate the deviation in system reliability as the system state switches to a failed state from an operating state given a specific time. In practice, the failed/operating probabilities of components are directly related to their reliability, which is a function of time. In summary, the past developed importance measures of components can be further improved to extend their utilities.

III. DEVELOPED IMPORTANCE MEASURES

This work extends the underlying concept of the Birnbaum importance measure to a novel measure of component importance. The Birnbaum importance measure considers the adverse effects of failed components on system reliability. However, component failure/operational probabilities are directly related to the reliability of individual components, which is a function of time. Failure/operational probabilities vary over time. Therefore, the developed importance measure considers this probability by calculating the expected values of component effects on system reliability to assess the importance of components for PM. The calculation of the expected values of effects is as follows.

$$I_j(t) = (R_S(1, r_j(t)) - R_S(t)) \times r_j(t) + (R_S(t) - R_S(0, r_j(t)) \times (1 - r_j(t)) \tag{6}$$

where $R_S(t)$ is the reliability of a system at time *t*; $R_S(1, r_j(t))$ is the reliability of a system when the *j*th component is operating at time *t*; $R_S(0, r_j(t))$ is the reliability of a system when the *j*th component fails at time *t*; $r_j(t)$ is the probability when the *j*th component is operating at time *t*; $(1 - r_j(t))$ is the probability when the *j*th component fails at time *t*; The value of $(R_S(1, r_j(t)) - R_S(t))$ indicates the positive effect when the *j*th component is operating at time *t*; $(R_S(t) - R_S(0, r_j(t))$ is the negative effect when the *j*th component is failed at time *t*; $I_j(t)$ is the expected value of system effect at time *t*. The integration of $I_j(t)$ values over mission duration is determined as the importance measure of components for PM, as follows.

$$I_j^T = \int_0^T I_j(t)dt \tag{7}$$

where I_j^T is the importance measure of the *j*th component during the mission duration *T*. The developed importance measures can be used in determining the maintenance priority of components for PM.

IV. PROPOSED IGA

The following sections describe the proposed IGA for minimizing periodic PM cost in series-parallel systems.

4.1 Construction of periodic PM model of the series-parallel system

The PM cost model is based on the work of Bris et al. [4], as follows.

$$\text{Minimize} \quad C_{PM} = \sum_{k=1}^{K} \sum_{i=1}^{E_K} \sum_{j=1}^{n_{e(i,k)}} C_j(e(i,k)) \tag{8}$$

$$\text{Subject to} \quad R_S(t) \ge R_0 \tag{9}$$

$$R_S(t)=\prod_{k=1}^{K}[1-\prod_{i=1}^{E_K}(1-R_i(t))] \tag{10}$$

where C_{PM} is total maintenance cost; $e(i,k)$ is the *i*th component of the *k*th parallel subsystem; $n_{e(i,k)}$ is the total number of instances of maintenance of the *i*th component of the *k*th parallel subsystem; $C_j(e(i,k))$ is the cost of the *j*th instance of maintenance of the *i*th component in the *k*th parallel subsystem; E_K is the number of components in the given *k*th parallel subsystem; *K* is the number of parallel subsystems; R_0 represents the allowable worst reliability value, and $R_S(t)$ is the reliability of the system at time *t*.

4.2 Construction of IGA

This study adopts real encoding to represent maintenance periods. Hence, each gene represents the maintenance period for a component. A chromosome comprises the maintenance periods of all components. A different combination of maintenance periods of all components forms a different chromosome. The proposed IGA has the following two stages.

Stage 1: Identify the combinations of important components

The values of importance measure, I_j^T, for all components are calculated using Eqs. (6) and (7). According, the importance sequence of components is determined as follows:

$$\mathbf{S}=\bigcup_{i=1}^{n}\{s_i\} \tag{11}$$

where s_i is the ith important component; n is the number of components in a system; and $\mathbf{S}$ is a set of importance sequence of components. According to $\mathbf{S}$, the important components of a series-parallel system are determined in the following iteration procedure.

1. Given the first one component in $\mathbf{S}$, optimize the periodic preventive maintenance model using the GA to obtain a total maintenance cost if feasible solutions exist.
2. Add a component according to the importance priority in $\mathbf{S}$, optimize the periodic preventive maintenance model using the GA to obtain a total maintenance cost if feasible solutions exist.
3. Repeat iteration 2 until all the components are involved when optimizing the periodic preventive maintenance model.

The combination of components with the lowest total maintenance cost is identified as the important components of a series-parallel system. The equation for identifying the important components can be expressed as

$$C_{PM}(\mathbf{S}_m)=\min\left[C_{PM}(\mathbf{S}_j)\right],\ j=1,\ 2,\ ...,\ m,\ ...,\ n \tag{12}$$

where $C_{PM}(\mathbf{S}_j)$ is the optimized total maintenance cost given the first j components in $\mathbf{S}$; $C_{PM}(\mathbf{S}_m)$ is the lowest maintenance cost of the first m components in $\mathbf{S}$, $1\le m\le n$. These m important components are substituted in the second stage to establish initial GA population and thereby optimize their maintenance periods. The other unimportant components do not implement maintenance work for the mission duration.

Additionally, this study employs RSM to systematically determine the optimal settings of crossover probability and mutation probability including the following steps.

Step 1: Plan the RSM experiments for crossover and mutation probabilities

The faced center cube central composite design (FCCD) from the RSM was adopted to plan experiments in which crossover probability and mutation probability are two experimental factors. In total, 13 experimental points involving 4 factorial points, 4 faced axial points, and 5 center points were designed. For further details of the central composite design, refer to Montgomery [16].

Step 2: Conduct RSM experiments and record experimental observations

The 13 planned FCCD experiments are conducted with various crossover and mutation probabilities, and the close-to-optimal solutions for the total maintenance cost under experiments are recorded.

Step 3: Establish the response surface model of total maintenance cost

The response surface model for total maintenance cost on crossover probability and mutation probability is established based on experimental observations. The lack-of-fit test is utilized to determine the appropriateness of the model. Normally, p value of lack of fit test greater than indicates the fitted model is appropriate at the significance level of . If a quadratic model is appropriate, the model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \varepsilon \tag{13}$$

where y represents the total maintenance cost; x_1 and x_2 are the linear effects of crossover probability and mutation probability on the total maintenance cost, respectively; $x_1 x_2$ indicates the interaction effects of crossover probability and mutation probability on the total maintenance cost; x_1^2 and x_2^2 are the quadratic effects of crossover probability and mutation probability on the total maintenance cost, respectively; β_0, β_j, β_{ij}, and β_{jj} are regression parameters; ε is a random error term.

Step 4: Determine the optimal combination of crossover probability and mutation probability

The optimal combination of crossover probability and mutation probability is determined based on the established response surface model obtained by step 3. Accordingly, chromosome evolution through breeding is imitated.

Stage 2: Optimize the maintenance periods.

The combination of the first m important components and the optimal parameters of crossover probability and mutation probability obtained from stage 1 form the basis to optimize the maintenance periods of a periodic PM model, performed by the following steps.

Step 1: Randomly generate maintenance periods of the first m important components to form initial population of chromosomes.

Step 2: Reproduce the initial chromosome population

The conventional roulette-wheel selection scheme is employed for reproductive and elimination procedures; the number of chromosome is the same as the initial population.

Step 3: Apply the crossover procedure to chromosomes

The uniform-crossover method was applied as the crossover procedure to generate offspring.

Step 4: Apply the mutation procedure to chromosomes

Step 5: Perform the adjustment mechanism

An adjustment mechanism is established to make the chromosomes move back to feasible area in case the chromosomes fall into infeasible area. Doing so can enhance the exploring ability of conventional GA. In the constructed series-parallel maintenance model, the chromosomes with reliability lower than the allowable worst system reliability represent infeasible solutions. The proposed adjustment mechanism includes the following two procedures.

<1>Shorten the maintenance periods of components

The maintenance period of the component scheduled to be maintained at the time the occurrence of the lowest reliability is shortened to increase system reliability.

<2>Determine if the reliability greater than allowable worst system reliability

Recompute the system reliability after shortening the maintenance period of components. If the computed reliability does not meet the system minimum requirement, then repeat <1> and <2> until the reliability greater than system requirement, namely the chromosome moves back into feasible area.

Step 6: Perform elitist conservation strategy

If the total maintenance cost during each generation is lower than a recorded best fitness value (namely, the elitism), the elitism is replaced by the champion; otherwise, the chromosome with highest total maintenance cost (namely, worst fitness value) in each generation is replaced by the elitism.

Step 7: Terminate the IGA

Terminate the IGA and output the optimized maintenance periods of all components if the total iterations surpass a predetermined value or the fitness does not improve in continually maximum iterations.

V. CASE STUDY

The PM model of a series-parallel system that was proposed by Bris et al. [4] is adopted herein to confirm the feasibility and practicality of the proposed algorithm. This system consists of four subsystems and 11 components. Components 1, 2, 3, 4 and 5 constitute the first subsystem. Component 6 is the second subsystem, which has a single unit. Components 7, 8, and 9 constitute the third subsystem. Components 10 and 11 consist of the fourth subsystem. Fig. 1 displays the reliability block diagram. Table 1 presents the component parameters, including the probability distribution, mean time to failure (MTTF), and maintenance cost for each component. The mission duration of 50 years is simulated. The allowable worst system reliability is 0.9. The goal is to optimize the maintenance times and minimize the maintenance cost during the mission duration.

Via the proposed IGA, this case was optimized in a stage-by-stage manner as follows.

Stage 1: Identify the combinations of important components.

The importance measures of 11 components, I_j^T values, are computed to form the importance sequence **S** = {5, 6, 11, 3, 1, 2, 10, 8, 9, 7, 4} using Eqs. (6) and (7). Table 2 lists the importance measures of all components for mission duration of 50 years. According to the proposed iteration procedure, the conventional GA is then applied with 5 repetitions under an initial population of 200 chromosomes—crossover probability is 0.86 and mutation probability is 0.13 obtained from RSM—to identify the important components. The GA is terminated at 200 iterations. Hence, five total maintenance costs can be obtained to calculate the average total maintenance cost when feasible solutions exist. First, for the case involving the first important component, the fifth component, no feasible solution exists. For the case involving the first two components, components five and six, no feasible solution was found. This iteration procedure is performed by adding one component according to the importance priority in the importance sequence until all components are involved. Table 3 summarizes the optimized average total maintenance cost for all iterations. Via Eq. (12), the set of , iteration seven, which has the lowest average total maintenance cost of 218.5, was identified as the combination of important components, = {5, 6, 11, 3, 1, 2, 10}. These important components, components 1, 2, 3, 5, 6, 10 and 11, are then substituted into stage two to establish an initial population and thereby optimize their maintenance periods. The components that are not included in do not implement maintenance works for the mission duration.

Noticeably, the determination of GA with a crossover probability of 0.86 and mutation probability of 0.13 using RSM for this case is as following steps.

Step 1: Plan the RSM experiments for crossover and mutation probabilities

The crossover and mutation probabilities are set as two designed factors of RSM experiments for the maintenance cost. Table 4 shows the allocation of the factors levels. The FCCD is utilized to produce the designed points. In total, 13 designed points are generated using the experimental design software DESIGN EXPERT.

Step 2: Conduct RSM experiments and record experimental observations

Experimental observations, total maintenance cost, obtained by the GA are recorded. Table 5 shows the RSM experiments and corresponding maintenance cost.

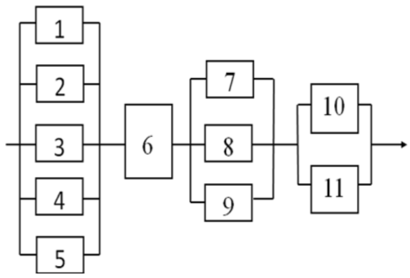

FIGURE 1. RELIABILITY BLOCK DIAGRAM [4]

TABLE 1
COMPONENT PARAMETERS [4]

Number of components	Probability distribution	MTTF (years)	Maintenance cost
1	exponential	12.059	4.1
2	exponential	12.059	4.1
3	exponential	12.2062	4.1
4	exponential	2.014	5.5
5	exponential	66.6667	14.2
6	exponential	191.5197	19
7	exponential	63.5146	6.5
8	exponential	438.5965	6.2
9	exponential	176.0426	5.4
10	exponential	13.9802	14
11	exponential	167.484	14

TABLE 2
IMPORTANCE MEASURES AND PRIORITY FOR =50 YEARS

Number of components	Importance measures	Priority
1	1.1957	5
2	1.1957	5
3	1.2268	4
4	0.0039	11
5	8.8588	1
6	6.0445	2
7	0.0948	10
8	0.1538	8
9	0.1359	9
10	0.9415	7
11	5.4180	3

TABLE 3
COMBINATIONS OF IMPORTANT COMPONENTS

Iterations	S_m	The combinations	The average total maintenance cost
1	S_1	5	No feasible solutions
2	S_2	5, 6	No feasible solutions
3	S_3	5, 6, 11	427.8
4	S_4	5, 6, 11, 3	280.3
5	S_5	5, 6, 11, 3, 1	241.2
6	S_6	5, 6, 11, 3, 1, 2	225.3
7	S_7	**5, 6, 11, 3, 1, 2, 10**	**218.5**
8	S_8	5, 6, 11, 3, 1, 2, 10, 8	226.8
9	S_9	5, 6, 11, 3, 1, 2, 10, 8, 9	235.5
10	S_{10}	5, 6, 11, 3, 1, 2, 10, 8, 9, 7	244.7
11	S_{11}	5, 6, 11, 3, 1, 2, 10, 8, 9, 7, 4	253.1

TABLE 4
FACTORS LEVELS

Factors	Low level	High level
Crossover probability	0	1
Mutation probability	0	1

Step 3: Establish the response surface model of total maintenance cost

According to the experiments, the response surface model of total maintenance cost was established. The p-value of lack-of-fit test is 0.0701, revealing that a quadratic response model was appropriate (p>0.05). The fitted model is as follows.

$$\hat{y} = 283.9 - 178.9x_1 - 53.8x_2 + 60.0x_1x_2 + 98.2x_1^2 + 46.2x_2^2 \quad (14)$$

where $\hat{y}$ is the predicted total maintenance cost; and x_1 and x_2 are the crossover and mutation probabilities, respectively. The coefficient of determinant for this model is $R^2 = 0.933$. Table 6 presents the analysis of variance (ANOVA)

TABLE 5
DESIGNED EXPERIMENTS AND TOTAL MAINTENANCE COST

Experimental points	Crossover probability	Mutation probability	Total maintenance cost
1	0	0	290.5
2	0	0.5	268.2
3	0	1	270.1
4	0.5	0	205.7
5	0.5	0.5	227.8
6	0.5	1	253.7
7	1	0	210
8	1	0.5	217.2
9	1	1	249.6
10	0.5	0.5	216.4
11	0.5	0.5	220.2
12	0.5	0.5	216.9
13	0.5	0.5	213.2

TABLE 6
ANOVA TABLE FOR TOTAL MAINTENANCE COST

Source	Sum of Squares	DF	Mean Square	F Value	P Value
Model	8578.91	5	1715.78	19.47	0.0006
A (Crossover probability)	3850.67	1	3850.67	43.69	0.0003
B (Mutation probability)	752.64	1	752.64	8.54	0.0223
A^2	1664.37	1	1664.37	18.89	0.0034
B^2	368.34	1	368.34	4.18	0.0802
AB	900.00	1	900.00	10.21	0.0152
Residual	616.90	7	88.13		
Lack of Fit	493.26	3	164.42	5.32	0.0701
Pure Error	123.64	4	30.91		
Cor Total	9195.81	12			

From ANOVA results, the linear and quadratic effects of crossover probability, and the linear effects of mutation probability on the solution of total maintenance cost are significant. Furthermore, the interaction effect between crossover probability and mutation probability is also significant. The significance level is 0.05. Fig. 2 shows the response surface diagram of the total maintenance cost solution for crossover probability and mutation probability.

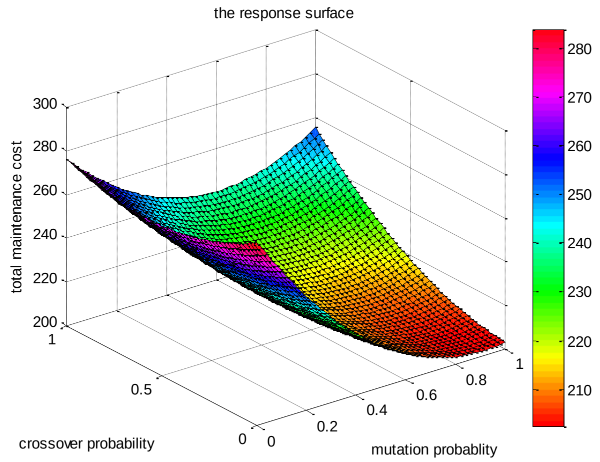

FIGURE 2. RESPONSE SURFACE DIAGRAM OF TOTAL MAINTENANCE COST

Step 4: Determine the optimal combination of crossover probability and mutation probability

Via mathematical programming, the optimal crossover and mutation probabilities are 0.86 and 0.13, respectively. These optimal settings are then substituted into the GA breeding process to approach the global optimum of the total maintenance cost solution.

Stage 2: Optimize maintenance periods

The randomly generated maintenance periods of seven components obtained from stage one form an initial population of chromosomes with seven genes. Each gene is a maintenance period of a component. Thus, the initial population of 200 chromosomes is established. The optimal settings of parameters obtained from RSM, including crossover probability is 0.86 and mutation probability is 0.13, are then substituted into the IGA search mechanism to approach the global optimum of the total maintenance cost solution. The magnitude of the adjustment mechanism to heighten system reliability by shortening component maintenance periods is set to 0.1 in this case. The IGA is terminated at 200 iterations. The optimized total maintenance cost for this case is 178.1. Table 7 lists the optimal maintenance periods of components for mission duration of 50 years. Fig. 3 shows the corresponding reliability curve. All reliability values exceed 0.9, satisfying the constraint of allowable worst reliability.

TABLE 7
OPTIMIZED MAINTENANCE PERIODS (T_M =50 years, $R_S(t) \geq 0.9$)

Number of components	1	2	3	5	6	10	11
Maintenance periods	21.47	17.08	9.63	25.78	13.40	32.04	11.24

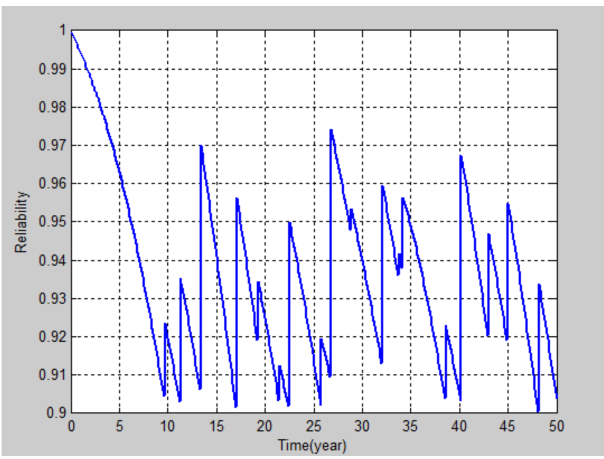

FIGURE 3. RELIABILITY CURVE (T_M =50 years, $R_S(t) \geq 0.9$)

To verify the effectiveness of the retrieval mechanism for the GA, this case is optimized using a conventional GA and proposed IGA simultaneously. The conventional GA outputs an inferior total maintenance cost of 241.7. However, the IGA efficiently reduces total maintenance cost at 178.1. Therefore, the proposed IGA improves the solving ability of the conventional GA. The IGA optimization results are further compared to those obtained by Bris et al. [4] and Samrout et al. [19]. Table 8 summarizes comparison results. The optimized total maintenance cost in this study is reduced to 178.1 from 238, which was obtained by Bris et al. [4]—resulting in a reduction of 59.9 for mission duration of 50 years. Compared with that acquired by Samrout et al. [19], the optimized total maintenance cost is reduced to 178.1 from 224.2, a reduction of 46.1 for mission duration of 50 years. The proposed IGA outperforms the approaches developed by Bris et al. [4] and Samrout et al. [19]. Therefore, the effectiveness of the proposed IGA in optimizing periodic preventive maintenance models can be confirmed.

TABLE 8
COMPARISONS OF THE TOTAL MAINTENANCE COST IN MISSION DURATION OF 50 YEARS

	conventional GA	Bris *et al.* [4]	Samrout *et al.* [19]	This study (IGA)	Compare with conventional GA	Compare with Bris et al. [4]	Compare with Samrout et al. [19]
					Reduction	Reduction	Reduction
$T_M = 50$	241.7	238.0	224.2	178.1	63.6	59.9	46.1

VI. CONCLUSIONS

Some superior meta-heuristic algorithms and improved algorithms have been proposed to resolve large complex problems in recent years. However, due to the diversity of the problems, a customized algorithm typically outperforms a general algorithm in solving specific problems. This study proposes an improved GA to minimize total periodic PM cost. A novel importance measure of component is proposed for PM. Furthermore, an adjustment mechanism is established to move the chromosomes from infeasible to feasible areas in order to enhance the exploratory ability of conventional GA. A case adopted from a previous study demonstrates the problem solving efficacy of the proposed IGA. This algorithm can be extended to solve large problems with complex series-parallel systems comprised of many subsystems or components. Moreover, the proposed IGA can be modified for non-periodic maintenance and imperfect maintenance models.

ACKNOWLEDGEMENTS

This work was supported by Ministry of Science and Technology of Taiwan (MOST 104-2218-E-012-002).

REFERENCES

[1] B.M. Baker and M.A. Ayechew, “A genetic algorithm for the vehicle routing problem. Computers & Operations Research,” vol. 30, 2003, pp.787-800.
[2] R. Battiti and G. Tecchiolli, “The reactive Tabu search. ORSA Journal on Computing,” vol. 6, 1994, pp.126-140.
[3] Z.W. Birnbaum, “On the importance of different components in a multicomponent system, Multivariate Analysis,” vol. 2 (SanDiego, Academic Press, 1969), pp.581-592.
[4] R. Bris, E. Chatelet and F. Yalaoui, “New method to minimize the preventive maintenance cost of series–parallel systems,” Reliability Engineering & System Safety, vol. 82, 2003, pp.247-255.
[5] P. Busacca, M. Marseguerra and E. Zio, “Multi-objective optimization by genetic algorithms: application to safety systems,” Reliability Engineering & System Safety, vol. 72, 2001, pp.59-74.
[6] J.S. Chen, J.Pan, H. Chao, and C. M. Lin, “A hybrid genetic algorithm for re-entrant flow-shop scheduling problem. Experts System with Applications,” 34, vol. 2008, pp.570-577.
[7] A.I. El-Gallad, M.E. El-Hawary and A.A. Sallam, “Swarming of intelligent particles for solving the nonlinear constrained optimization problem. Engineering Intelligent Systems for Electrical Engineering and Communications,” vol. 9, 2001, pp.155-163.
[8] J.B. Fussell, “How to caculate system safety and reliability characteristics. IEEE Trans on Reliability,” 24, 1975, pp.169-174
[9] D. E. Goldberg, Genetic algorithms in search, optimization and machine learning, MA: Addison Wesley, 1989.
[10] J.H. Holland, “Adaptation in natural and artificial systems,” Ann Arbor: University of Michigan Press, 1975.
[11] A. Hoyland and M. Rausand, System reliability theory: models, statistical methods and applications, NJ: Wiley-Interscience, 2004.
[12] X. Hu and R.C. Eberhart, “Solving constrained nonlinear optimization problems with particle swarm optimization,” Proc. 6th Conf. on World Multiconference on Systemics, Cybernetics and Informatics, 2002, pp.203-206.
[13] R.C. Leou, “A new method for unit maintenance scheduling considering reliability and operation expense,” Electrical Power & Energy Systems, vol. 28, 2006, pp.471-481.
[14] C.H. Lie and Y.H. Chun, “An algorithm for preventive maintenance policy,” IEEE Transactions on Reliability, 1986, pp.71-75.

[15] M. Marseguerra and E. Zio, "Optimizing maintenance and repair policies via a combination of genetic algorithms and Monte Carlo simulation. Reliability Engineering & System Safety," vol. 68, 2000, pp.69-83.

[16] D.C. Montgomery, Design and analysis of experiments, vol. 6, NY: John Wiley & Sons, 2005.

[17] A. Muller, A. C. Marquez and B. Iung, "On the concept of e-maintenance: Review and current research. Reliability Engineering & System Safety," vol. 93, 2008, pp.1165-1187.

[18] K.E. Parsopoulos and M.N. Vrahatis, "Particle swarm optimization method for constrained optimization problems," Proc. 2nd Conf. on Euro-International Symposium on Computationa Intelligence, 2002, pp.214-220.

[19] M. Samrout, F. Yalaoui, E. Chatelet and N. Chebbo, "New methods to minimize the preventive maintenance cost of series–parallel systems using ant colony optimization," Reliability Engineering & System Safety, vol. 89, 2005, pp.346-354.

[20] H.M. Shieh, and M.D. May, "Solving the capacitated clustering problem with genetic algorithm," Journal of the Chinese Institute of Industrial Engineers, vol. 18, 2001, pp. 1-12.

[21] Y.T. Tsai, K.S. Wang and H.Y. Teng, "Optimizing preventive maintenance for mechanical components using genetic algorithms," Reliability Engineering & System Safety, vol. 74, 2001, pp.89-97.

[22] Y.T. Tsai, K.S. Wang and L.C. Tsai, "A study of availability-centered preventive maintenance for multi-component systems," Reliability Engineering & System Safety, vol. 84, 2004, pp.261-270.

[23] H. Wang, "A survey of maintenance policies of deteriorating systems," European Journal of Operational Research, vol. 139, 2002, pp.469-489.