Availability Optimization for Repairable n-Stage Standby System by Applying Tabu-GA Combination Method

Gia-Shie Liu

***Abstract*—This study aims at the availability optimization problem for n-stage standby system under different resource and design configuration constraints by applying Tabu-GA combination method. From the point of view of logistics engineering, availability optimization applied in the initial system development period, plays a key role to affect system reliability, system maintenance planning, logistics requirements, and related costs during system planned life cycle. In general, system availability can be improved by increasing component reliability level, component repair rate or the number of components in each subsystem. This proposed model combines Tabu method with Genetic Algorithm to solve system availability optimization problem. Through our method applied in the initial phase of system design and development, we can find the optimal allocation of component redundancy number, reliability and maintainability levels to minimize the total system cost under different configuration constraints such as weight, volume, and system availability requirements. The proposed numerical examples are demonstrated based on different system constraint requirements and parameter values. Through a simulation study of 30 times of calculations by applying this proposed combination method, stable results are clearly showed. Consequently, all numerical results and simulation studies clearly show that the proposed availability optimization model and Tabu-GA combination method developed in this paper can help solving system availability optimization problem in the initial system design and development period.**

***Index Terms*—Availability, genetic algorithm, n-Stage standby system, tabu-GA combination method, tabu search.**

I. Introduction

Besides the aerospace and defense industry, availability has now been considered as a very important design criterion in many other fields including telecommunication system, computer system and electrical power system, etc. Wang [1] defines availability indicating the probability that repairable systems maintain the function at a specific moment. It is also noted that system availability is a concept closely related to reliability and refers to the scale of measuring the reliability of repairable system [2]. Since availability comprises both reliability and maintainability parameters, it can evaluate the effectiveness of repairable systems more precisely than reliability.

This Paper intends to perform availability allocation, which allocates the availability for each subsystem or component to maximize or minimize the objective function based on system's configuration requirements or other resource constraints. But, few literature have been published for this kind of availability allocation problem ([2]-[8]). Most of them formulated the problem of availability allocation as a multi-objective optimization problem to maximize the system availability and minimize the total system cost ([2]-[5])

Concerning on the difficulty to evaluate the appropriate weighting parameters for the above multi-objective availability optimization problems, this research, will focus on minimizing the total system cost to find out the optimal number of redundant components of a system and the optimal failure and maintenance rates for each component in that system by conforming to different configuration constraints, such as system availability, reliability requirements and weight, volume etc.

This proposed availability allocation problem extends the reliability-redundancy allocation problem ([9]-[18]), which includes two decision variables such as the number of component, the failure rate of each component in each subsystem, by adding one more decision variable, the repair rate of each component for each subsystem. For solving reliability-redundancy allocation problems, a couple of famous combination methods have been published. These methods are generally developed with different combinations of search methods and heuristic approaches. These combination methods are proved to be very efficient to solve different type of reliability-redundancy allocation problems by applying two appropriate heuristic methods to find the optimal discrete decision variable and continuous decision variable respectively ([10]-[13], [15], [18]). This paper will follow the same philosophy to develop the appropriate combination method to solve the availability allocation problem developed by this research.

In recent years, meta-heuristic methods have been successfully applied to handle several reliability optimization problems and availability allocation problems. Observing these literatures, various Genetic algorithms are applied to find the optimal number of redundant components for reliability optimization problems [14] or to obtain the optimal number of components, the optimal failure rate and repair rate of each component in each subsystem simultaneously for availability optimization problems ([2], [4], [5], [19], [20]). As a member of meta-heuristic algorithm, Genetic Algorithm has proved itself to be widely accepted by many scholars in the field of reliability and availability optimization to search for the optimal solution based on various discrete and continuous decision variables. Moreover, other members of meta-heuristic approaches such as non-equilibrium simulated annealing [17] and Tabu search method [16], are almost

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applied to find the optimal number of redundancy for reliability optimization problems. According to the above observations, all these meta-heuristic algorithms are showed to be able to provide solutions close to the optimal solution with very good efficiencies for various reliability redundancy allocation problems or availability redundancy allocation problems.

The model developed in this paper combines Tabu Search with Genetic Algorithm to solve system availability optimization problem. This proposed combination method is called Tabu-GA combination method in this paper. In this Tabu-GA combination method, Genetic Algorithm is applied to handle continuous decision variables including failure rates and repair rates of components of all subsystems, and Tabu Search is used to handle discrete decision variables, the redundancy number of components of all subsystems. Since Genetic Algorithm takes chromosome mechanism and fitness function as its evaluation criteria, it is very appropriate and efficient to take care of two kinds of continuous decision variables of this proposed model by Genetic Algorithm. Besides, according the above good results of many literatures, Tabu Search will be very suitable to be applied to obtain the optimal discrete decision variables, which is redundancy number of components in this proposed model.

II. PPROBLEM DESCRIPTION AND FORMULATION

Notation

x_j Number of components in subsystem *j*

$\overline{X}$ Vector of number of components in each subsystem

λ_j Failure rate of components in subsystem *j*

$\overline{\lambda}$ Vector of failure rate of components used in each subsystem

μ_j Repair rate of components in subsystem *j*

$\overline{\mu}$ Vector of repair rate of components used in each subsystem

mc_j Repair cost rate of components in subsystem *j*

α_j , β_j Parameters representing the inherent reliability characteristics of each component in subsystem *j*,

$C_s(\vec{X}, \vec{\lambda}, \vec{\mu})$, System cost objective function

p_j product of weight and volume per component in subsystem *j*

P limitation on product of weight and volume

w_j , W Weight of one component in subsystem *j*, limitation on weight

a_j Component availability of component *j*

$\overline{A}$ Vector of availability of each subsystem

$A_S(\vec{X}, \overline{\lambda}, \overleftarrow{\mu})$ System availability function

$A_j(x_j, \lambda_j, \mu_j)$ Availability function of subsystem *j*

$A_s^{'}$ Lower bound of system availability

A_j^L Lower bound of availability of subsystem *j*

A_j^U Upper bound of availability of subsystem *j*

C Set of subsystems which have lower bound in availability

C^U Set of subsystems which have upper bound in availability

t The life time of system

$R_j(t) = r_j = e^{-\lambda_j t}$ Reliability of components used in subsystem *j* at time *t*

r_j Component reliability in subsystem *j*

$\overline{R}$ Vector of reliability of each subsystem

n Number of subsystems in the system

In this paper system cost objective function is minimized by conforming to those constraints such as system design configurations, resource capacities, system and subsystem availability requirements. The main reason for focusing this type of problem is that a new system is generally developed to meet the planned performance requirements as lower cost as possible in the real world. The system structure considered in this paper is n-stage standby system. It means that all subsystems are connected in series, and these subsystems are all of standby configurations. The number of components x_j of all subsystem *j*, the component failure rate λ_j of all subsystem *j*, and the component repair rate μ_j of all subsystem *j*, are the decision variables to be determined to obtain the optimal solution in this proposed method. The template problem is expressed as:

$$\text{Min } C_s(\vec{X}, \overline{\lambda}, \overleftarrow{\mu}) = \sum_{j=1}^{n} [\alpha_j (\lambda_j)^{-\beta_j} + \mu_j \times mc_j][x_j + \exp(x_j/4)] \quad (1)$$

s.t

$$\sum_{j=1}^{n} p_j (x_j)^2 \le P \quad (2)$$

$$\sum_{j=1}^{n} w_j x_j \times \exp(x_j/4) \le W \quad (3)$$

$$A_S(\vec{X}, \overline{\lambda}, \overleftarrow{\mu}) \ge A_S^{'} \quad (4)$$

$$A_j(x_j, \lambda_j, \mu_j) \ge A_j^L, \text{ for some } j \text{ in } C \quad (5)$$

$$A_j(x_j, \lambda_j, \mu_j) \le A_j^U, \text{ for some } j \text{ in } C^U \quad (6)$$

According to the above template problem, equation (1) is the objective function which focuses on system total cost. Equation (2) is the general form of system design configuration constraint of weight, and equation (3) is the general form of system design configuration constraint of the product of weight and volume. Equation (4) is the general form of system availability requirement constraint, equation (5) is the low bound threshold constraint for some subsystem availability requirement, and equation (6) is the upper bound threshold constraint for some subsystem availability requirement.

In this proposed model, since n-stage standby system is considered, the subsystem availability function and system availability function on equation (4), (5) and (6) have the following forms.

$$A_j(x_j,\lambda_j,\mu_j) = [1-[\sum_{k=0}^{x_i}(\frac{\lambda_i}{\mu_i})^k]^{-1}(\frac{\lambda_i}{\mu_i})^{x_i}]$$

$$A_S(\vec{X},\bar{\lambda},\overleftarrow{\mu}) = \coprod_{j=1}^{n} A_j(x_j,\lambda_j,\mu_j)$$

$$= \coprod_{j-1}^{n}[1-[\sum_{k=0}^{x_i}(\frac{\lambda_i}{\mu_i})^k]^{-1}(\frac{\lambda_i}{\mu_i})^{x_i}]$$

To set up the problem, several assumptions need to be made as follows.

1) Assume all components have the characteristics of electrical component (i.e. $R(t)=e^{-\lambda t}$)
2) Assume life time of system t = 1000.
3) All stages (subsystems) are connected in series, i.e., 1-out-of-n: F configuration.
4) Only a single mode of failure is assumed.
5) All components in the same subsystem have the same failure rates.
6) All components in the same subsystem have the same repair rate..
7) Assume component availability applied in this paper is inherent availability: $a_j = \frac{\mu_j}{\mu_j+\lambda_j}$
8) All subsystems and all components used in each subsystem are S-independent.

III. The Proposed Availability Optimization Combination Methods

This proposed model develops Tabu-GA combination method to solve system availability optimization problem with a two-module process. In the major module phase, Tabu Search is applied to search for the appropriate redundancy number of components first. In the sub-module phase, based on the selected redundancy number of components in the first phase, Genetic Algorithm is then applied to find the optimal failure rates and repair rates of components of all subsystems simultaneously. The detailed procedures for this proposed combination methods are described as follows

A. Tabu Major Module Phase

Step 1:

1) Set up the values of parameters including α_j, β_j, mc_j, P_j, P, w_j, W.
2) Set up the initial number of iteration TabuIte=1. Set up the threshold of iteration TabuMaxIte=200.

Step 2: Set up the initial base point $\overline{X}^0$ randomly.

Step 3: To check if the initial base point $\overline{X}^0$ satisfies constraints of weight, volume, availability requirements. If yes, go to Step 4, or go back to Step 2.

Step 4: Let the base point $\overline{X}^b = \overline{X}^0$. Pass $\overline{X}^b$ into GA sub-module to find the related optimal failure rates and repair rates of components of all subsystems, $\overline{\lambda}^*(\overline{X}^b), \overline{\mu}^*(\overline{X}^b)$ and calculate system total cost $C_S(\vec{X}^b,\overline{\lambda}^*(\vec{X}^b),\overline{\mu}^*(\vec{X}^b))$.

Step 5: Let the optimal point $\overline{X}^* = \overline{X}^b$, the optimal system total cost $C_s^* = C_S(\vec{X}^b,\overline{\lambda}^*(\vec{X}^b),\overline{\mu}^*(\vec{X}^b))$

Step 6: Generate neighboring candidate points, $N(\overline{X}^b)$, which satisfy constraints of weight, volume, availability requirements. Pass all these candidate points into GA sub-module to find the related optimal failure rates and repair rates of components of all subsystems, and calculate system total costs for all neighboring points in the candidate list.

Step 7: Choose the candidate point $\overline{X}'$ with the lowest system total cost $C_S(\vec{X}',\overline{\lambda}^*(\vec{X}'),\overline{\mu}^*(\vec{X}'))$ within the candidate list.

Step 8: If $\overline{X}'$ is not in the Tabu list, go to Step 10.

Step 9: If this candidate $\overline{X}'$ follows Aspiration criterion, $C_S(\vec{X}',\overline{\lambda}^*(\vec{X}'),\overline{\mu}^*(\vec{X}'))<C_s^*$, go to Step 10, or go back to Step 7 to choose the next best candidate $\overline{X}'$ from the candidate list.

Step 10: let $\overline{X}^b = \overline{X}'$ and Implement the Tabu move.

Step 11: Update the Tabu list.

Step 12: If $C_S(\vec{X}^b,\overline{\lambda}^*(\vec{X}^b),\overline{\mu}^*(\vec{X}^b))<C_s^*$, go to Step 13, or go to Step 14.

Step 13: $\overline{X}^* = \overline{X}^b$, $C_s^* = C_S(\vec{X}^b,\overline{\lambda}^*(\vec{X}^b),\overline{\mu}^*(\vec{X}^b))$

Step 14: If *Ite* < *MaxIte*, go back to Step 6, or Stop. Record the optimal solution, $\overline{X}^*$, $\overline{\lambda}^*(\overline{X}^*)$, $\overline{\mu}^*(\overline{X}^*)$, $C_s^*(\vec{X}^*,\overline{\lambda}^*(\vec{X}^*),\overline{\mu}^*(\vec{X}^*))$

B. GA Sub-Module Phase

Based on the selected redundancy number of components of some subsystem obtained from Tabu major module in the first phase, Genetic Algorithm is then applied to find the optimal failure rates and repair rates of components of all subsystems simultaneously in this second module. The detailed procedure for GA module is described as follows:

Step 1:

1) Set up the initial amount of iteration Ite=1. After the simulation experiment, set up the defined threshold of iteration MaxIte=200.
2) After the simulation experiment, set up crossover probability cr-rate = 0.95, mutation probability mu-rate = 0.5, and chromosome population equal to 200.
3) Define the fitness function as follows:

$$C_j(x_j,\lambda_j,\mu_j) = \alpha_j(\lambda_j)^{-\beta_j} + \mu_j * mc_j][x_j + \exp(x_j/4)]$$

4) Set up the optimal fitness function value cjmin equal to a very large number

Step 2: Generate the initial 200 chromosomes with the length of 30.binary genes. All chromosomes use their first 15 binary genes to represent the related failure rates λ_j, which are between 0.0000001 to 0.001, and use their last 15 binary genes to represent the related repair rates μ_j, which are between 0.0000032 to 0.032.

Step 3: Decode the binary genes of chromosomes to real decision variables λ_j and μ_j. The decoding formula is described as follows:

$F_j = L_j + \frac{U_j - L_j}{2^{15}-1}\sum_{k=1}^{15} b_k 2^{k-1}$ where

L_j is the low bound of the real value of decision variable.

U_j is the upper bound of real value of decision variable.

F_j is the real value of decision variable.

b_k the *k*-th binary gene.

Step 4: To check if the chromosomes conform to the availability requirement constraint: $A_S(\vec{X}, \bar{\lambda}, \overleftarrow{\mu}) \geqq A_S'$. If yes, go to Step 5, or generate new chromosomes to replace those un-qualifying chromosomes and go back to Step 3.

Step 5:

1) Pass λ_j and μ_j decoded from all chromosome into the fitness function to calculate their related fitness function values, $C_j(x_j, \lambda_j, \mu_j)$
2) If $Min\, C_j(x_j, \lambda_j, \mu_j)$ < cjmin, set up cjmin= $Min\, C_j(x_j, \lambda_j, \mu_j)$, and let the related failure rate to be λ_j^*, and the related repair rate to be μ_j^*

Step 6: Sort all these fitness function values of all chromosomes, and choose the chromosomes to the reproduction group by applying Roulette wheel selection.

Step 7: Select every pair of chromosomes randomly through the reproduction group to implement the crossover operations.

Step 8: For each pair of chromosomes, generate a crossover probability P_c. If P_c < c*r-rate*, go to Step 9, or go to Step 10.

Step 9: The two-point crossover operation is activated according to a probability P_c for each selected pair of chromosomes. One cross point is selected randomly from the part of the first 15 binary genes, which represents the related failure rate λ_j; the other cross point is selected randomly from the part of the last 15 binary genes, which represents the related repair rate μ_j. Interchange of the genes between two selected chromosomes is within the range of the selected pairs of cross points.

Step 10: Generate a mutation probability P_m for all new chromosomes generated after crossover operations. If P_m < *mu-rate*, go to Step 11, or go to Step 12.

Step 11: The mutation operation of two selected mutation points is implemented according to a probability P_m for all chromosomes selected for mutation operations. One mutation point is selected randomly from the part of the first 15 binary genes, which represents the related failure rate λ_j; the other mutation point is selected randomly from the part of the last 15 binary genes, which represents the related repair rates μ_j. Implement the mutation change of two selected genes for all chromosomes selected for mutation operations (Change the value of the selected genes from 1 to 0 or from 0 to 1)

Step 12: If *Ite* < *MaxIte*, go to Step 3, or Stop .Pass the optimal solution, including *cjmin*, λ_j^*, μ_j^*, back to the major module.

IV. Numerical Examples and Discussions

In this section, we assume that one R&D team is assigned to develop a new n-stage standby system, which needs to meet some specific system requirements. As we mentioned above, availability optimization in the initial system development period greatly affects maintenance activities, logistics requirements, and related life cycle cost during system's life cycle. This R&D team is required to find the optimal allocation of component redundancy number, reliability and maintainability levels for each subsystem to minimize the total system cost and meet the constraints for weight, volume, and system availability requirements.

The proposed numerical example is demonstrated based on different system constraint requirements and parameter values. In addition, a simulation study of 30 times of calculations is implemented to test the stability of this proposed Tabu-GA combination method. Before implementing these numerical examples, Table I presents all parameters or the related information we need as follows.

TABLE I: Parameters Used in the Subsequent Examples

Parameters	*Subsystem(j)* 1	2	3	4	5
$\alpha_j (10^{-5})$	2.33	1.45	0.541	8.05	1.95
β_j	1.5	1.5	1.5	1.5	1.5
mc_j	5000	5000	5000	5000	5000
p_j	1	2	3	4	2
w_j	7	8	8	6	9
t	**1000**				

A. The Proposed Numerical Example

This is a typical n-stage standby system problem. There are totally 5 standby subsystems in this system. The limit on product of weight and volume is 150. The limit on weight is 200. The low bound of system availability is 0.9. The corresponding objective function and constraints are described as follows:

$$Min\, C_S(\vec{X}, \bar{\lambda}, \overleftarrow{\mu}) = \sum_{j=1}^{5}[\alpha_j(\lambda_j)^{-\beta_j} + \mu_j * mc_j][x_j + \exp(x_j/4)]$$

s.t.

$$\sum_{j=1}^{5} p_j (x_j)^2 \le 150$$

$$\sum_{j=1}^{5} w_j x_j \times \exp(x_j/4) \le 200$$

$$\prod_{j-1}^{n}[1 - [\sum_{k=0}^{x_i}(\frac{\lambda_i}{\mu_i})^k]^{-1}(\frac{\lambda_i}{\mu_i})^{x_i}] \ge 0.9$$

The results obtained by Tabu-GA combination methods are showed in Table II,

TABLE II: OPTIMAL SOLUTION OBTAINED BY TA-GA COMBINATION METHOD

Decision Variables	*Subsystem(j)*				
	1	2	3	4	5
$\overline{X}^*$	3	3	2	3	2
$\overline{\lambda}^*$ (e-003)	0.3261	0.2749	0.1507	0.5963	0.2555
$\overline{\mu}^*$	0.0012	0.0010	0.0010	0.0017	0.0015
$\overline{A}^*$	0.9852	0.9838	0.9808	0.9710	0.9750
$\overline{R}^*$	0.9785	0.9861	0.9804	0.9094	0.9492
System Cost =	236.8314				
System Availability =	0.9000				
Running Time	33916 sec.				

B. *The Steady Analysis for Tabu-GA Combination Method*

A simulation study of 30 times of calculations by applying this proposed Tabu-GA combination method is implemented and the results are showed in the following Table III, Table IV.

TABLE III: A SIMULATION STUDY OF 30 TIMES OF CALCULATIONS FOR SYSTEM COST

System Cost					
238.5523	237.9881	237.2907	237.2985	237.5286	237.3956
237.5865	237.3061	236.8314	237.3586	237.8384	237.7512
237.9826	237.6536	237.4000	237.2616	237.2716	237.0119
236.9508	237.3956	237.2809	237.2275	237.0944	237.0752
237.4588	237.7175	237.1438	237.5461	237.4499	237.1303

Average system Cost: 237.4259
Standard Deviation: 0.3561

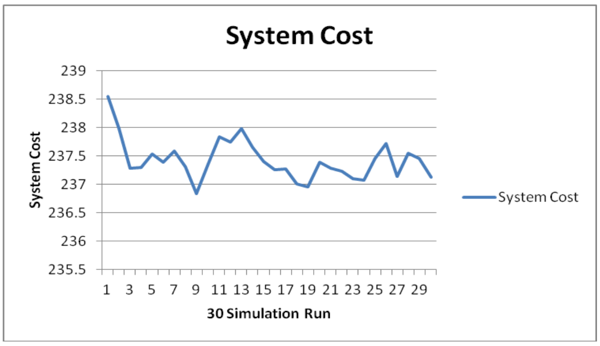

Fig. 1. A simulation study of 30 times of calculations for system cost

According to the results of Table III and Fig. 1, the average system cost is 237.4259 and the standrd deviation is 0.3561. Therefore, it can be concluded that the results obtained by this proposed Tabu-GA combination method are obviously very stable.

TABLE IV: A SIMULATION STUDY OF 30 TIMES OF CALCULATIONS

CPU Running Time (e+004 seconds)								
3.4483	3.4718	3.4596	3.6066	3.4273	3.3840	3.3936	3.4050	3.3916
3.4519	3.3964	3.4403	3.3910	3.3929	3.3663	3.4290	3.4357	3.5113
3.4159	3.3903	3.3579	3.3806	3.3942	3.4364	3.4766	3.3969	3.4090
3.4085	3.3896	3.4074						

Average CPU Running Time: 3.4222
Standard Deviation: 0.3561: 0.0492

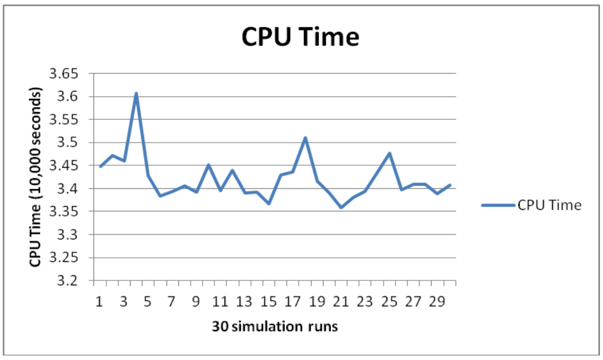

Fig. 2. A simulation study of 30 times of calculations for CPU time

According to the results of Table IV and Fig. 2, the average CPU running time is 34222 seconds and the standard deviation of CPU running time is 492 seconds. Therefore, it can be concluded that the CPU running time of this proposed Tabu-GA combination method are obviously very stable.

V. CONCLUSION REMARKS

This paper develops a combination method to combine Tabu method with Genetic Algorithm to solve system availability optimization problem for n-stage standby system under different resource and design configuration constraints. The proposed numerical examples are illustrated to acquire the optimal allocation of component redundancy number, reliability level and maintainability rate to minimize the total system cost under different configuration constraints such as weight, volume, and system availability requirements.

This paper also implements a simulation study of 30 times of calculations by applying this proposed Tabu-GA combination method. The results in Table III show that the average system cost is 237.4259 and the standard deviation of system cost is 0.3561. Furthermore, the results in Table IV show that the average CPU running time is 34222 seconds, and the standard deviation of CPU running time is 492 seconds. Therefore, it can be concluded that this proposed

Consequently, all numerical results and simulation studies clearly show that the proposed availability optimization model and Tabu-GA combination method developed in this paper can help solving system availability optimization problem in the initial system design and development period..

REFERENCES

[1] Z. H. Wang, *Reliability engineering theory and practice*, 5th ed. Taipei Quality Control Society of Republic of China, 1992.
[2] Y. S. Juang, S. S. Lin, and H. P. Kao, "A knowledge management system for series-parallel availability optimization and design," *Expert Systems with Applications*, vol. 34, pp. 181-193, 2008.
[3] P. G. Busacca, M. Marseguerra, and E. Zio, "Multiobjective optimization by genetic algorithms: Application to safety systems," *Reliability Engineering and System Safety*, vol. 72, pp. 59–74. 2001.
[4] C. H. Chiang and L. H. Chen, "Availability allocation and multi-objective optimization for parallel-series systems," *European Journal of Operational Research*, vol. 180, pp. 1231-1244, 2007.
[5] C. Elegbede and K. Adjallah, "Availability allocation to repairable systems with genetic algorithms: A multi-objective formulation," *Reliability Engineering and System Safety*, pp. 82, 319–330, 2003.
[6] T. A. Varvarigou and S. Ahuja, "MOFA: A model for fault and availability in complex services," *IEEE Transaction on Reliability*, vol. 46, no. 2, pp. 222–232, 1997.

[7] H. Garg, “Fuzzy Multiobjective Reliability Optimization Problem of Industrial Systems using Particle Swarm Optimization,” *Journal of Industrial Mathematics*, vol. 2013, no. 2013, Article ID 872450, pp. 9.

[8] H. Garg and S. P. Sharma, “Reliability redundancy allocation problem of pharmaceutical plant,” *Journal of Engineering Science and Technology*, vol. 8, no. 2, pp. 208 - 216, 2013.

[9] D. H. Chi and W. Kuo, “Optimal design for reliability and development cost,” *IEEE J. Selected Areas in Communications*, vol. 8, no. 2, pp. 276-281, 1990.

[10] K. Gopal, K. K. Aggarwal, and J. S. Gupta, "A new method for solving reliability optimization problem," *IEEE Trans. on Reliability*, vol. R-29, pp. 36-38, Jan. 1980.

[11] W. Kuo, H. H. Lin, Z. K. Xu, and W. X. Zhang, "Reliability optimization with the Lagrange multiplier and the branch-and-bound technique," *IEEE Transactions on Reliability*, vol. R-36, pp. 624-630, Dec. 1987.

[12] F. A. Tillman, C. L. Hwang, and W. Kuo, "Determining component reliability and redundancy for optimum system reliability," *IEEE Transactions on Reliability*, vol. R-26, pp. l62-165, August 1977.

[13] Z. Xu, W. Kuo, and H. H. Lin, "Optimization limits in improving system reliability," *IEEE Transactions on Reliability*, vol. 39, pp. 51-60, April 1990.

[14] D. W. Coit and A. Smith, “Reliability optimization of series-parallel systems using a genetic algorithm,” *IEEE Transactions on Reliability*, vol. 45, no. 2, pp. 254-260, June, 1996.

[15] M. Hikita, Y. Nakagawa, K. Nakashima, and H. Narihisa, “Reliability optimization of system by a surrogate-constraints algorithm,” *IEEE Transactions on Reliability*, vol. 41, no. 3, pp. 473-480, 1992.

[16] S. Kulturel-Konak, A. E. Smith, and D. W. Coit, “Efficiently solving the redundancy allocation problem using tabu search,” *IIE Transactions*, vol. 35, pp. 515-526, 2003.

[17] V. Ravi, B. S. N. Murty, and P. J. Reddy, “Nonequilibrium simulated annealing – algorithm applied to reliability optimization of complex systems,” *IEEE Transactions on Reliability*, vol. 46, no. 2, pp. 233-239, 1997.

[18] G. S. Liu, “A combination method for reliability-redundancy optimization,” *Engineering Optimization*, vol. 38, no. 4, 485-499, 2006.

[19] S. Martorell, A. Sanchez, S. Carlos, and V. Serradell, “Alternatives and chanllenges in optimizing industrial safety using genetic algorithms,” *Reliability Engineering and System Safety*, vol. 86, no. 1, pp. 25-38, 2004.

[20] M. Rani, S. P. Sharma, and H. Garg, “Availability redundancy allocation of washing unit in a paper mill utilizing uncertain data,” *Elixir Mechanical Engineering*, vol. 39 C, pp. 4627 – 4630, 2011.

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