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Maintenance resources optimization applied to a manufacturing system

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Abstract

This paper presents an availability optimization of an engineering system assembled in a series configuration, with redundancy of units and corrective maintenance resources as optimization parameters. The aim is to reach maximum availability, considering as constraints installation and corrective maintenance costs, weight and volume. The optimization method uses a Genetic Algorithm based on biological concepts of species evolution. It is a robust method, as it does not converge to a local optimum. It does not require the use of differential calculus, thus facilitating computational implementation. Results indicate that the methodology is suitable to solve a wide range of engineering design problems involving allocation of redundancies and maintenance resources.

Keywords: Genetic algorithms; Availability; Redundancy optimization; Maintenance resources

1. Introduction

There are two ways of increasing availability of an engineering system: by increasing the availability of each component, and by using redundant components.

Availability of a component can be increased by improving reliability and maintainability. If reliability is increased, the system can work for longer periods of time; if the maintenance program is improved, the system can be repaired quickly.

Reliability is the probability that a system or component will perform its design function successfully at an interval of time [0,*t*]. The reliability function can easily be obtained by failure time analysis of components or systems, and is complementary to the cumulative distribution function of failure times.

A statistical distribution is used to represent the curves of reliability and cumulative distribution functions. The exponential distribution is characterized by a constant failure rate in the time domain, which is suitable for components or systems with long life, such as electronic components. The Weibull distribution is suitable for fatigue failure and crack propagation, typical of mechanical systems. Other statistical distributions, such as normal, lognormal, Rayleigh and Gamma can be applied in failure analysis or maintenance analysis.

Maintenance analysis has repair time as the random variable. It results in another probabilistic parameter, maintainability, which is the ability to renew a system or component in a determined period of time, enabling it to continue performing its design functions.

The use of redundant components increases availability; however, it also increases design and maintenance costs, along with volume and weight. Therefore, optimization methods are necessary to determine how many redundancies to use in each component or subsystem, in order to maximize availability while observing constraints of cost, weight, and volume. The same can be said about the amount of maintenance resources to be allocated to each subsystem.

Traditional methods, such as the Lagrange Multiplier [1], are inefficient with problems involving large number of parameters, because they demand complex mathematics, making computational implementation difficult and lacking in flexibility. Besides, some search methods can converge only to local optima.

The Genetic Algorithm [2,3] is a search method based on concepts of biological evolution and reproduction. Previous works indicate that a Genetic Algorithm is recommended for problems involving complex mathematical expressions

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Nomenclature

A	availability	k	number of digits
b	a digit of a binary number	MTBF	mean time between fail
c	component cost	MTTR	mean time to repair
C	system cost	n	number of components
cm	component maintenance cost	q	probability of failure
CM	system maintenance cost	rec	amount of corrective maintenance resources
crec	corrective maintenance resources cost	v	component volume
d	dependability ratio	V	system volume
d_1	dependability ratio without application of maintenance resources	w	component weight
		W	system weight
e	minimum value of real or integer variable	x	real or integer variable
f	maximum value of real or integer variable	y	number of redundancies in a subsystem
i	index	λ	failure rate
I	impact of maintenance resources in the dependability ratio	μ	repair rate

in their modeling. An important advantage is that it does not require the use of differential calculus.

Genetic Algorithms have been used by several authors in reliability problems. Kumar et al. [4], Painton and Campbell [5], Rubinstein et al. [6], Levitin [7,8], Hsieh et al. [9], Coit and Smith [10] have chosen the Genetic Algorithm to solve redundancy allocation problems and other reliability optimization problems. Yang et al. [11] applied Genetic Algorithm in reliability allocation in nuclear power plants. A hybrid Genetic Algorithm was used by Taguchi, Yokota and Gen [12] in reliability optimal design. Castro and Cavalca [13] applied a number of optimization methods to redundancy allocation problems; in particular, the Genetic Algorithm and Lagrange Multipliers were compared.

Multi-state system reliability can also be optimized by Genetic Algorithm [14,15]. Multi-state system reliability is defined as the ability to maintain a specific performance level.

Gen and Kin [16] made a study of the state-of-art of reliability design based on Genetic Algorithm; their paper includes many references to applications of this method in reliability optimization.

Safety system can be also optimized by the application of Genetic Algorithm technique. Busacca et al. [17] proposed a multi-objective Genetic Algorithm optimization applied to safety system.

Levitin [18] proposed a multi-level protection in series-parallel systems and used Genetic Algorithm to reach an optimal configuration of the protection system. An algorithm for solving the protection cost minimization problem subject to survivability constraint is presented in the paper. A Genetic Algorithm is used in this minimization.

Genetic Algorithm was also used as an optimization tool in preventive maintenance applied to mechanical components [19].

Levitin and Lisnianski [20] proposed an optimization procedure that minimizes the total system cost, considering failure and repair time. Replacement frequency, preventive and corrective maintenance actions are taken into account.

Castro and Cavalca [21] developed an availability optimization, with redundancy allocation and team maintenance action as parameters.

Elegbede and Adjallah [22] developed a methodology based on Genetic Algorithms and experiments plan to optimize the availability and the cost of reparable parallel-series systems.

The aim of this paper is to present a procedure of availability optimization. Availability has a wider scope than reliability, as it takes into account maintenance time analysis in addition to failure time analysis. The procedure is based on Genetic Algorithm, which is suitable for problems with this degree of complexity. Only corrective maintenance is contemplated. The variable maintenance resources represents all maintenance actions—replacement, repair, maintenance team action, and corrective maintenance. This variable can be expressed as percentage of resources, which in turn can be measured by their cost.

2. Availability optimization problem

There are two approaches to increasing system availability. The first is to increase the availability of each component through increase of failure time and/or decrease of repair time. In this case, it is important to place the availability and dependability analysis of a product within the decision process on economic and technical feasibility. The second approach is to introduce redundant components or subsystems.

Both bring increased costs to the system; redundant components increase volume and weight as well. Therefore, optimization methods are necessary to keep costs, volume and weight within acceptable limits, while achieving high availability levels.

2.1. Availability analysis

Availability A, or the probability of a system's successful operation in a determined period of time, can be calculated by the ratio between life time and total time between failures of the equipment.

$$A = \frac{\text{life time}}{\text{total time}} = \frac{\text{life time}}{\text{life time} + \text{repair time}} \tag{1}$$

Life time is represented by mean time between failure (MTBF), which can be obtained from failure analysis. Mean time to repair (MTTR) can be evaluated from maintenance analysis and represents the repair time as follows:

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \tag{2}$$

In availability analysis, an exponential distribution is initially assumed to be representative for the reliability and maintainability statistical models. The MTBF is the inverse of the failure rate; in this case they are constant:

$$\text{MTBF} = \frac{1}{\lambda} \tag{3}$$

Similarly, the MTTR is the inverse of the repair rate:

$$\text{MTTR} = \frac{1}{\mu} \tag{4}$$

Availability A can be expressed by the equation below:

$$A = \frac{\mu}{\mu + \lambda} \tag{5}$$

When the reliability and maintainability are represented by exponential distributions, a linear relation between MTBF and MTTR is established for a constant value of availability (Ertas [23], 1993):

$$\text{MTTR} = \left(\frac{1-A}{A}\right)\text{MTBF} \tag{6}$$

2.2. Dependability analysis

Dependability is another important design parameter (Wohl [24], 1996), because it provides a single measurement of the performance conditions by combining failure and repair rates, associated to reliability and maintainability respectively. This concept is defined as the probability that a component does not fail, or does fail and can be repaired in an acceptable period of time. An important characteristic of dependability is that it allows simultaneous analysis of costs, reliability and maintainability.

Failure rate and repair rate are assumed as constant values for the dependability analysis, characterizing exponential distributions in both cases.

The dependability ratio is the ratio between repair rate μ and failure rate λ.

$$d = \frac{\mu}{\lambda} = \frac{\text{MTBF}}{\text{MTTR}} \tag{7}$$

The lower the value of dependability ratio, the greater the need for maintenance in the system. Cost considerations will determine whether the proposed equipment is economically and technically viable.

The relationship between availability and dependability ratio can be obtained from the combination

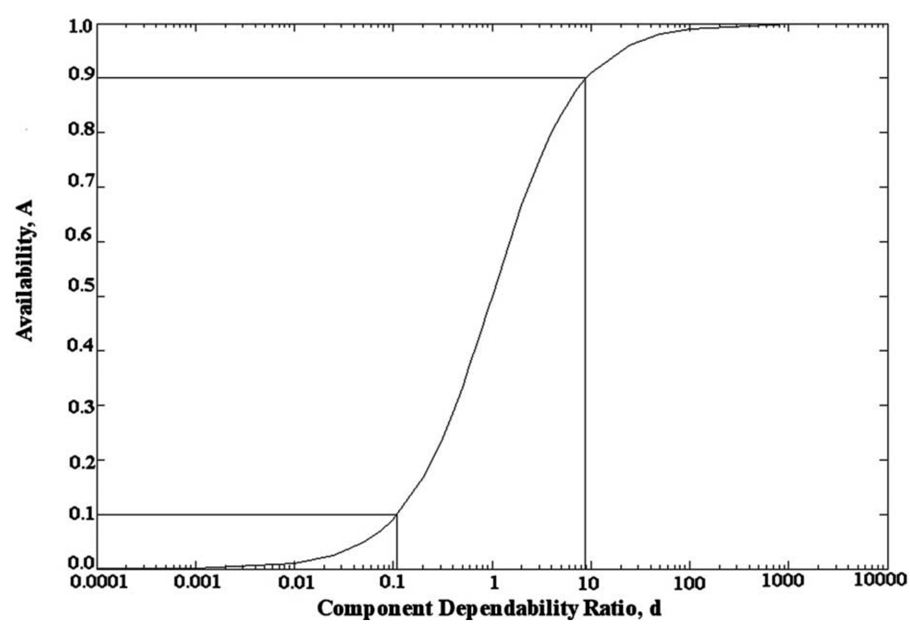

Fig. 1. Relation between availability and dependability.

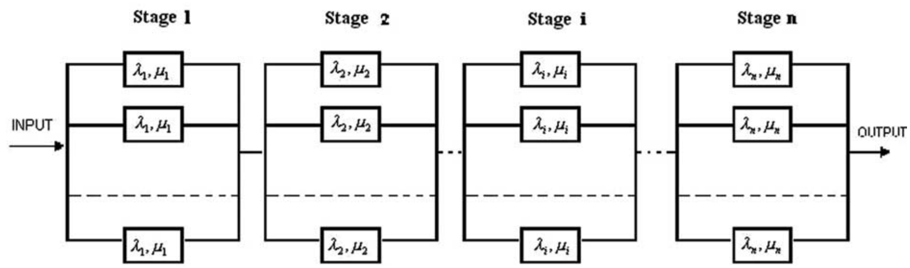

Fig. 2. Redundant system.

of Eqs. (5) and (7):

$$A = \frac{\mu}{\mu + \lambda} = \frac{\mu/\lambda}{1 + \mu/\lambda} = \frac{d}{1 + d} \tag{8}$$

Fig. 1 shows a significant increase in the dependability ratio if the availability value is above 0.9, and a corresponding decrease if the availability value is less than 0.1 (Ertas [23], 1993). These effects mean great sensitivity of the dependability ratio in these regions. In the region where the availability is higher than 0.9, an extreme increase of maintenance is necessary for a small increase of the availability value, which generates high costs. Therefore, the region where the availability varies from 0.1 to 0.9 is suggested as economically and technically viable.

3. Problem formulation

A redundant system can be represented by a series of parallel systems, as observed in Fig. 2.

The availability of this system can be obtained by the Eq. (9), where A_i is the availability of the components of subsystem i, and y_i is the number of redundant components in subsystem i.

$$A_S = \prod_{i=1}^{n} [1 - (1 - A_i)^{y_i}] \tag{9}$$

Considering an exponential distribution of time between failures, the availability of each component A_i can be represented by Eq. (8). Replacing A_i in Eq. (9) by Eq. (8), the availability as function of the dependability ratio of each subsystem is obtained:

$$A_S = \prod_{i=1}^{n} \left[1 - \left(\frac{1}{1 + d_i}\right)^{y_i}\right] \tag{10}$$

The total cost of the system can be obtained by the sum of the product of each component cost by the number of components in that stage, as shown in Eq. (11):

$$C \geq \sum_{i=1}^{n} c_i y_i \tag{11}$$

System weight and volume can be similarly calculated:

$$W \geq \sum_{i=1}^{n} w_i y_i \tag{12}$$

$$V \geq \sum_{i=1}^{n} v_i y_i \tag{13}$$

The corrective maintenance cost of the system for a fixed time T can be obtained by Eq. (14):

$$\mathrm{CM}(T) \geq \sum_{i=1}^{n} \mathrm{rec}_i\, \mathrm{crec}_i + \sum_{i=1}^{n} q_i(T) y_i \mathrm{cm}_i \tag{14}$$

where rec_i is the amount of corrective maintenance resources, y_i is the number of components in each stage, crec_i is the corrective maintenance resources cost, cm_i is the corrective maintenance cost of the subsystem i, and $q_i(T)$ is the failure probability of a component in subsystem i, which is given by Eq. (15) for an exponential distribution.

$$q_i(T) = 1 - e^{-\lambda_i T} \tag{15}$$

By corrective maintenance resources we mean the complete maintenance support: maintenance team, equipments, financial resources and other means to get better MTTR.

In order to describe the influence of corrective maintenance resources on availability value, the impact index I is introduced, defined as the amount by which the MTTR decreases if 100% of corrective maintenance resources are applied to a specific component. The impact index expresses the dependability ratio sensitivity to the corrective maintenance resources on a specific component. The dependability ratio d_i of a component at the subsystem i is given by:

$$d_i = [(I - 1)\mathrm{rec}_i + 1] d_{1i} \tag{16}$$

where d_{1i} is the dependability ratio when no maintenance resources are applied.

For example, if the dependability ratio of a component d_{1i} without application of maintenance resources is 10, and the impact in the MTTR is equal to 3.5, an application of 100% of maintenance resources in this component will change the dependability ratio to 35. Fig. 3 shows the variation of the dependability ratio with the variation of

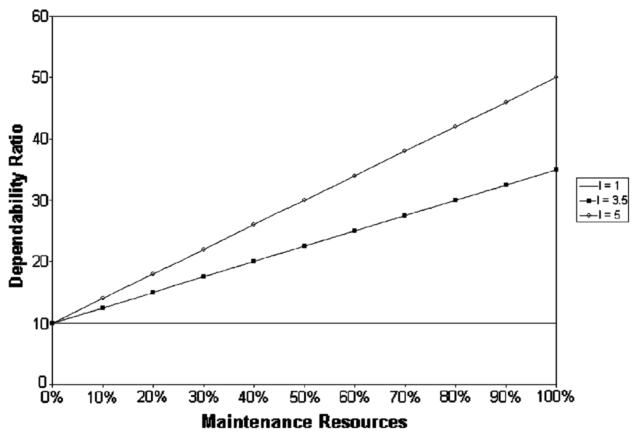

Fig. 3. Influence of maintenance resources in dependability ratio.

maintenance resources for three different values of the impact index I.

The first approach in Eq. (16) considers the maintenance resources directly related to the dependability ratio, since the maintainability model can be considered an exponential distribution. In this case, the increase of maintenance is directly proportional to the repair rate μ.

Therefore, the availability of a redundant system, as a function of the number of redundant components and corrective maintenance resources, is given by:

$$A_S = \prod_{i=1}^{n} \left[1 - \left(\frac{1}{1 + [(I-1)\text{rec}_i + 1] d_{1i}} \right)^{y_i} \right] \tag{17}$$

The objective of the optimization process is to find the number of components and the amount of corrective maintenance resources that maximize the system availability subject to the following constraints:

1. Design cost (Eq. (11));
2. System weight (Eq. (12));
3. System volume (Eq. (13));
4. Corrective maintenance cost (Eq. (14)).

4. Genetic Algorithm

The search space, determined by the restrictive conditions, and the objective function, are the only parameters necessary for some search algorithms such as the Evolution Strategy (Michalevicz [25], 1996) and Genetic Algorithm (Mitchell [26], 1996).

A Genetic Algorithm is a search strategy that employs random choice to guide a highly exploitative search, striking a balance between exploration of the feasible domain and exploitation of 'good' solutions (Holland [3], 1992). This strategy is analogous to biological evolution.

Different to the classic optimization algorithms, the Genetic Algorithm (GA) does not work with only one point in the search space, but with a group of points simultaneously. The number of points is previously determined by a parameter known as population size.

The GA does not need to use differential calculus. It can be considered a robust method, because it is not influenced by local maximum or minimum, discontinuity or noise in the objective function.

GA operators are the instruments used by the algorithm to reach the optimum point of the function. Four operators, described by Goldberg [27], were developed in the computer program: mutation, crossover, inversion and selection.

Binary numbers traditionally represent a Genetic Algorithm individual. They allow to work with integer and real numbers together in the same optimization process; decoding transforms this variable in binary numbers. However, it is possible to use different kinds of codes, such as genes that are represented by integer and real numbers. This work considers binary numbers, due to the problem of working with real and integer simultaneously.

The GA applied to the reliability optimization had a considerable increase in the 1980s and 1990s, which is shown by the evaluation of Kuo and Prasad [28]. Some other examples of these applications are shown in the works [4–22]. In the work of Hisieh, Chen, Bricker [10], the redundant number and the reliability of the components of each subsystem (stage) are optimized for three different systems, which is very similar to the proposed problem, where the availability of the components of each subsystem and the number of redundancies are optimized.

4.1. Genetic Algorithm steps

The Genetic Algorithm steps are described below.

1. Form an initial generation;
2. Make generation = 1;

Table 1
System data

Subsystem	MTBF	MTTR	Design cost	Weight	Volume	Corrective maintenance cost	Corrective maintenance resources cost
1	500	50	50	50	55	60	7
2	550	35	55	45	50	40	3
3	600	40	55	80	70	45	4
4	750	30	40	35	35	30	2
5	500	30	60	70	65	50	5

Table 2
System parameters

	Design cost	Weight	Volume	Maintenance cost	Avail-ability
Maximum allowed values	$1000	1000	1000	$500	XXX
Values obtained for optimum availability	$930	995	980	$499.40	99.99%

3. Select 50% of the best individuals (closest to the optimum point);
4. Form new individuals using mutation, crossover and inversion, until the population size is reached;
5. Make generation = generation + 1;
6. If generation is equal to the total number of generations then stop, otherwise go to step 3.

4.2. Genetic Algorithm parameters

There are five GA parameters that influence the process time and the objective function convergence. As the GA is a search algorithm, the increase of the operation time brings about better objective function convergence.

In order to study the influence of the parameters involved in process time and convergence of the optimization process, the problem on the Section 7 (Tables 1 and 2) was simulated, varying the GA parameters separately, using the values given in Section 7. The GA parameters are:

- Total number of generations: this is the stop condition of the Genetic Algorithm. Increase of the total number of generations results in a linear increase of the process time;
- Population size: the number of individuals, represented by their chromosomes, in each generation. Increase of this parameter increases the probability of objective function convergence. However, the process time increases substantially, as seen in Fig. 4;
- Mutation probability: the probability of mutation occurrence. Normally, the increase of mutation probability leads to poorer values of availability (Fig. 5). However, mutation is useful because by provides diversity in the population it helps avoid convergence to local optima.
- Crossover probability: the probability of the crossover occurrence. The increase of crossover probability does not significantly influence the availability values (Fig. 6).
- Inversion probability: the probability of the inversion occurrence. As the probability of inversion increases, the availability of the system reaches better values, as shown in Fig. 7.

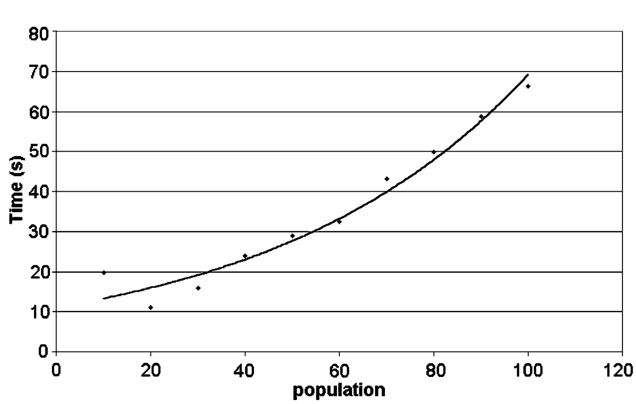

Fig. 4. Population influence on process time.

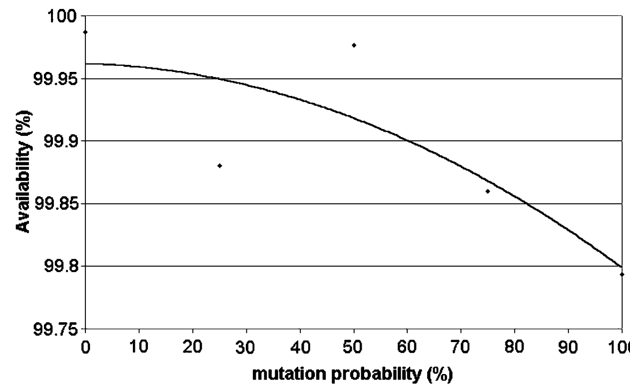

Fig. 5. Mutation influence on the availability value.

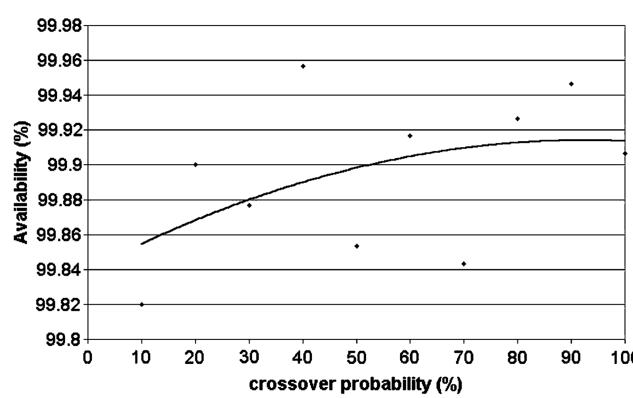

Fig. 6. Crossover influence on the availability value.

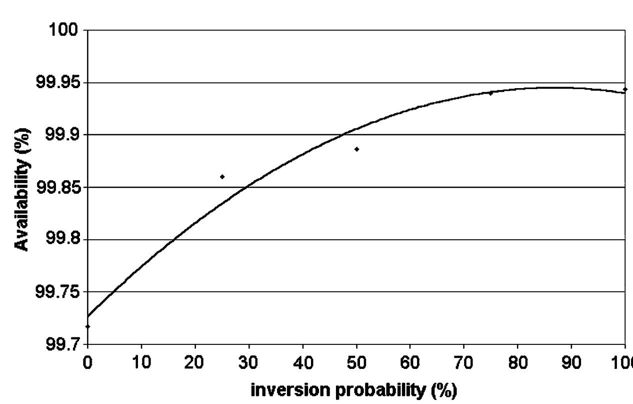

Fig. 7. Inversion influence on the availability value.

Table 3
Optimum solution

Subsystem	Redundancies	Corrective maintenance resources (% of all available resources)
1	4	9
2	3	37
3	3	37
4	4	6
5	4	6

5. Numerical simulation

In order to analyze the results of the proposed problem, a system with five subsystems was chosen. The MTBF, MTTR, weight and volume of each component are in Table 1. The design, maintenance and maintenance resources costs are also shown in Table 1.

The constraints considered in this problem are maximum design and maintenance costs, weight of the system and volume of the system. Table 2 shows the constraint values for the problem (maximum allowed values).

The Genetic Algorithm parameters for this simulation are:

- Total number of generations: 5000;
- Population size: 50;
- Probability of mutation: 10%;
- Probability of crossover: 60%;
- Probability of inversion: 60%.

In order to get the corrective maintenance cost, the value of the cumulative failure distribution in the time domain is necessary. Time T is set to 100 time units (the same unit as MTBF and MTTR). The impact variable I is set to 3.5. The optimum solution for the simulation is shown in Table 3 (in terms of percentiles of all available maintenance resources), and the system characteristics for the optimum solution are given in Table 2 (values obtained for optimum availability):

6. Conclusions

The Genetic Algorithm efficiently solves complex problems of availability optimization.

In our example, several solutions were found with a final availability above 99.99%, which is considered satisfactory, given the complexity of the data.

It is important to choose adequate values for the GA parameters–total number of generations, population size, and probability of mutation, crossover and inversion. Guidelines are suggested for that choice.

This work regards cost as a constraint, rather than an objective function to be optimized. Therefore, a future work is planned to develop a GA-based multi-objective optimization procedure to find maximum availability and minimum cost simultaneously.

The main contribution of this work is the availability optimization taking into account redundant components and maintenance resources, applying Genetic Algorithm as a robust search method.

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