Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.17.(2) 2025,pp.Math 153–158

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Enhancing ROSS Network Reliability Through Evolutionary Optimization Techniques

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ARTICLE INFO

Article history:

Received: 07/05/2025

Rrevised form: 11/06/2025

Accepted : 19/06/2025

Available online: 30/06/2025

Keywords: Genetic algorithms, particle swarm optimization, evolutionary algorithms, reliability allocation, reliability optimization.

ABSTRACT

This research aims to develop computational models to improve resource allocation and increase the reliability of a ROSS (Relay-based Opportunistic Spectrum Sharing) network. The focus is on using two intelligent algorithms, the genetic algorithm (GA) and the particle swarm algorithm (PSO), to achieve efficient optimization. A mathematical model is constructed that determines relay locations and spectrum sharing methods to reduce the probability of failure and increase reliability. The algorithms are based on evaluating an objective function that takes into account spectrum efficiency, network delay, and connection reliability. The results show that using GA and PSO leads to significant performance improvements compared to traditional methods. The impact of the number of relays and secondary users on allocation efficiency is also analyzed. Combining the two algorithms contributes to accelerating the achievement of near-optimal solutions. Finally, the proposed model provides a general framework that can be applied to various types of dynamic spectrum networks.

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https://doi.org/10.29304/jqcsm.2025.17.22221

1. Introduction

This system was initially studied by scholars Aggarwal [2], Hatem, and Imad [3-10] because to its technological significance for the engineering of space industries. Subsequently, this system was examined since it was believed to be a complex network, which supported determining the reliability of each network path. Furthermore, Saad et al. [11,12.13] have focused on this approach while examining the issue of increasing dependability. Ideal reliability assignments were also discussed in this essay [14].An evolutionary technique like "Genetic algorithm (GA) and Particle Swarm Optimization (PSO)" can be used to tackle the majority of optimization problems. In the 1970s, at the University of Michigan, the idea of genetic analysis emerged [15,16]. Because genetic algorithms employ recurrent processes to find the desired alternatives, they are categorized as global search heuristics. GA typically provides

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simple answers to a variety of issues. GA exploits several biological processes, including reproduction, mutation, crossover or recombination, and selection. Because GA can handle both discrete and continuous variables, it can be utilized to tackle complicated optimization problems. Many industries, including data processing, energy systems, timing, configuration, and optimization, have embraced GA. A novel distributed paradigm like Swarm Intelligence (SI) can effectively address the optimization difficulties. According to two different input sources, each particle in PSO represents a potential alternative that is updated during the decision-making process [8,9]. One's personal experiences provide the basis of the first (cognitive behavior), whereas peer experiences form the basis of the second (social conduct). Put another way, after making a decision, people often think that the options offered by their neighbors are too good and that the trend toward the best option is positive. Even though PSO has proven its ability to tackle a wide range of optimization problems in several methods, it still takes a long time to solve complex engineering problems [17-25]. In an effort to determine which algorithm is more potent, this study contrasts and analyzes PSO and GA.

1. ROSS optimization and reliability allocation

Examine a spaceship ROSS made up of reliability-related components. We utilize the following notes:

$C_i(R_i)$ = element i cost for each $0 \le R_i \le 1$ equal component of reliability i ,where R_s is reliability of the system and the formula:

$$C(R_1, \dots, R_n) = \sum_{i=1}^{n} a_i c_i (R_i) \tag{1}$$

is the entire system cost, where a_i exceeds 0; RG stands for the system reliability objective. Because of the system's modular design and the distinct roles played by each component, there are numerous alternative outcomes. A range of system components, each with varying levels of reliability, provide us with the same capacity. The ultimate objective is the system's capacity to appropriately distribute resources to all or specific components. Nonlinear programming requires problems [9, 16, 17]. The limitation has a function and comes with costs that may be studied, even though it is not linear.

$$\textbf{Minimized } C(R_i, \dots, R_i) = \sum_{i=1}^{n} a_i C_i(R_i) \;\; for\ all\ \ a_i > 0, \tag{2}$$

Subject to:

$$R_s \ge R_G$$

$$0 \le R_i \le 1 \quad for\ all\ \ i = 1, \dots, n$$

Assume that $C_i(R_i)$ meets certain requirements and that the partial cost function is fair [12]. Positive, differentiated functions that increase from $\left[\Longrightarrow \frac{dC_i}{dR_i} \ge 0\right]$.

The function of component costs for the Euclidean convexity $C_i(R_i)$ is comparable to the fact that its derivatives $\frac{dC_i}{dR_i}$ are monotonically increased, i, e. $\frac{d^2C_i}{dR_i^2} \ge 0$.

Reaching an all-out framework cost base is the aim of the previous plan, and the system reliability constraint is decreased subject to R_G [12].

2. A model of exponential viability based

Assume that $R_{i,max}$ is maximum reliability and $0 < f_j < 1$ is the a feasibility factor [12] , and $R_{j,min}$ is minimum reliability.

$$C_j(R_j) = \exp[(1 - f_j)\frac{R_j - R_{j,min}}{R_{j,max} - R_j}] \tag{3}$$

$R_{j,\ min} \le R_j \le R_{j,max}$ $, j = 1,2, \dots, m.$

The optimization problem becomes

$$Minimize\ C\left(R_j,\dots,R_j\right)=\sum_{j=1}^{m} a_j\ \exp[(1-f_j)\frac{R_j-R_{j,min}}{R_{j,max}-R_j}],$$

$$in\ which\quad j=1,2,\dots,m.$$

Applied in:

$$R_s \geq R_G$$

$$R_{j,min} \leq R_j \leq R_{j,max} \quad ,j=1,\dots,m\,.$$

3. GA method

To find the optimum options for the genetic algorithm, a list of potential solutions—referred to as people, animals, or phenotypes—to the optimization issue is produced. Substitutions are typically represented as strings of 0 and 1 in a binary system, although alternative encodings can also be done [13]. Each candidate solution has a set of characteristics (its chromosomes or genetic makeup) that it can be tweaked and modified. A population is referred to as a generation at each iteration of the iterative process, which typically starts with a randomly formed group of individuals Every generation evaluates the fitness of each population member; relevance is often the importance of the goal function of resolving an optimization issue. The fittest people in the existing civilization are randomly selected, and their genomes are edited (potentially reassembled and randomly altered) to create a new generation. The new generation of candidate alternatives is used in the algorithm's subsequent iteration. The algorithm normally comes to an end when either the maximum number of generations is achieved or the population has gained the required level of fitness.

4. Implementation of GA

After every iteration, GA generates the most fit members using a predetermined fitness feature Fig.2. The GA basic flow chart is given at the front.

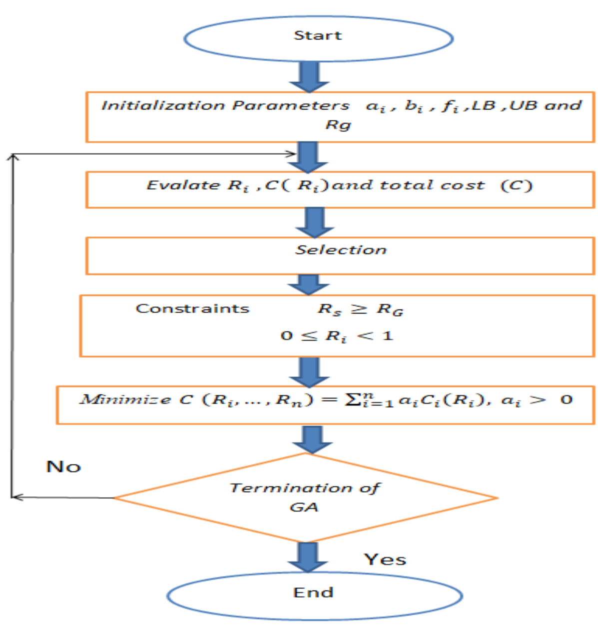

Figure 2 The Genetic Algorithm Flow Chart

5. PSO method

A group of individuals with the right number of characteristics or values to add to a swarm problem space is called a swarm of particles [17, 14]. People create communities so that they can share information. The collection of points surrounding a specific location, all of which are within a given radius of the stated point," is how mathematics defines a neighborhood. The bit string "01110" has five bits, for example. The bit that exits the supplied point (middle bit) is number three. The entire bit string will fit inside a size 3 neighborhood, along with two on the left and two on the right. Despite having structures that differ significantly from the topologies of the ANN, these neighborhoods can have several topologies, just like the ANN. Spherical or star-shaped topologies are common in particle swarm locales.

6. Implementation of PSO

Random number generation is necessary for the evolutionary algorithm PSO. The quality and quantity of the produced statistics impact the output of the PSO algorithm. The first iteration is spread out throughout the whole search space. The basic PSO implementation is shown in Fig. 2.

7. Problem description

The same key, accreditation, accounts for 90% of a spacecraft's ROSS, as depicted in Figure(3), at any one time. At a specified time, 90% system reliability is the target. The supplied system's polynomial reliability was verified by applying the probability theorem approach.

$$R_S = R_1 R_2 R_5 R_7 + R_1 R_3 R_5 R_7 + R_1 R_3 R_6 R_7 + R_1 R_4 R_6 R_7 + R_1 R_2 R_3 R_5 R_7 \\ - R_1 R_3 R_4 R_6 R_7 - R_1 R_3 R_5 R_6 R_7 - R_1 R_2 R_4 R_5 R_6 R_7 - R_1 R_2 R_3 R_4 R_5 R_6 R_7$$

The problem of optimization turns into

$$Minimize \quad C(R_j, \dots, R_m) = \sum_{j=1}^{m} a_j \exp[(1 - f_j) \frac{R_j - R_{j,min}}{R_{j,max} - R_j}], \tag{4}$$

$$in\ which\ j = 1,2, \dots, m.$$

Applied in:

$$R_s \geq R_G$$

$$R_{j,\ min} \leq R_j \leq R_{j,max}, \ j = 1, \dots, m.$$

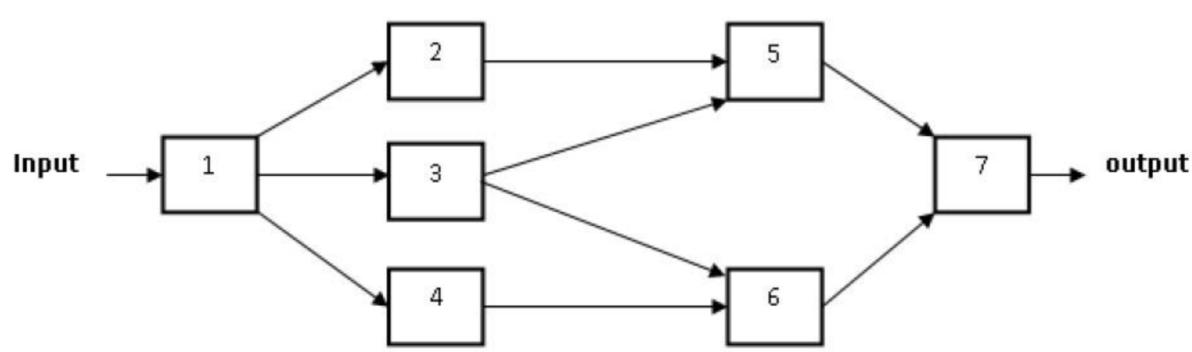

Figure 3. a spacecraft's ROSS.

8. Optimal of reliability allocation

The reliability allocation findings from applying the GA to the system were published in [19]. Additionally, when using the PSO algorithm, the outcomes were in the system's reliability allocation, as indicated in the accompanying table.

Components	GA	PSO
R_1	00.98	00.97
R_2	00.91	00.9
R_3	00.92	00.66
R_4	00.91	00.9
R_5	00.93	00.7
R_6	00.93	00.7
R_7	00.98	00.97

Table 1. Particle optimization flow chart with an applied cost function for the best dependability allocation using PSO and GA.

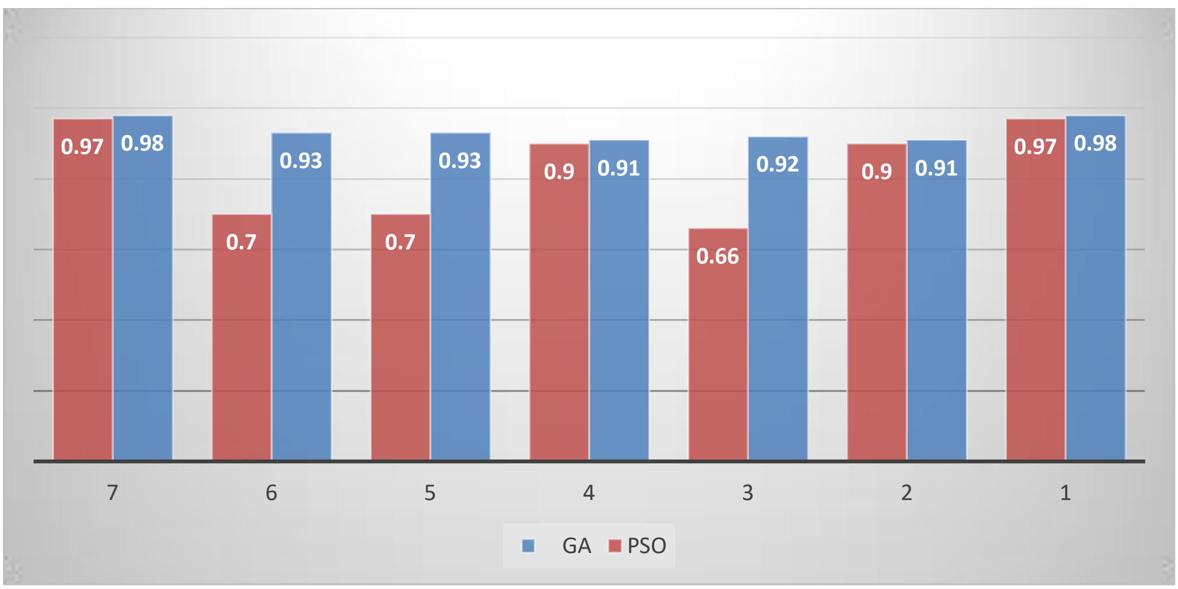

Figure 4. Using a feasibility factor model and PSO and GA, reliability allocation is carried out.

9. Discuss the results

The results of the genetic algorithm's reliability allocation were the best way to distribute each system component based on where it was located within the system. The R1 value was equal to the R7 value, which was 0.98; the R5 value was equal to the R6 value, which was 0.93; and the R3 value was equal to 0.92. Consequently, R2 equals R4 and its value (0.91).The allocation of the particle swarm optimization produced the following results: R1 and R7 component values were equal (0.97), R2 and R4 component values were equal (0.9), R3 component values were equal (0.66), and R5 and R6 component values were also equal (0.7).

Conclusion

In this research, effective computational models are presented to optimize resource allocation and enhance the reliability of the ROSS network using GA and PSO algorithms. The results demonstrate that both algorithms are capable of improving network performance in terms of reducing failure rates and increasing spectrum utilization efficiency. The combination of GA and PSO also proved effective in accelerating the search for near-optimal solutions and reducing computational time. The proposed model is flexible and adaptable to changes in the number of nodes, iterations, or users, making it a powerful tool for dynamic network planning. Future research recommends expanding the study to include more complex realistic scenarios, taking into account changing channel conditions and environmental factors.

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