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Najat Abbas Abd Ali Al-Taie
Ministry of Education
Directorate of Education
Babylon, Iraq

Rusul Mohammed Hussein AL-Shmary
Ministry of Education
Directorate of Education
Babylon, Iraq

Corresponding Author:
Najat Abbas Abd Ali Al-Taie
Ministry of Education
Directorate of Education
Babylon, Iraq

Particle Swarm optimization algorithm-based optimization and allocation method for improving ARPANET network reliability

Najat Abbas Abd Ali Al-Taie and Rusul Mohammed Hussein AL-Shmary

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Abstract

In this paper, we study the expansion of complex systems industry, communication devices, and networks, and the complexity of communication infrastructure. For ARPA networks such as ARPANET, providing integrated broadband service is very necessary. The modern technology used in ARPANET and the changing traffic patterns have attracted much scientific research attention to the design of network topology. Most researchers in topology design have proposed techniques based on expensive exchange-based devices. We have presented a realistic model of ARPA network in this study. The structure of ARPA network includes network optimization. We proposed the application of Particle Swarm Optimization (PSO) to optimize ARPA network, and we also estimated the appropriate distribution of each system component using the logarithmic model cost function. The results of the study are shown by the (PSO) algorithm, and it has good optimization and allocation results.

Keywords: Reliability allocation, reliability optimization, and enhanced particle swarm optimization (PSO)

Introduction

This study investigated the most efficient methods for ensuring the reliability of the Advanced Research Projects Agency (ARPA) network (Abuali *et al.*, 1994) ^[1]. The system's reliability was measured by calculating the shortest paths within the connectivity matrices. According to H. Sulaiman *et al.* (2023b) ^[4], "all paths are determined using Boolean algebra, followed by eliminating nodes to create minimal paths" (Hasslinger *et al.*, 2005) ^[11]. The reliability function was analyzed to understand the security level of the implemented advanced system. The paper also addressed the mathematical challenge of optimizing reliability while considering the network's operational history. Reliability requirements for any component of a complex system are determined by its importance and the optimization of its location. The primary objectives are to reduce overall costs while enhancing the system's lifespan and reliability (Abuali *et al.*, 1994; Elbaum & Sidi, 1996) ^[1, 7]. Some components may require extensive customization, based on where they are in the framework, to increase overall dependability. Engineers face various challenges when optimizing mechanical and electrical systems (H Sulaiman *et al.*, 2023a; Kirkpatrick, 1984) ^[3, 14]. The aim is to enhance the distribution and reliability of complex systems while minimizing costs, which can be represented by factors such as weight, volume, or other parameters. One of the key factors in determining a component's reliability is ensuring that the model is cost-based, which validates the input component. The recommended cost factor settings can be modified (Abed *et al.*, 2019) ^[2], allowing technologists to evaluate how the scheme changes over time and determine whether each component meets basic reliability standards. Additionally, the model must consider the accuracy of the input system analysis. In larger systems, certain scenarios can pose significant challenges, leading to an increased workload, particularly when basic systems are involved. The results were obtained using the atom swarm optimization (PSO) algorithm, which assistances solve improvement issues with intricate systems. A logarithmic model was used to calculate costs.

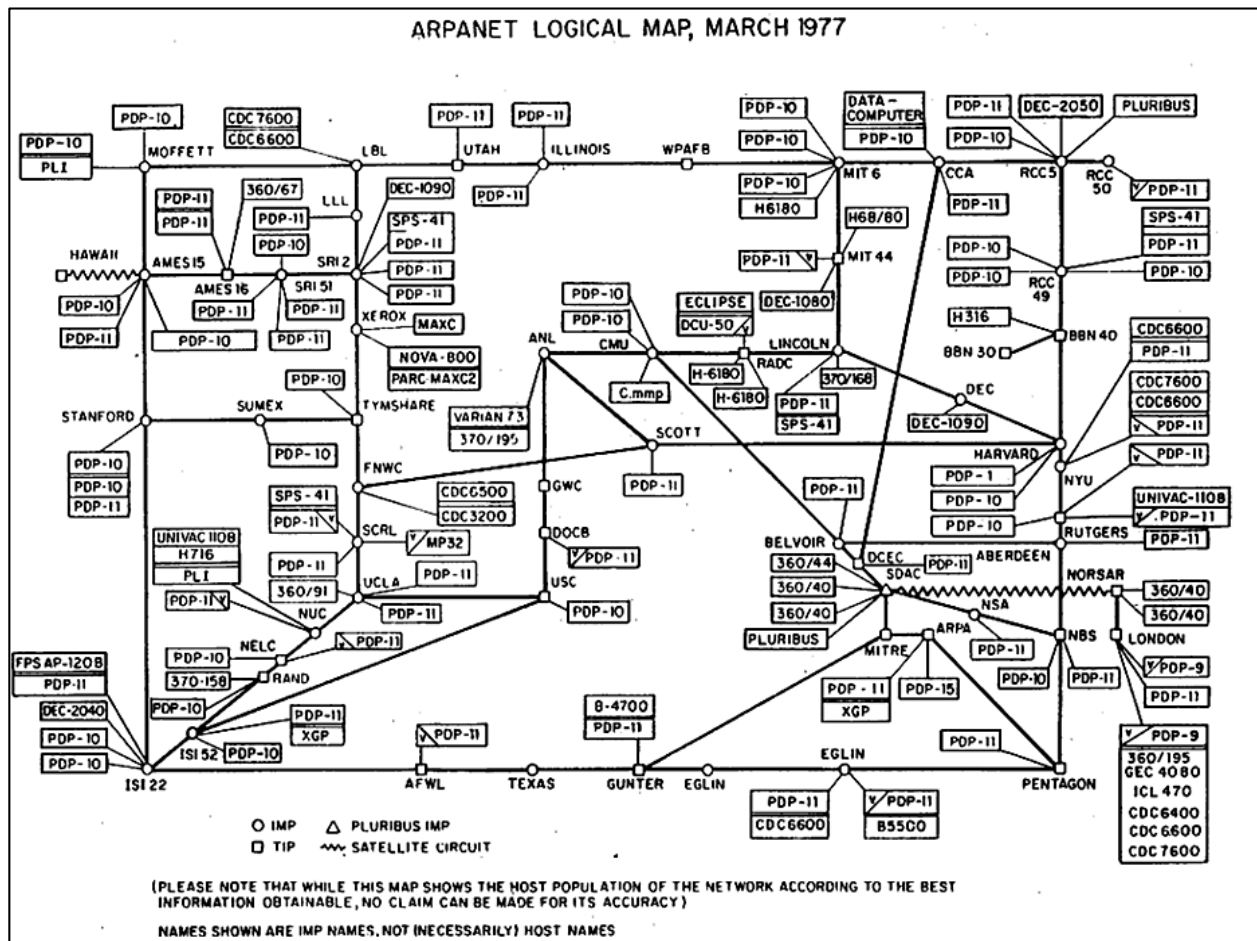


Fig 1: ARPA network, schematic map.

Network optimization and (ARPA) reliability allocation

Deliberate a (ARPA) system anywhere machineries relevant to reliability are provided [1, 5]. The succeeding proceedings are employed by us:

$$C_i(R_i) = (\text{cost of section});$$

$$0 \leq R_i \leq 1 = (\text{dependability as an section});$$

$$R_s = (\text{reliability of the scheme});$$

$$C(R_1, \dots, R_n) = \sum_{i=1}^n a_i c_i(R_i) \quad (\text{is the overall cost of the system, where } a_i > 0);$$

RG attitudes for "systems reliability" goal.

The end goal is its capacity to assign resources to all or specific components in a proper way. Nonlinear developing necessitates problems [2, 3, 16], and the limit is still essential even if it is not linear, and it may be examined in terms of costs. Its modular architecture and the different roles that each component plays lead to a number of possible outcomes. Our power is the sum of the numerous distinct systems parts, each of that's has a distinct amount of dependability.

$$\text{Minimize } C(R_1, \dots, R_i) = \sum_{i=1}^n a_i \ln \left(\frac{1}{1-R_i} \right),$$

"Subject to:

$$R_s \geq R_G$$

$$0 \leq R_i < 1, \text{ in which } i = 1, \dots, n \quad (1)$$

Assume that $[C_i(R_i)]$ satisfies specific criteria and that the part cost purpose is equitable. Differentiated, optimistic purposes that rise from $\left[\Rightarrow \frac{dC_i}{dR_i} \geq 0 \right]$. Are known by the name [8].

Its derivatives are identical to the Euclidean convexity $[C_i(R_i)]$ part costs function,

$$\frac{dC_i}{dR_i}, \text{ are monotonically raised, i.e., } \left[\frac{d^2 C_i}{dR_i^2} \geq 0 \right].$$

"The previous approach reduces the constraint on system reliability by obtaining an all-out framework cost foundation, subject to RG" [12].

Optimization of Particle Swarms (PSO)

The presence of the distinctive ARPA gene highlights the use of Particle Swarm Optimization (PSO) as an unconventional method for network optimization [3, 4]. PSO operates through well-defined steps, which include encoding, initialization, evaluation, cloning, crossover, mutation, and termination [6, 7].

- **Encoding:** In this stage, the mutable quantity in the optimization delinquent are encoded as genes. A set of leading chromosomes is randomly selected from a pool of chromosomes. The population consists of these randomly chosen chromosomes, with the size of the population determined by the arbitrary number of chromosomes.
- **Evaluation:** Reproduction aims to minimize the number of harmful chromosomes in the offspring while maximizing beneficial ones. Every chromosome in the

population is given a fitness score determined by the gene order; the fitness value indicates the chance of a chromosome's survival when the gene order changes. Replicated mitochondria are assessed based on fitness indicators derived from various genetic combos.

- **Crossover:** Maternal and paternal chromosomes are switched during this stage. To serve as paternal chromosomes, two chromosomes are chosen at random from the population. At crossover points which are selected so that there are fewer crossover spots than there are genes on the chromosome genes are switched. Two new chromosomes are then created by combining the genes from both parent chromosomes. This step focuses on where the crossing points intersect.
- **Mutation:** During mutation, a new chromosome is created that differs from the existing population. A random selection process is used to select a modified chromosome, and among its genes, one distorted genetic factor is randomly selected and its worth is changed. This process is repeated until the population's average fitness level stabilizes.

Decoding the best chromosome in the neighborhood is the last step in resolving the optimization problem. In a previous study, PSO was partially applied to construct an ARPA network to improve bandwidth [13, 14]. However, the overall ARPA network planning problem dismissed meta-inference. While particle swarm optimization relies on genetic evolution, it disregards the knowledge generation process inherent to cultural progress. As stated by renowned evolutionary biologist Richard Dawkins, "Cultural transmission is analogous to genetic transmission in that, although basically conservative, it can give rise to a form of evolution".

One drawback of PSO-based systems is their rapid convergence on local preferences. The enhanced version of PSO, however, provides a solution to this issue by employing local search strategies to refine outcomes. In this experiment, the particle swarm optimization algorithm was used as the local search method, aiming to consistently improve the current fitness level. The algorithm continues searching for improved states, halting only when a more optimal state is found.

Use in a complex scheme

To facilitate estimations, we wish to set up the "ARPA" network so that each of its parts are connected in series or parallel. The following describes the dependability of a series network with n components and a parallel network:

$$R_s = \prod_{i=1}^n R_i \quad (2)$$

$$R_s = 1 - \prod_{i=1}^n (1 - R_i) \quad (3)$$

In this case, $[R_i]$ means the module i 's reliability, while $[R_N]$ signifies the ARPA net's dependability [6, 8].

Equations (1) and (2) will be used to comparison each composite net's dependability with the providing p smallest paths.

$$R_s = 1 - \prod_{z=1}^p (1 - \prod_{j=\alpha}^{\omega} R_j) \quad (4)$$

In this case, " α " represents the index of the first module of a minimal path, while " ω " represents the index of the last component.

In order to assess the consistency of the complicated system shown in Figure 2, one might utilize Equation (3).

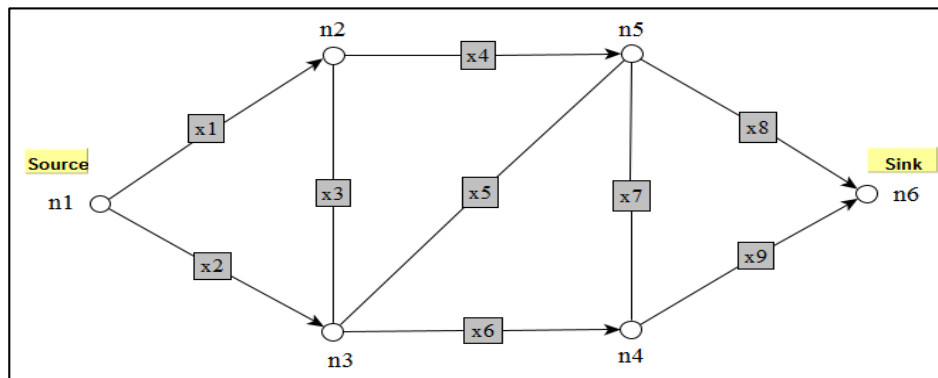


Fig 2: Adapted ARPA network

$$S = \{Mps_1 = \{x_1 x_4 x_8\}, Mps_2 = \{x_2 x_5 x_8\}, Mps_3 = \{x_2 x_6 x_9\}, Mps_4 = \{x_1 x_3 x_5 x_8\}, \\ Mps_5 = \{x_1 x_3 x_6 x_9\}, Mps_6 = \{x_1 x_4 x_7 x_9\}, Mps_7 = \{x_2 x_3 x_4 x_8\}, Mps_8 = \{x_2 x_5 x_7 x_9\}, \\ Mps_9 = \{x_2 x_6 x_7 x_8\}, Mps_{10} = \{x_1 x_3 x_5 x_7 x_9\}, Mps_{11} = \{x_1 x_3 x_6 x_7 x_8\}, \\ Mps_{12} = \{x_1 x_4 x_5 x_6 x_9\}, Mps_{13} = \{x_2 x_3 x_4 x_5 x_8\}\}$$

$$R_s = 1 - [1 - p_r\{x_1 x_4 x_8\}] \times [1 - p_r\{x_2 x_5 x_8\}] \times [1 - p_r\{x_2 x_6 x_9\}]$$

$$\times [1 - p_r\{x_1 x_3 x_5 x_8\}] \times [1 - p_r\{x_1 x_3 x_6 x_9\}] \times [1 - p_r\{x_1 x_4 x_7 x_9\}]$$

$$\times [1 - p_r\{x_2 x_3 x_4 x_8\}] \times [1 - p_r\{x_2 x_5 x_7 x_9\}] \times [1 - p_r\{x_1 x_2 x_6 x_7\}]$$

$$\times [1 - p_r\{x_2 x_6 x_7 x_8\}] \times [1 - p_r\{x_1 x_3 x_6 x_7 x_8\}] \times [1 - p_r\{x_1 x_4 x_5 x_6 x_9\}]$$

$$\times [1 - p_r\{x_2 x_3 x_4 x_5 x_8\}] \quad (5)$$

Note: When the i -th constituent is positive, then $[R_i = 1]$, and when it flops, then $R_i = 0 \forall i = 1, \dots, 9$, these chief to

$$R_i^n = R_i^{[7, 15]}.$$

"Applying the previous statement to equation (5) results in the following polynomial".

$$\begin{aligned}
 R_S = & R_1 R_4 R_8 + R_2 R_5 R_8 + R_2 R_6 R_9 + R_1 R_3 R_5 R_8 + R_2 R_3 R_4 R_8 + R_1 R_3 R_6 R_9 + R_1 R_4 R_7 R_9 \\
 & + R_2 R_5 R_7 R_9 + R_2 R_6 R_7 R_8 - R_1 R_2 R_3 R_4 R_8 - R_1 R_2 R_3 R_5 R_8 - R_1 R_2 R_4 R_5 R_8 \\
 & - R_1 R_2 R_3 R_6 R_9 - R_1 R_3 R_4 R_5 R_8 - R_2 R_3 R_4 R_5 R_8 + R_1 R_3 R_5 R_7 R_9 + R_1 R_3 R_6 R_7 R_8 \\
 & + R_1 R_4 R_5 R_6 R_9 + R_2 R_3 R_4 R_7 R_9 - R_2 R_5 R_6 R_7 R_8 - R_1 R_4 R_7 R_8 R_9 - R_2 R_5 R_6 R_7 R_9 \\
 & - R_2 R_5 R_6 R_8 R_9 - R_2 R_5 R_7 R_8 R_9 - R_2 R_6 R_7 R_8 R_9 + 2 R_1 R_2 R_3 R_4 R_5 R_8 - R_1 R_2 R_3 R_4 R_7 R_9 \\
 & - R_1 R_2 R_3 R_5 R_7 R_9 - R_1 R_2 R_3 R_6 R_7 R_8 - R_1 R_2 R_4 R_5 R_6 R_9 - R_1 R_2 R_4 R_5 R_7 R_9 \\
 & - R_1 R_2 R_4 R_6 R_7 R_8 - R_1 R_3 R_4 R_5 R_6 R_9 - R_1 R_2 R_4 R_6 R_7 R_9 - R_1 R_3 R_4 R_5 R_7 R_9 \\
 & - R_1 R_3 R_4 R_6 R_7 R_8 - R_1 R_2 R_4 R_6 R_8 R_9 - R_1 R_3 R_4 R_6 R_7 R_9 - R_1 R_3 R_5 R_6 R_7 R_8 \\
 & - R_2 R_3 R_4 R_5 R_7 R_9 - R_2 R_3 R_4 R_6 R_7 R_8 - R_1 R_3 R_4 R_6 R_8 R_9 - R_1 R_3 R_5 R_6 R_7 R_9 \\
 & - R_2 R_3 R_4 R_6 R_7 R_9 - R_1 R_3 R_5 R_6 R_8 R_9 - R_1 R_4 R_5 R_6 R_7 R_9 - R_2 R_3 R_4 R_6 R_8 R_9 \\
 & - R_1 R_3 R_5 R_7 R_8 R_9 - R_1 R_4 R_5 R_6 R_8 R_9 - R_2 R_3 R_4 R_7 R_8 R_9 - R_1 R_3 R_6 R_7 R_8 R_9 \\
 & + 2 R_2 R_5 R_6 R_7 R_8 R_9 + R_1 R_2 R_3 R_4 R_5 R_6 R_9 + 2 R_1 R_2 R_3 R_4 R_5 R_7 R_9 + 2 R_1 R_2 R_3 R_4 R_6 R_7 R_8 \\
 & + 2 R_1 R_2 R_3 R_4 R_6 R_7 R_9 + R_1 R_2 R_3 R_5 R_6 R_7 R_8 + 2 R_1 R_2 R_3 R_4 R_6 R_8 R_9 + R_1 R_2 R_3 R_5 R_6 R_7 R_9 \\
 & + R_1 R_2 R_4 R_5 R_6 R_7 R_8 + R_1 R_2 R_3 R_4 R_7 R_8 R_9 + R_1 R_2 R_3 R_5 R_6 R_8 R_9 + 2 R_1 R_2 R_4 R_5 R_6 R_7 R_9 \\
 & + R_1 R_3 R_4 R_5 R_6 R_7 R_8 + R_1 R_2 R_3 R_5 R_7 R_8 R_9 + 2 R_1 R_2 R_4 R_5 R_6 R_8 R_9 + 2 R_1 R_3 R_4 R_5 R_6 R_7 R_9 \\
 & + R_2 R_3 R_4 R_5 R_6 R_7 R_8 + R_1 R_2 R_3 R_6 R_7 R_8 R_9 + R_1 R_2 R_4 R_5 R_7 R_8 R_9 + 2 R_1 R_3 R_4 R_5 R_6 R_8 R_9 \\
 & + R_2 R_3 R_4 R_5 R_6 R_7 R_9 + 2 R_1 R_2 R_4 R_6 R_7 R_8 R_9 + R_1 R_3 R_4 R_5 R_7 R_8 R_9 + R_2 R_3 R_4 R_5 R_6 R_8 R_9 \\
 & + 2 R_1 R_3 R_4 R_6 R_7 R_8 R_9 + R_2 R_3 R_4 R_5 R_7 R_8 R_9 + 2 R_1 R_3 R_5 R_6 R_7 R_8 R_9 \\
 & + 2 R_2 R_3 R_4 R_6 R_7 R_8 R_9 + R_1 R_4 R_5 R_6 R_7 R_8 R_9 - 2 R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 \\
 & - 3 R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_9 - 3 R_1 R_2 R_3 R_4 R_5 R_6 R_8 R_9 - 2 R_1 R_2 R_3 R_4 R_5 R_7 R_8 R_9 \\
 & - 4 R_1 R_2 R_3 R_4 R_6 R_7 R_8 R_9 - 2 R_1 R_2 R_3 R_5 R_6 R_7 R_8 R_9 - 3 R_1 R_2 R_4 R_5 R_6 R_7 R_8 R_9 \\
 & - 3 R_1 R_3 R_4 R_5 R_6 R_7 R_8 R_9 - 2 R_2 R_3 R_4 R_5 R_6 R_7 R_8 R_9 + 5 R_1 R_2 R_3 R_4 R_5 R_6 R_7 R_8 R_9.
 \end{aligned}$$

Implementation of PSO

The evolutionary method known as "PSO" needs the generation of chance statistics. The PSO algorithm's result

depends on the quantity and caliber of statistics generated. The first iteration traverses the search space. A overview of (PSO) use is shown in Figure 3.

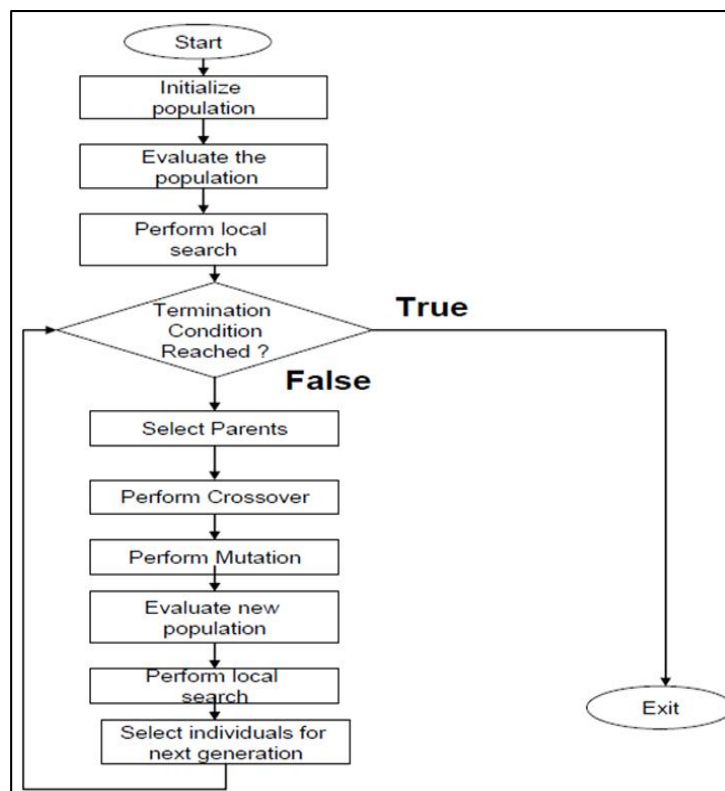


Fig 3: Particle Optimization Flow Chart

The Logarithmic model

Let $(0 < R_i < 1, i = 1, \dots, n)$ and a_i , are constants, $(i = 1, 2, \dots, n)$.^[12, 16] "proposed it in the following format".

$$C_i(R_i) = a_i \ln \left(\frac{1}{1 - R_i} \right), a_i > 0, i = 1, \dots, n$$

Therefore, the problem with optimization is:

$$\text{Minimize } C(R_1, \dots, R_i) = \sum_{i=1}^n a_i \ln \left(\frac{1}{1-R_i} \right),$$

$$i = 1, 2, \dots, n.$$

Subject to:-

$$R_s \geq R_G$$

$$0 \leq R_i < 1, i = 1, \dots, n$$

Table 1: Optimizing reliability allocation with the use of PSO and a cost function

Components	PSO
R_1	0.91
R_2	0.92
R_3	0.87
R_4	0.85
R_5	0.87
R_6	0.85
R_7	0.88
R_8	0.9
R_9	0.9
R_{system}	0.94

Conclusion

This study aims to allocate and enhance the reliability of the previously discussed complex network. The system optimization problem, which utilizes computer science methods, partitions the reliability of each component within the network. This challenge can also be approached as a nonlinear software design problem, incorporating restrictions related to human and substantial capitals (ARPA network reliability). The particle swarm optimization (PSO) technique, which considers the positions of various components within the complex network, was employed to address the optimal reliability allocation problem. The maximum and lowermost reliability allocations for the first and second mechanisms, as well as the fourth and sixth machineries, are detailed in the table above. The total system reliability allocation is ($R_s=0.94$). A key advantage of this model is that all calculations can be performed using mathematical software, as the allocation results were derived using the "Matlab" program, version R2020a.

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