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An Reliability Allocation and Optimization Genetic Algorithm Approach to (ARPA) Network

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***Abstract:** As communication infrastructures become more complicated, the telecommunications industry is expanding, which is why there is interest in creating an integrated broadband service for digital networking technologies like the Advanced Research Projects Agency Network (ARPANET). The topological design of the (ARPANET) has become a significant study topic because to the evolving traffic patterns and new technology employed in ARPANETs. The majority of researchers have addressed the issue of topological design and have put forth solutions that depend on expensive interchange-based equipment. We suggested a practical ARPA network model in this study. Network optimization is a component of ARPA Network design. To improve the ARPA network, we put forth a GA-based approach, and we also used the exponential cost function to determine how much of each component of the system should be allocated. According to study findings, Enhanced GA generates significantly better answers than Simple GA.*

***Keywords:** Allocation of Reliability, Optimization of Reliability, and Enhanced Genetic Algorithms (GA).*

1. INTRODUCTION

In this study, we investigated how to determine the ideal assignment for the Advanced Research Projects Agency (ARPA) network's dependability [9, 10]. Short pathways across connection matrices were used to calculate the reliability of the aforementioned system. All paths are obtained using boolean algebra, and nodes are then eliminated to produce minimum paths [3, 6, 11, 12]. To find out more about how safe it is to utilize the installed sophisticated system, the reliability function is discovered. Despite the history of networks, in this paper we also investigate the mathematical problem of allocating optimal reliability. Each part of a

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complicated system has dependability standards based on the optimization and significance of the site. While reducing total expenses, the objective is to lengthen system life and reliability [1, 5, 7]. Some components may require extensive customization, which varies from component to component depending on their position in the system, in order to increase overall reliability. When working to enhance mechanical and electrical systems, engineers face several difficulties [4, 6, 14]. Along with the cost of the system, which can be described in terms of volume, weight, or other metrics, this study also focuses on the distribution and enhancement of the reliability of complex systems. The model must be cost-based in order to verify the accuracy of the input component, which is one of two fundamental requirements that establish this component's dependability. The proposed cost factor's specifications can be changed. Engineers can use this to analyze the system adaptations and make plans for achieving the minimal reliability standards for each machine part. Second, the model must consider how analytically sound the input system is. In some circumstances, simple systems provide a significant issue that can develop into a significant effort in larger systems. Genetic algorithms (GA), which aid in resolving optimization issues in complicated systems, were used to acquire the results. The cost was computed using an exponential behavior model.

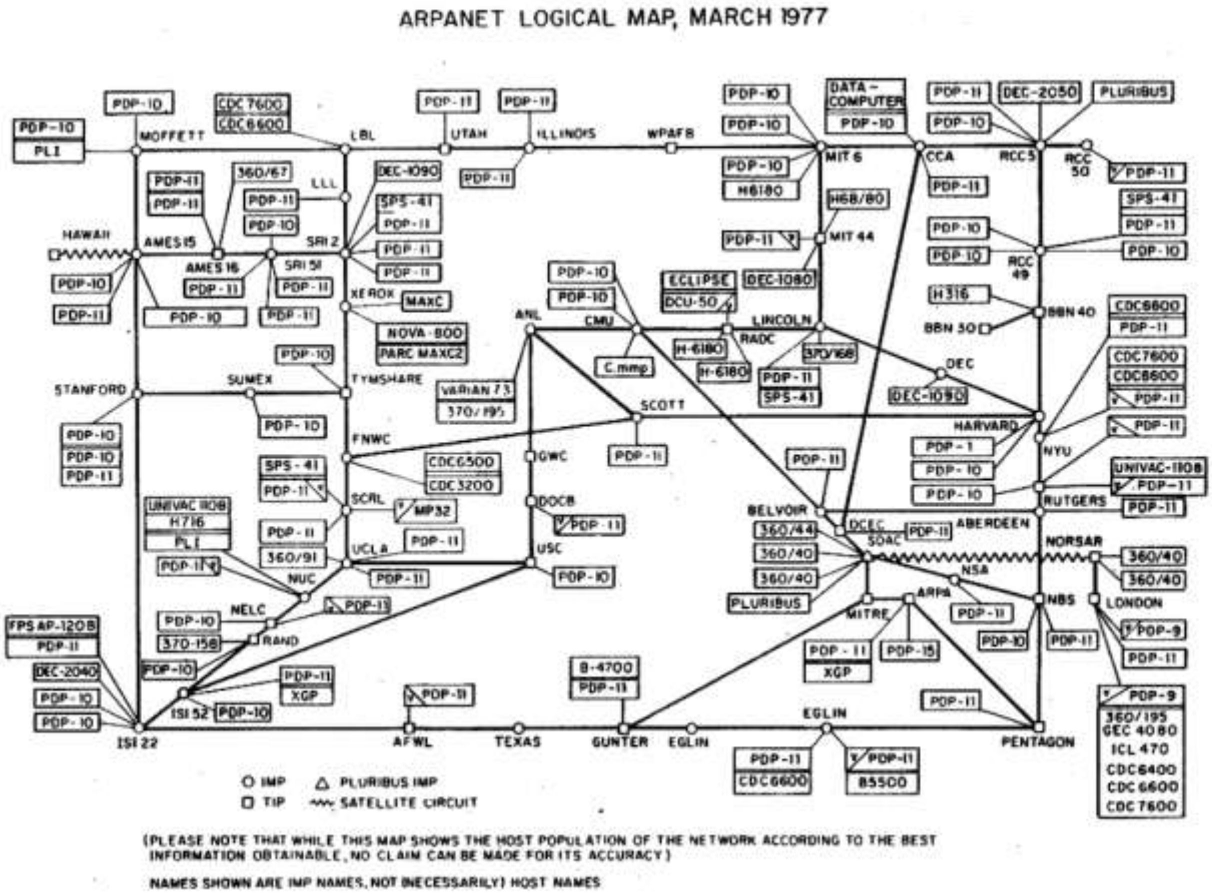

Figure 1: ARPA network, schematic map.

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(ARPA) network optimization and reliability allocation

Think about a (ARPA) network with reliability-related components [1, 17]. We make use of the notes below:

$C_i(R_i)$ = element *i* cost;
$0 \leq R_i \leq 1$ = reliability *i* component;
R_s = reliability of the system;
$C(R_1, \ldots, R_n) = \sum_{i=1}^{n} a_i c_i(R_i)$ is the total system cost, in which a_i is greater than 0;
RG = objective of systems reliability.

Due to the modular structure of the system and the distinctive roles that each component plays, there are numerous potential outcomes. We receive the same capacity from a range of system components, each of which has varying degrees of dependability. The final objective is for the system to be able to correctly distribute resources to all components or chosen ones. Nonlinear programming requires problems [2, 3, 16]. The constraint, despite not being linear, has a purpose and incurs costs that can be investigated:

$$Minimized\ C(R_i, \ldots, R_i) = \sum_{i=1}^{n} a_i C_i(R_i),\ a_i > 0,$$

Subject to:

$$\begin{gathered} R_s \geq R_G \\ 0 \leq R_i < 1, in\ which\ i = 1, \ldots, n \end{gathered} \tag{1}$$

Let the partial cost function be reasonable and $C_i(R_i)$ satisfies some conditions [8], Positive, differentiated functions, increasing from $\left[\Rightarrow \frac{dC_i}{dR_i} \geq 0\right]$.

The part costs function of the Euclidean convexity $C_i(R_i)$ analogous to the reality that its derivatives $\frac{dC_i}{dR_i}$ are monotonically increased, i, e. $\frac{d^2C_i}{dR_i^2} \geq 0$.

Subject to R_G, the system reliability limitation is reduced, and the prior plan's goal is to reach an all-out framework cost base [12].

Genetic Algorithm

A network can be optimized using GA, an atypical optimization technique [3,4,18]. (ARPANET). Encoding, initiation, evaluation, cloning, crossover, mutation, and termination are a few of the GA procedures [6,7] that can be succinctly outlined. Coding: In this step, the variables in the optimization problem are represented as genes. The major chromosomes are chosen at random from among those carrying various genes. The population is made up of these arbitrary chromosomes, whose size is determined by the arbitrary number of chromosomes. Assessment: Each chromosome in the community is given a specific value called fitness that is related to the gene's order. The fitness value of a chromosome in a

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population is used to evaluate the chromosome's likelihood of survival due to variations in gene order. Varied genetic configurations result in different fitness values for reproductions of evaluation chromosomes. The goal of reproduction is to provide the following generation more healthy chromosomes while fewer unhealthy ones are present. Crossover: In this process, the chromosomes of the mother and father are switched. As parent chromosomes, two chromosomes are chosen at random from the population. The genes are swapped between the crossing locations, which are chosen to have a lower number of crossing points than there are genes in the chromosome. Genes from each of the parent chromosomes are used to create two new chromosomes. The intersection of two points is what is meant by this activity. Mutation: A mutation process is utilized to create a new chromosome that is distinct from the chromosomes found in the population. The chromosome that has been altered is chosen at random. From among the many genes in the modified chromosome, the mutant gene is chosen at random, and then its value flips to another value. The procedure is repeated until there is very little variation in the population's average level of fitness. As a final step toward solving the optimization problem, the best chromosome in the neighborhood is decoded. To increase bandwidth, GA was utilized in earlier research from a different angle and partially for the construction of the ARPA network [13,14]. Meta-inference was not applied to the challenge of overall ARPA network planning. Gene evolution serves as the foundation for genetic algorithms. GA does not account for the knowledge produced by cultural evolution. The quick convergence of local Optima is one drawback of GA-based technologies. This restriction can be circumvented with enhanced GA. Local search algorithms are included into upgraded GA phases to produce better solutions. The hill climb algorithm is the local search method taken into consideration in this work. The fundamental principle of hill climbing is to always go toward a better state than the one you are in right now. When these states become accessible, the algorithm looks for them; if no such states become available, the method stops.

Implementation in a complex system

To estimate the ARPA network, we want to convert it to a more accessible network, as if we turn it into a network whose components are related in a series or parallel manner. The reliability of a series and parallel networks with n components is, respectively:

$$R_s = \prod_{i=1}^{n} R_i \tag{2}$$

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

Here R_N represents the reliability ARPA network and R_i is the reliability of the component i [6,8].

From equations (1) and (2) we will compare the reliability of each complex network with p minimum paths that are given via

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

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Here α is the index of the first component, and ω is the index of the last component of a minimal pa z.
The reliability of a complex network in Fig. 1 below can be calculated by Equation (3).

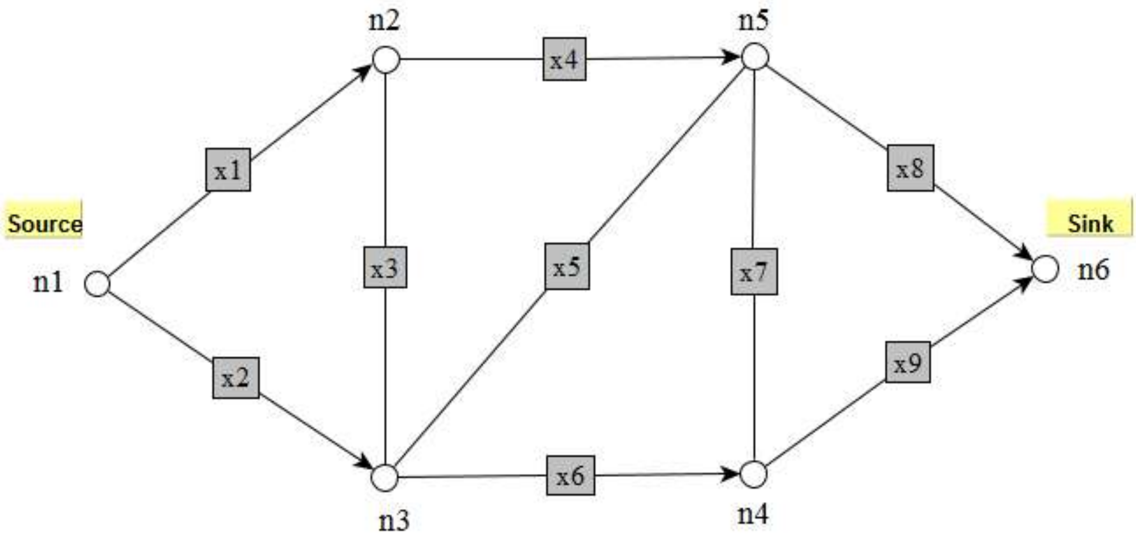

Figure 2. Modified ARPA network

$$S = \{Mps_1 = \{x_1x_4x_8\}, Mps_2 = \{x_2x_5x_8\}, Mps_3 = \{x_2x_6x_9\}, Mps_4 = \{x_1x_3x_5x_8\}, Mps_5 = \{x_1x_3x_6x_9\}, Mps_6 = \{x_1x_4x_7x_9\}, Mps_7 = \{x_2x_3x_4x_8\}, Mps_8 = \{x_2x_5x_7x_9\}, Mps_9 = \{x_2x_6x_7x_8\}, Mps_{10} = \{x_1x_3x_5x_7x_9\}, Mps_{11} = \{x_1x_3x_6x_7x_8\}, Mps_{12} = \{x_1x_4x_5x_6x_9\}, Mps_{13} = \{x_2x_3x_4x_5x_8\}\}$$

$$R_s = 1 - [1 - p_r\{x_1x_4x_8\}] \times [1 - p_r\{x_2x_5x_8\}] \times [1 - p_r\{x_2x_6x_9\}] \times [1 - p_r\{x_1x_3x_5x_8\}] \times [1 - p_r\{x_1x_3x_6x_9\}] \times [1 - p_r\{x_1x_4x_7x_9\}] \times [1 - p_r\{x_2x_3x_4x_8\}] \times [1 - p_r\{x_2x_5x_7x_9\}] \times [1 - p_r(x_1x_2x_6x_7)] \times [1 - p_r\{x_2x_6x_7x_8\}] \times [1 - p_r\{x_1x_3x_6x_7x_8\}] \times [1 - p_r\{x_1x_4x_5x_6x_9\}] \times [1 - p_r\{x_2x_3x_4x_5x_8\}] \quad (5)$$

Note: When the $i-\text{th}$ component succeeds, then $R_i = 1$, and when it fails, then $R_i = 0$ $\forall\, i = 1, \cdots, 9$, these lead to
$R_i^n = R_i$ [7,15].

By using the note above, equation (5) becomes the following polynomial

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$$
\begin{aligned}
R_S = {} & R_1R_4R_8 + R_2R_5R_8 + R_2R_6R_9 + R_1R_3R_5R_8 + R_2R_3R_4R_8 + R_1R_3R_6R_9 + R_1R_4R_7R_9 \\
& + R_2R_5R_7R_9 + R_2R_6R_7R_8 - R_1R_2R_3R_4R_8 - R_1R_2R_3R_5R_8 - R_1R_2R_4R_5R_8 \\
& - R_1R_2R_3R_6R_9 - R_1R_3R_4R_5R_8 - R_2R_3R_4R_5R_8 + R_1R_3R_5R_7R_9 + R_1R_3R_6R_7R_8 \\
& + R_1R_4R_5R_6R_9 + R_2R_3R_4R_7R_9 - R_2R_5R_6R_7R_8 - R_1R_4R_7R_8R_9 - R_2R_5R_6R_7R_9 \\
& - R_2R_5R_6R_8R_9 - R_2R_5R_7R_8R_9 - R_2R_6R_7R_8R_9 + 2R_1R_2R_3R_4R_5R_8 - R_1R_2R_3R_4R_7R_9 \\
& - R_1R_2R_3R_5R_7R_9 - R_1R_2R_3R_6R_7R_8 - R_1R_2R_4R_5R_6R_9 - R_1R_2R_4R_5R_7R_9 \\
& - R_1R_2R_4R_6R_7R_8 - R_1R_3R_4R_5R_6R_9 - R_1R_2R_4R_6R_7R_9 - R_1R_3R_4R_5R_7R_9 \\
& - R_1R_3R_4R_6R_7R_8 - R_1R_2R_4R_6R_8R_9 - R_1R_3R_4R_6R_7R_9 - R_1R_3R_5R_6R_7R_8 \\
& - R_2R_3R_4R_5R_7R_9 - R_2R_3R_4R_6R_7R_8 - R_1R_3R_4R_6R_8R_9 - R_1R_3R_5R_6R_7R_9 \\
& - R_2R_3R_4R_6R_7R_9 - R_1R_3R_5R_6R_8R_9 - R_1R_4R_5R_6R_7R_9 - R_2R_3R_4R_6R_8R_9 \\
& - R_1R_3R_5R_7R_8R_9 - R_1R_4R_5R_6R_8R_9 - R_2R_3R_4R_7R_8R_9 - R_1R_3R_6R_7R_8R_9 \\
& + 2R_2R_5R_6R_7R_8R_9 + R_1R_2R_3R_4R_5R_6R_9 + 2R_1R_2R_3R_4R_5R_7R_9 + 2R_1R_2R_3R_4R_6R_7R_8 \\
& + 2R_1R_2R_3R_4R_6R_7R_9 + R_1R_2R_3R_5R_6R_7R_8 + 2R_1R_2R_3R_4R_6R_8R_9 + R_1R_2R_3R_5R_6R_7R_9 \\
& + R_1R_2R_4R_5R_6R_7R_8 + R_1R_2R_3R_4R_7R_8R_9 + R_1R_2R_3R_5R_6R_8R_9 + 2R_1R_2R_4R_5R_6R_7R_9 \\
& + R_1R_3R_4R_5R_6R_7R_8 + R_1R_2R_3R_5R_7R_8R_9 + 2R_1R_2R_4R_5R_6R_8R_9 + 2R_1R_3R_4R_5R_6R_7R_9 \\
& + R_2R_3R_4R_5R_6R_7R_8 + R_1R_2R_3R_6R_7R_8R_9 + R_1R_2R_4R_5R_7R_8R_9 + 2R_1R_3R_4R_5R_6R_8R_9 \\
& + R_2R_3R_4R_5R_6R_7R_9 + 2R_1R_2R_4R_6R_7R_8R_9 + R_1R_3R_4R_5R_7R_8R_9 + R_2R_3R_4R_5R_6R_8R_9 \\
& + 2R_1R_3R_4R_6R_7R_8R_9 + R_2R_3R_4R_5R_7R_8R_9 + 2R_1R_3R_5R_6R_7R_8R_9 \\
& + 2R_2R_3R_4R_6R_7R_8R_9 + R_1R_4R_5R_6R_7R_8R_9 - 2R_1R_2R_3R_4R_5R_6R_7R_8 \\
& - 3R_1R_2R_3R_4R_5R_6R_7R_9 - 3R_1R_2R_3R_4R_5R_6R_8R_9 - 2R_1R_2R_3R_4R_5R_7R_8R_9 \\
& - 4R_1R_2R_3R_4R_6R_7R_8R_9 - 2R_1R_2R_3R_5R_6R_7R_8R_9 - 3R_1R_2R_4R_5R_6R_7R_8R_9 \\
& - 3R_1R_3R_4R_5R_6R_7R_8R_9 - 2R_2R_3R_4R_5R_6R_7R_8R_9 + 5R_1R_2R_3R_4R_5R_6R_7R_8R_9.
\end{aligned}
$$

Implementation of GA

After each cycle, GA selects the fittest members using a predetermined fitness function. Figure 3 displays the fundamental GA flowchart on the front.

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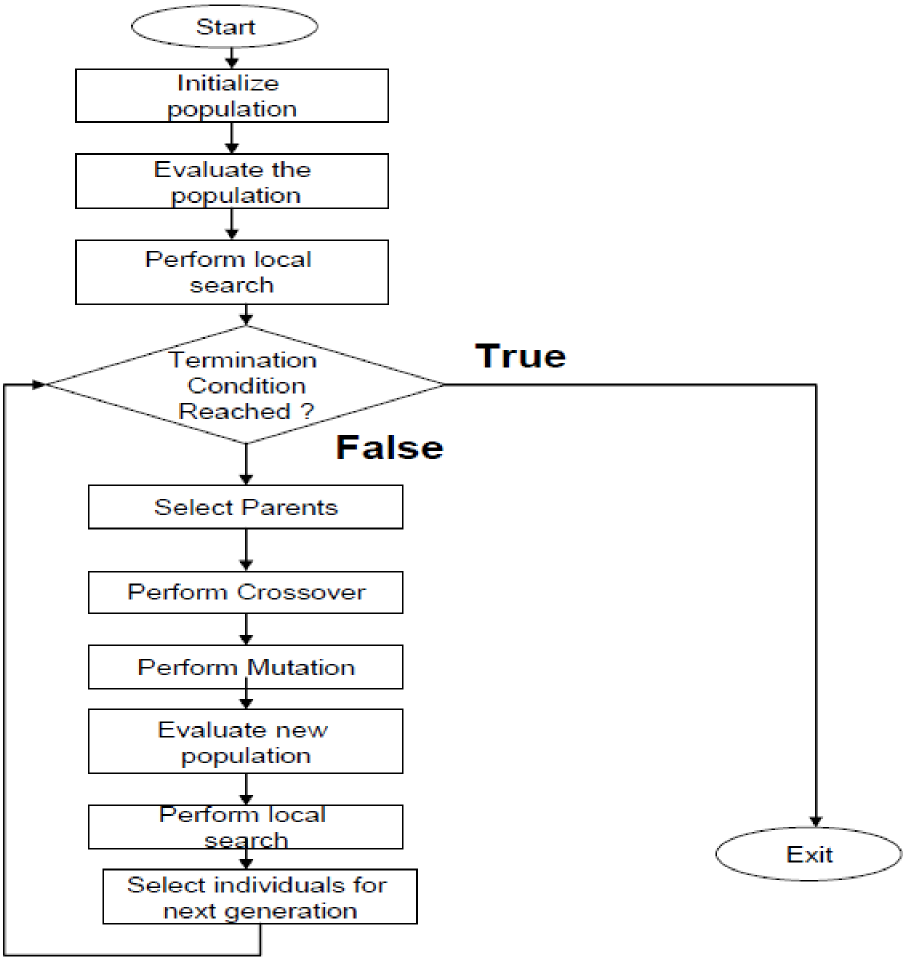

Figure 3. Flow chart of Particle Optimization

An exponential feasibility model based

Assume $0 < f_i < 1$ is a feasibility factor [12,16], $R_{i,max}$ is maximum reliability, and $R_{i,min}$ is minimum reliability.

$$C_i(R_i) = \exp[(1-f_i)\frac{R_i - R_{i,min}}{R_{i,max} - R_i}],$$
$$R_{i,min} \le R_i \le R_{i,max}, i = 1,2, \dots, n.$$

The optimization problem becomes

$$Minimize\ C(R_i, \dots, R_i) = \sum_{i=1}^{n} a_i\ \exp[(1-f_i)\frac{R_i - R_{i,min}}{R_{i,max} - R_i}],$$
$$in\ which\ i = 1,2, \dots, n.$$

Subjected to :

$$R_s \ge R_G$$

$$R_{i,min} \le R_i \le R_{i,max}, i = 1, \dots, n.$$

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Table 1: Allocating reliability in the best possible way using GA and a cost function.

Components	GA
R_1	**0.95**
R_2	**0.95**
R_3	**0.85**
R_4	**0.8**
R_5	**0.87**
R_6	**0.8**
R_7	**0.87**
R_8	**0.94**
R_9	**0.94**
R_{system}	**0.98**

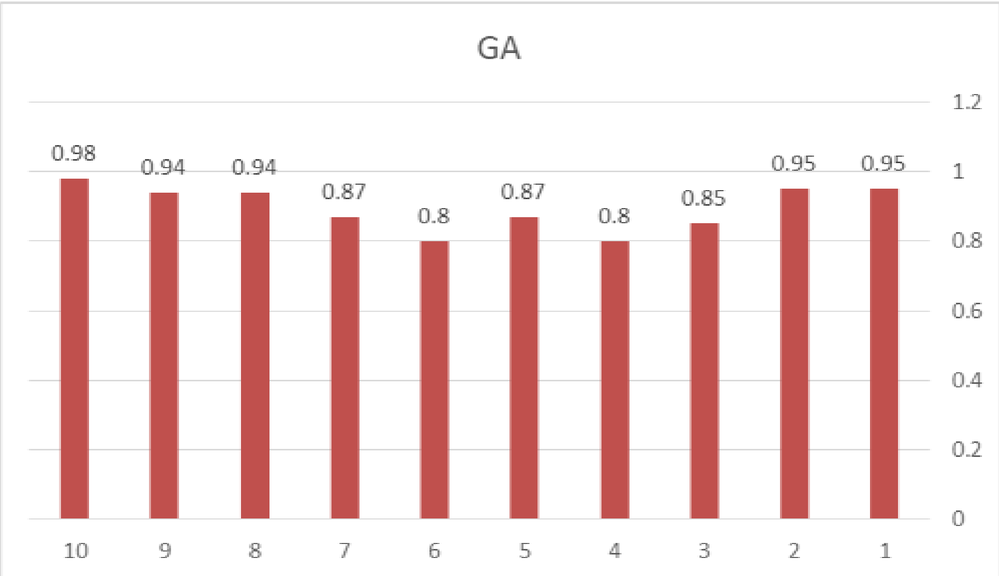

Figure 4: using GA to distribute reliability while utilizing the provided feasibility factor model.

2. CONCLUSION

In this study, the topic of increasing reliability for a certain complicated network is covered. The issue of system optimization that distributes the dependability of each system component utilizing computational techniques. Additionally, this issue has been explored as a nonlinear programming issue with a function for cost and labor constraints (ARPA network reliability). Given the locations of these components in the network complex, the genetic algorithm was used to solve the problem of optimal network reliability assignment. The total assignment of

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the system was calculated and was (Rs = 0.98), as well as the highest and lowest assignments of the first and second components in the network and the fourth and sixth components in the network, as shown in the above table. The benefit of this paradigm is that each program will be able to perform mathematical computations, since Matlab software, version R2020a, was utilized to find the assignment results.

3. REFERENCES

1. Abuali F.N., Schoenefeld D.A., & Wainwright R.L. (1994), Terminal assignment in a communications network using genetic algorithms. Proc. 22nd Annual ACM Computer Science Conference (CSC'94), Phoenix, Arizona, USA, 74-81.
2. ABED, Saad Abbas; SULAIMAN, Hatem Kareem; HASSAN, Zahir Abdul Haddi. Reliability Allocation and Optimization for (ROSS) of a Spacecraft by using Genetic Algorithm. In : Journal of Physics: Conference Series. IOP Publishing, 2019. p. 032034.
3. Balakrishnan A., Magnanti T., and Wong T. (1989), "A Dual-Ascent Procedure for large scale uncapacitated Network Design", INFORMS Operation Research, 37, pp. 716-740.
4. Chardaire P., Kapsalis A., Mann J.W., Rayward-Smith V.J. and Smith G.D., (1995), "Applications of Genetic Algorithms in Telecommunications", In J. Alspector, R. Goodman, T.X. Brown (Eds.), Proceedings of the 2nd International Workshop on Applications of Neural Networks to Telecommunications, 290-299.
5. Davis L., Cox A., Qiu Y.(1993), "A Genetic Algorithm for Survivable Network Design", Proc. Fifth International Conference on Genetic Algorithms, Morgan Kauffman, 1993, pp 408-415.
6. Davis L., Coombs S.(1987), "Genetic Algorithm and Communication Link Speed Design: Theoretical Considerations", Proc. Second International Conference on Genetic Algorithms, Lawrence Erlbaum, 1987, pp 252256.
7. Elbaum R. & Sidi M. (1995), "Topological design of local area networks using genetic algorithms", IEEE INFOCOM'95, Boston, Massachusettes, USA, v1, 64-71.
8. Gerla M., Monteiro J. A. S., Pazos R.(1989), "Topology Design and Bandwidth Allocation in ATM Nets", IEEE. JSAC, Vol. 7, No. 8, pp. 1253-1262.
9. Gerla M., Kleinrock L.(1977), "On the topological design of Distributed Computer Networks", IEEE Transactions on Communications, Vol. 25, No. 1, pp.55- 67.
10. Goldberg DE. (1991), Genetic Algorithm in search , optimization and machine learning, NewYork, Addison Wesley,1991.
11. Hasslinger, G., Schnitter, S., Franzke, M. (2005), "The Efficiency of Traffic Engineering with regard to Link Failure Resilience", Telecommunication Systems Journal 29 , 2005, 109-130.
12. Kim S. B., Kim M. J., Lee S. I.(1995), "Mathematical models for Dimensioning of ATM Networks" , IEEE GLOBECOM'95, Singapore, 1995
13. X. Feng, X. Zhu, W. Zhao, and X. Li, Reliability of Electric Vehicle with Wind Turbine Based on Particle Swarm Optimization. Chemical Engineering Transactions, 66, 1291-1296, (2018).

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14. Kirkpatrick S, Gelatt C. D., Vechhi M. P.(1993), "Optimization by Simulated Annealing" Science, 220, pp 671-680.
15. Liu Xian (2003), " Network capacity allocation for traffic with time priorities", Int. J. Network Mgmt 2003, vol. 13 pp. 411-417.
16. Miguel Rios, Vladimir Marianov, and Cristian Abaroa (2005), "Design of Heterogeneous Traffic Networks Using Simulated Annealing Algorithms", ICOIN 2005, LNCS 3391, pp. 520-530.
17. Minoux M.(1987), "Network Synthesis and Dynamic Network Optimization." Annals of Discrete mathematics, 31:283–324.
18. Raychaudhuri D. and Wilson D.(1994), "ATM-Based Transport Architecture for Multiservices Wireless Personal Communication Networks ", IEEE Journal On Selected Areas In Communications, vol 12, No 8, pp 1401 – 1413.

