



OPTIMAL PARTICLE SWARM FOR RELIABILITY ALLOCATION TO COMPLEX SYSTEM

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Abstract

In this work, a reliability function is computed for a complex system, along with an optimal reliability distribution among the components of the system to be built. The majority of research to date has adopted exponentially increasing closed functions to relate cost and reliability, despite the fact that it is generally known that component cost is an increasing function of its reliability. In fact, these functions are sometimes ill-defined or difficult to generate, and so it often makes sense to discuss cost-reliability connections between separate datasets. We consider scenarios where each component is offered in a range of reliability levels at varying prices. The nonlinear integer program is the result of a design optimization challenge. We introduce particle swarm optimization (PSO) to calculate system reliability assignment for each system component as well as to calculate overall system reliability since each system configuration has an equivalent representation as either serial communication of parallel subsystems or parallel communication of serial subsystems. The cost of each component of the system was determined using the exponential behavior feasibility factor cost function.

Keywords: Optimization , reliability, reliability allocation , complex system

1. Introduction

In this research, we looked at the complicated system's installed reliability [9, 10]. By leveraging short pathways across connection matrices, this system's



dependability was discovered. All paths are obtained using Boolean algebra, and nodes are then eliminated to produce minimal paths [3, 6, 11, 12].

To find out more about how safe it is to utilize the installed sophisticated system, a reliability function is sought after. Despite the historical basis of the networks, we also examine the mathematical issue of distributing optimal reliability in this study. Based on location importance, the dependability standards for each component of a complex system are optimized. The objective is to increase the system's lifespan and dependability while lowering overall costs [5, 7, 8].

Depending on where they are located in the system, some components may require a high allocation in order to increase overall reliability. Engineers encounter a number of challenges when trying to improve mechanical and electrical systems [4, 6, 14].

This study focuses on the reliability of complex systems as well as the distributing and enhancing the system cost, which can be expressed in terms of size, weight, or other metrics. There are two main elements that affect this component's dependability: The model must be cost-based before the input element may be validated. The suggested cost parameter's specifications can be altered. This facilitates the engineers' analysis of the financial allocations for each system and planning for the attainment of the bare minimum dependability required for each machine component. The analytical dependability of the input system must also be considered by the model. When applied to bigger systems, simple systems can occasionally pose a substantial challenge. The outcomes were obtained using the Particle Swarm, a tool for complicated systems to tackle optimization issues. An exponential behavior feasibility factor were used to calculate the cost.

2. complex system optimization and reliability allocation

Take into account a complicated system with components linked to reliability [5, 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;

$C(R_1, \dots, R_n) = \sum_{i=1}^n a_i c_i(R_i)$ is the total system cost, in which a_i is greater than 0;

RG = objective of systems reliability.

There are many possible outcomes due to the system's modular design and the unique functions of each component. The same capacity is provided to us via a



variety of system components, each with various degrees of dependability. The system's ability to correctly allocate resources to all components or selected ones is the ultimate goal. Problems are necessary for nonlinear programming [9, 16, 17]. Despite not being linear, the constraint serves a purpose and incurs costs that can be researched:

$$\begin{aligned}
 & \text{Minimized } C(R_i, \dots, R_i) = \sum_{i=1}^n a_i C_i(R_i), \quad a_i > 0, \\
 & \text{Subject to: } R_s \geq R_G \\
 & 0 \leq R_i < 1, \text{ in which } i = 1, \dots, n
 \end{aligned} \tag{1}$$

Let the partial cost function be reasonable and $C_i(R_i)$ satisfies some conditions [12], 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. $\frac{d^2C_i}{dR_i^2} \geq 0$.

The system reliability restriction is lowered under R_G , and the prior plan's objective is to achieve an all-out framework cost base [12].

3. implementation in a complex system

In order to estimate the complex system, we need to transform it into a more approachable network, similar to how we would transform a series of objects into a parallel network. In parallel and series networks with n components, the dependability 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 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

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



Here α is the index of the first component, and ω is the index of the last component of a minimal path z . Equation can be used to determine the dependability of the complicated network in Fig. 1

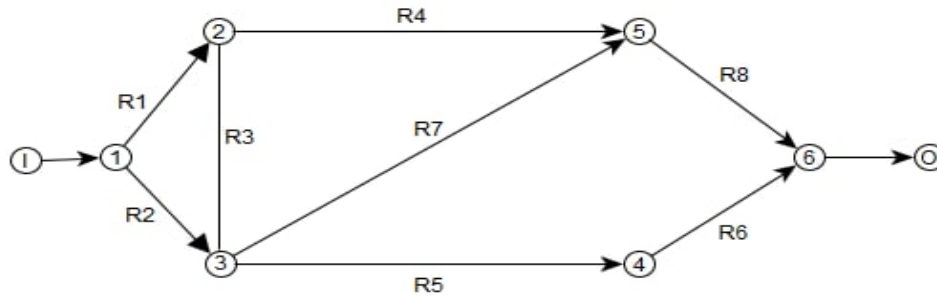


Figure 1: Complex Network

The sets:

$$S = \{\{x_1x_4x_8\}, \{x_2x_5x_6\}, \{x_2x_7x_8\}, \{x_1x_3x_5x_6\}, \{x_2x_3x_4x_8\}, \{x_1x_3x_7x_8\}, \}$$

$$R_S = 1 - [1 - p_r(x_1x_4x_8)] \times [1 - p_r(x_2x_5x_6)] \times [1 - p_r(x_2x_7x_8)] \times [1 - p_r(x_1x_3x_5x_6)] \times [1 - p_r(x_2x_3x_4x_8)] \times [1 - p_r(x_1x_3x_7x_8)] \quad (5)$$

Note: When the i – th component succeeds, then $R_i = 1$, and when it fails, then $R_i = 0 \forall i = 1, \dots, 8$, these lead to $R_i^n = R_i$ [7,9]. By using the note above, equation (5) becomes the following polynomial .

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

4. PSO method

A swarm of particles is a collection of entities with the ideal number of attributes or values to include in a swarm problem space [17, 14].

Communities of people form so that information can be shared. Using the bit string "01110" as an example, a neighborhood is defined in mathematics as "the set of points around a certain position, each within a specified distance from the stated point." The third bit is the one that leaves the location that is given (middle bit). The full bit string, two on the left and two on the right, will fit in the neighborhood of size 3. These neighborhoods can have a range of topologies, despite the fact that their structures are substantially different from the topologies of the ANN. In particle swarm settings, a spherical or star-shaped topology is frequent.

4.1. Implementation of PSO

The evolutionary algorithm PSO requires the creation of random numbers. The PSO algorithm's output is influenced by the caliber and volume of the statistics that are generated. The initial iteration is dispersed across the entire search area. Fig. 2 displays the fundamental implementation of the PSO.



Figure 2. Flow chart of Particle Optimization



4.2. A calculus-based exponential feasibility model

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

$$C_i(R_i) = \exp\left[(1 - f_i) \frac{R_i - R_{i,min}}{R_{i,max} - R_i}\right],$$

$$R_{i,min} \leq R_i \leq R_{i,max}, i = 1, 2, \dots, n.$$

The issue with optimization arises

Minimize $C(R_1, \dots, R_n) = \sum_{i=1}^n a_i \exp\left[(1 - f_i) \frac{R_i - R_{i,min}}{R_{i,max} - R_i}\right]$, in which $i = 1, 2, \dots, n$.

Subjected to : $R_s \geq R_G$, $R_{i,min} \leq R_i \leq R_{i,max}, i = 1, \dots, n$.

Table 1:
 Optimum reliability allocation utilizing PSO and GA with an applied cost function.

Components	PSO	COST
R_1	0.94	196.3699
R_2	0.95	854.0588
R_3	0.66	1.3376
R_4	0.94	196.3699
R_5	0.82	3.0938
R_6	0.88	7.9465
R_7	0.94	196.3699
R_8	0.95	854.0588
R_{system}	0.98	2.3096e+03

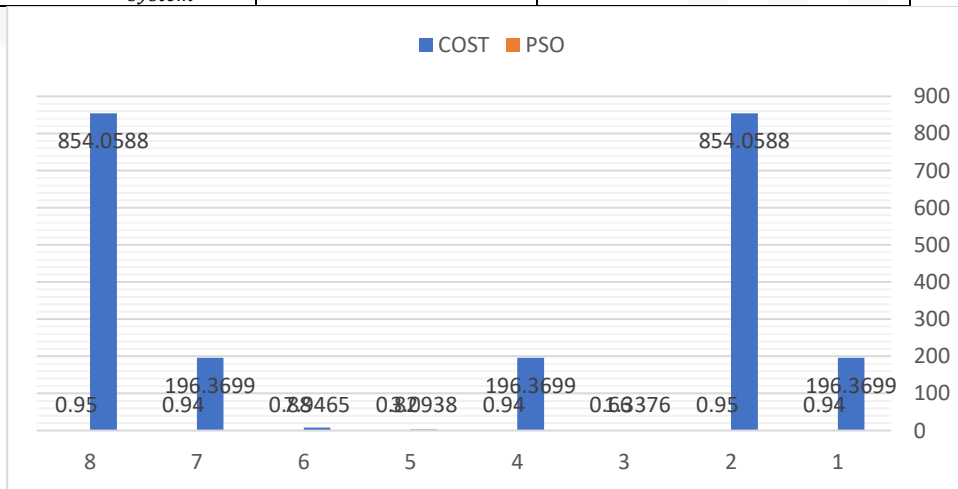


Figure 2: Utilizing PSO to allocate reliability using the given feasibility factor model



5. Conclusion

In this research, the topic of increasing the reliability of a given complex network is addressed. A system optimization problem where the reliability of each component of the system is designed using engineering principles. A nonlinear programming problem with a cost function and labor constraints has also been used to address this topic (reliability of complex systems). The reliability assignment problem was addressed using particle swarm optimization, and the results are, we come to the conclusion that the viability factor model, described above and having values of $R_s = 0.98$. Similar to the dependency allocation problem, component (2, 8) received the largest allocation and cost, while component (3, 5), as shown in the tables above, received the least allocation. Because of where these parts are located within the complex system. The benefit of this model is that each program will be able to do the very difficult mathematical techniques used.

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