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# A multi-objective strategy for solving the redundancy allocation problem in reliable systems via the NSGA-II algorithm


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## Highlights

- A novel MOP method for Redundancy Allocation Problem using NSGA-II.
- Enhances reliability while reducing cost, weight, and volume.
- Refines POSs via K-Means clustering for streamlined decision-making.
- Applied to avionics systems, balancing reliability and resources.
- Improves reliability and cost-effectiveness in complex systems.




## Abstract

This study proposes a novel Multi-Objective Optimization (MOP) method to tackle the Redundancy Allocation Problem (RAP) in reliable systems using the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The research aims to improve System Reliability (SR) while simultaneously reducing cost, weight, and volume, addressing the inherent trade-offs in system design. NSGA-II generates Pareto-Optimal Solutions (POSs), which are further refined using K-Means Clustering to facilitate decision-making and reduce cognitive load. An illustrative application in avionics systems demonstrates the method's ability to balance reliability with resource constraints effectively. Results show that clustering POSs simplifies decision-making during optimal configuration design. Overall, this approach enhances both reliability and cost-effectiveness, offering broad potential for safety-critical engineering applications.



**Keywords**

reliability engineering, redundancy assignment problem, multi-objective evolutionary algorithm, pareto-optimal configurations, solution clustering techniques


## 1. Introduction

Metaheuristics are used to solve complex manufacturing and aerospace intricate soft-computing problems. The bi-objective RAP is considered to improve system availability and dependability. MOPSO is dominate, while NSGA-II performs effectively. Standby and activation modes reduce errors and accelerate recovery, improving system performance. Markov, Binomial, Fault Tree Analysis (FTA), and Monte Carlo Simulations (MCSs) are restrictive for system availability and dependability analysis [1]. RAP and RRAP are the 2 main types of Reliability Optimization Problems (ROP) that optimize system redundancy. RAP optimizes the quantity and kind of redundant components, while RRAP addresses the reliability of uncertain components. Active, cold-standby, and mixed redundancy are common. Metaheuristic Algorithms (MAs) like GA and PSO are commonly utilized to address non-convex, high-dimensional problems. Recent improvements include Component Mixing (CM) and strategy selection to improve reliability. This paper offers a bi-objective RRAP model with CM and optimal strategy selection that uses Markov-based reliability computation to maximize SR and reduce costs [2]. SR is crucial, and redundancy allocation (RAP) improves reliability by parallelizing redundant components. RAP components work in active, standby, or mixed modes, and many methodologies have been tested to maximize system performance. The


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problem's NP-hardness makes MAs like GA and PSO popular. Recent research has developed Multi-Objective Redundancy Allocation Problems (MORAP) to maximize dependability and minimize cost and weight. This work offers two new redundancy algorithms for subsystems with non-homogeneous components, overcoming previous research's assumptions. The NSGA-II algorithm optimizes dependability and cost for the suggested multi-objective problem [3]. Industrial system breakdowns may induce cascading performance and availability problems. Subsystem failures' interdependencies should be grasped to enhance system robustness. Earlier work has investigated these interrelations through FTA and Markov modeling. The paper aims to optimize system expenses and exploit system availability in mixed failure dependency series-parallel systems. The problem is solved through Pareto optimization, the NSGA-II, and the Multi-Objective Hoopoe Heuristic (MOHH). Fuzzy decision procedures differentiate and contrast the optimum compromise outcomes [4]. Complex, uncertain engineering systems require excellent performance and robustness. Multi-performance optimization optimizes conflicting performance metrics, whereas robust design optimization provides parameter-resistant solutions. Engineers decouple design components and assess resilience by volume using the box-shaped solution space method. Current methods value space over efficiency. Recent MOP methods balance performance with durability, although many need analytically specified performance functions, limiting their use to black-box systems [5].

### 1.1. Literature review

Early studies established that RAPs are computationally difficult, with Chern [6] formally demonstrating the NP-hard nature of redundancy allocation in series systems, which motivated the widespread use of heuristic and metaheuristic algorithms rather than exact methods. Later foundational work by Kuo and Prasad [7] provided a comprehensive overview of system-reliability optimization and highlighted the limitations of classical analytical models in handling real-world constraints, especially when systems exhibit mixed structures or include repairable components. These early insights laid the foundation for more advanced modeling frameworks that moved beyond simple series–parallel configurations. In this direction, Tian et al. [8] introduced a joint reliability–redundancy optimization approach for multi-state series–parallel systems, demonstrating that multi-state behavior and performance levels substantially change the nature of the optimization landscape compared to binary-state assumptions.

As system complexity grew, research shifted toward models incorporating load sharing, repairable elements, and heterogeneous components. For instance, Sharifi et al. [9,10] developed several formulations addressing inspection-interval optimization and condition-based maintenance for k-out-of-n load-sharing systems under hybrid mixed redundancy strategies, showing that maintenance scheduling, degradation behavior, and redundancy decisions interact strongly in determining overall system performance. Meanwhile, Kayedpour et al. [11] examined systems with repairable components and proposed a multi-objective RAP that accounts for instantaneous availability and redundancy strategy selection, reflecting a move toward lifecycle-aware optimization rather than static design alone. The incorporation of multi-state components has become increasingly common, as shown by Zhang et al. [12], who investigated strength–redundancy allocation in multi-state systems using the artificial bee colony algorithm, highlighting the importance of modeling both component capability levels and redundancy structures simultaneously. These works collectively illustrate a clear evolution from classical binary-state formulations to richer, more realistic models that capture degradation patterns, loading effects, and heterogeneous component behavior.

Parallel to these modeling advances, substantial progress has occurred in the development of metaheuristic and evolutionary algorithms tailored to RAP. Huang [13] introduced a particle-based simplified swarm optimization approach that provided competitive performance with relatively simple parameterization, while Kim et al. [14] employed parallel genetic algorithms to simultaneously optimize redundancy levels and redundancy strategies, including active, standby, and mixed schemes. More recently, Ouyang et al. [15] developed an improved particle swarm optimization method capable of handling mixed redundancy strategies and heterogeneous components, reflecting the increasing need for algorithms that can deal with complex design spaces involving both discrete and continuous variables. Another line of research has focused on exploiting system abstractions such as survival signatures; for example, Huang et al. [16] proposed a heuristic survival-signature-based approach that allows scalable reliability–redundancy allocation for systems where traditional modeling quickly becomes intractable. In addition, Yeh et al. [17] introduced general active redundancy models and accompanying algorithms that expand the feasible design space while offering enhanced flexibility for high-reliability applications. To address emerging challenges in large-scale and high-dimensional RAP instances, Nath and Muhuri [18] proposed evolutionary optimization approaches for many-objective RAPs, emphasizing the need for algorithms that preserve diversity and convergence quality when the number of objectives increases.

Recent studies increasingly combine sophisticated modeling with advanced optimization strategies. Modibbo et al. [19] introduced a unified framework for optimization and estimation in reliability allocation problems, demonstrating how design decisions and parameter estimation can be jointly addressed to improve robustness and practical applicability. Other works, such as those by Zaretalab et al. [20], incorporate supply-chain and multi-state component considerations, emphasizing the practical complexities encountered in real engineering systems where redundancy decisions interact with procurement and component reliability. Similarly, Zhang et al. [21] proposed a general model for optimizing RAP and RRAP in k-out-of-n: G systems with mixed redundancy strategies, demonstrating how modern formulations unify several classical RAP variants into broader and more flexible frameworks suitable for modern reliability engineering challenges. Collectively, these studies show that contemporary research trends favor integrated, multi-state, multi-strategy, and preference-aware optimization, often supported by evolutionary algorithms designed to capture knee regions of the Pareto front and assist decision makers in complex design settings. Ding and Cui [22] introduced a stochastic framework for human-powered electricity generation (HPEG) that combines Monte Carlo uncertainty quantification, multi-component fatigue modeling, and Pareto optimization. Their approach models human biomechanical performance, incorporating physiological and environmental factors. The framework advances stochastic modeling for biomechanical systems and supports decentralized energy solutions for sustainable development and climate adaptation.

Alozie et al. [23] examined how Site Reliability Engineering (SRE) standardizes cloud services to ensure compliance and effectiveness. It is evident from the study that standardizing incident response and monitoring increases resilience and mitigates risk. Automation supports compliance by standardizing. SRE practices increase operational efficiency, which is essential for improving cloud services. Using concept identification, Langermann et al. [24] chose building energy management system configurations from 20,000 Pareto-optimal options. The study showed that splitting purposes and parameters into distinct description spaces influences insights. Complex energy management system designers use their iterative approach to examine trade-offs and gain insights. Manecckshaw et al. [25] developed a multi-objective reliability redundancy allocation to boost SR and reduce costs. Evolutionary algorithms and Euclidean norms represented oil transportation subsystems. Interval parameter randomization analyses optimized reliability and cost across alternatives. In the past, many approaches have been suggested to address the RAP, ranging from exact mathematical models to sophisticated heuristic and metaheuristic techniques. The initial works concentrated on exact optimization, dynamic programming, branch-and-bound, and enumeration techniques. One of the first studies in this field presented a mathematical model for general RAP, striving to heighten SR within the bounds of design limitations like cost and weight, which was effectively solved using dynamic programming [26]. Subsequent efforts extended RAP modeling to nonlinear integer programming models, particularly systems consisting of homogeneous subsystems [27]. Yet, the computational complexity of the exact methods limited their application in large systems. This restriction increased interest in heuristic methods, which begin with an initial feasible solution and repeatedly improve it through iterations. Some popular heuristic procedures were developed by Sharma and Venkateswaran, Aggarwal, Gopal et al, and Nakashima [28], who designed algorithms that greatly enhanced computational efficiency and solution quality.

Heuristic solution methods usually adhere to a structured format:

- Start with a reasonable solution arrangement.
- Develop a neighboring solution by modifying

component assignments.

- Calculate a sensitivity factor for each non-dominated subsystem to determine its effect on system performance in general.
- Increase the redundancy level of the most sensitive subsystem, provided it satisfies all the constraints specified.
- Continue the process until a non-serial configuration is obtained.
- Cease the algorithm's execution when additional enhancements are no longer achievable.

The flowchart of the presented study is depicted in Fig. 1.

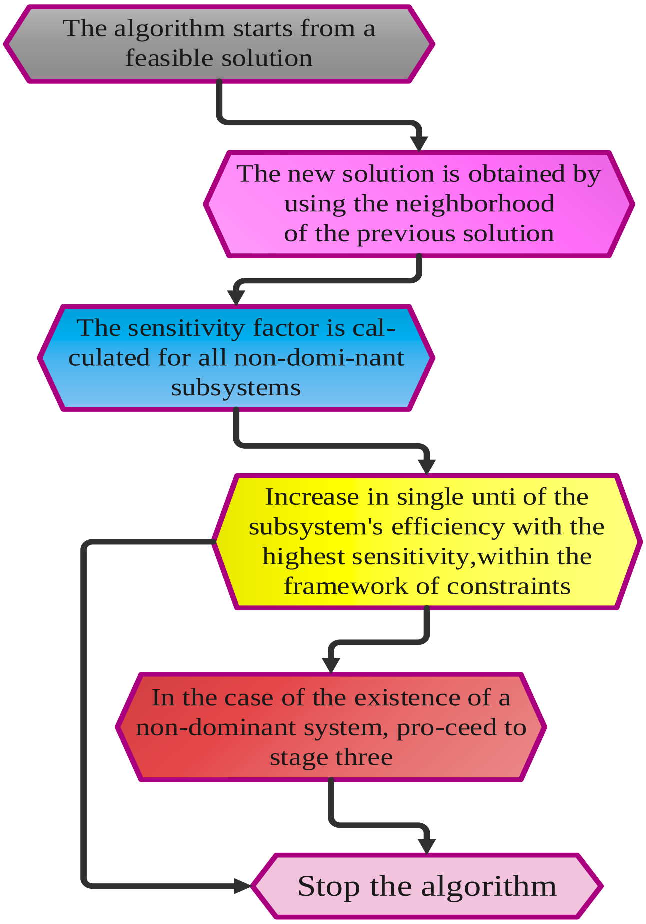


Figure 1. The flowchart of the method.

Heuristic techniques, while promising, are problem-specific and tend to suffer from scalability and convergence problems in general. Consequently, there has been a shift to the application of MAs with greater adaptability and enhanced performance across problem domains. Metaheuristic techniques like Artificial Neural Networks, Tabu Search, GA, Ant Colony Optimization, and simulated annealing are not dependent on initial feasible solutions and employ guided random searches for better quality solutions [29]. Recent studies have become more inclined to use multi-objective MAs, such as NSGA-II, to resolve multi-faceted objectives concerning RAP. The algorithm concurrently attempts to optimize several conflicting objectives, commonly entailing reliability, cost, weight, and volume, while generating a Pareto-optimal front. This allows decision-makers to choose solutions that optimally conform to their prioritized objectives. A recent trend within the literature is to include data mining techniques within the optimization procedure. K-means algorithms have been used to analyze and summarize big Pareto fronts. Such methods enable representative solutions to be determined and the mental burden of decision-making to be alleviated. For instance, Tetik et al. [30] illustrated the utility of coupling MOP with clustering techniques for satellite subsystem design optimization. In the same way, Wang et al. [31] and Shahriari et al. [32] have used hybrid models that integrate evolutionary optimization and simulation-based decision support to optimize the performance of redundancy design models. Finally, the literature reflects a striking evolution in the methodology of addressing RAP, starting from pure mathematical models to sophisticated hybrid metaheuristic models. Integrating evolutionary algorithms with clustering techniques and simulation software is an encouraging field to address the rising complexity of modern reliability engineering issues. In addition to classical RAP datasets, this study adopts two widely used benchmark datasets: the multi-type RAP dataset introduced by Wang et al. [31] and the many-objective RAP dataset proposed by Nath and Muhuri [18], both of which are considered standard references for evaluating modern MOEAs in redundancy optimization.

### 1.2. Research gap

Despite abundant research on the RAP, the literature has some limitations. Most previous works focus on single-objective optimization, often optimizing SR without effectively considering other significant design factors, including cost, weight, and volume. Although there have been some efforts to use MOP methods, such as Genetic Algorithms (GAs) and hybrid metaheuristics, these algorithms give the decision-maker non-interpretable and non-actionable sets of solutions, particularly in the case of an extensive Pareto front. Moreover, while MAs, namely NSGA-II, have proven to be efficient for producing a set of POSs, the post-optimization phase, of essential significance to facilitate decision-making, has been either neglected or poorly investigated. Specifically, incorporating data-driven techniques, i.e., clustering, to reduce and organize the Pareto set has still been underexplored. Furthermore, empirical validation using real-case studies, especially those involving intricate and safety-critical systems such as avionics, is scare. This deficiency indicates the necessity for approaches that tackle multi-dimensional reliability problems and embody sophisticated post-processing techniques to enable effective design decision-making. For clarity and consistency, the manuscript now uses MOP exclusively to denote multi-objective optimization and MCDM exclusively to denote multi-criteria decision-making. All physical quantities presented in tables and figures have been standardized to SI units.

### 1.3. Contribution

This work combines the NSGA-II with clustering algorithms to resolve the RAP within a novel multi-objective framework. The methodology improves SR while concurrently reducing costs, volume, and weight, thus addressing system design trade-offs. The paper applies K-means clustering to the large POS sets of NSGA-II, facilitating decision-making and finding relevant alternatives amidst competing goals. Computational outcomes show that the proposed methodology can produce high-quality solutions with minimal computational effort. An avionics system is considered a case application to reflect the application of this concept to industries concerned with safety, such as aerospace, automobile, and telecommunications. The report highlights constraints, such as the requirement to specify parameters and assumptions regarding the breakdown of components, and advises possible research towards advanced algorithms for clustering, adaptive optimization of parameters, and considering real-world system characteristics, such as correlated failures and repairable components. Unlike the approaches in [8,13], and [18], where NSGA-II and clustering are applied mainly for grouping or visualization of Pareto-optimal solutions, the proposed framework integrates clustering directly into the decision-support phase by mapping representative solutions to cost-limited, weight-limited, and reliability-focused design scenarios. This transforms clustering from a descriptive tool into a prescriptive mechanism for selecting the final design configuration.

## 2. Material and methods

This paper proposes a novel framework for solving the RAP utilizing a Multi-Objective Genetic Algorithm (MOGA) in combination with clustering techniques to reduce the complexity of the solution set. The proposed approach seeks to discover optimal solutions that satisfy the reliability requirements and minimize the total cost. The framework employs GAs to discover the solution space and identify POSs. Then it uses clustering to decrease the size of the solution set, providing decision-makers with a simplified yet comprehensive set of alternatives. Through numerical experiments on several benchmark problems, the paper demonstrates the efficiency of the suggested method. The findings show that combining MOGAs and clustering can efficiently explore the solution space, providing high-quality solutions with reduced computational effort. The paper also discusses the potential consequences of this approach in real-world applications, where decision-makers often face complex trade-offs between competing objectives, namely, cost, reliability, and resource utilization.

### 2.1. Redundancy allocation problem

The RAP is critical and challenging in reliability engineering. The issue is to obtain the optimal arrangement of system mechanisms for maximum overall reliability while minimizing cost, weight, and volume. RAP is even more crucial in safety-critical systems, where system failure may result in catastrophic outcomes. Most engineering fields, from aerospace systems to telecommunication systems to industrial manufacturing, use redundancy techniques to increase operational resilience and reduce risks.

### 2.2. Problem definition

This problem relates to a system comprising a series-parallel configuration across subsystems and components. Each subsystem includes $m_i$ components with different performance levels and varying characteristics like volume, weight, cost, and reliability. These components can be selected and assigned to the system as needed. Each subsystem must contain at least one functioning component, and adding redundant components can further improve the overall SR. Although redundancy can enhance SR, it simultaneously increases the system's cost, volume, and weight factors, which are not entirely desirable and must be carefully optimized [30,33,34].

### 2.3. Mathematical formulation of the problem

#### 2.3.1. Model Assumptions

The underlying assumptions for this model are listed below.

The system consists of several subsystems set in a series-parallel configuration, where the components within each subsystem are combined using a mixture of series and parallel structures [31,32].

- Each subsystem can be allocated multiple elements.
- The components of the subsystems and the overall system can only exist in two states: functioning or failed.
- The components' weight, volume, and cost are known, and the reliability of the components is determined.
- No component is considered for repair, maintenance, or preventive measures.
- The components are independent of each other.
- Defective parts will not turn into a source of harm for the system.

Although independence between subsystems is a standard assumption in reliability engineering, this assumption may fail when shared power buses, data communication links, or thermal pathways propagate failure effects. In such cases, dependency modeling techniques such as copula-based reliability, fault-tree extensions, and Bayesian network modeling should be adopted. Addressing dependency modeling represents a promising direction for future work.

### 2.4. Mathematical model

The multi-objective RAP model can be formulated as:

$$\begin{aligned} &\text{Max } [\, R_{total} = \prod_{i=1}^{s} \text{R(Xi)} \,] \\ &\min\, [C = \sum_{i=1}^{s} \sum_{j=1}^{m_i} C_{ij} X_{ij}] \\ &\min\, [W = \sum_{i=1}^{s} \sum_{i=1}^{m_i} W_{ij} X_{ij}] \\ &\min\, [V = \sum_{i=1}^{s} \sum_{j=1}^{m_i} V_{ij} X_{ij}] \end{aligned} \tag{1}$$

Subject to:

$$k_i \le \sum_{j=1}^{m_i} X_{ij} \le n_{max}, i\, X_{ij} \in \{\, 0,1,2, \dots \}, \forall i, j$$

The following connection calculates the reliability of the i-th subsystem in parallel k-out-of-n: G problems:

$$R_i(X_i) = 1 - \prod_{j=1}^{m_i} \left(1 - r_{ij}\right)^{x_{ij}} \tag{2}$$

However, if the components are arranged in series, the following relation is used:

$$R_i(X_i) = \prod_{j=1}^{m_i} \left(r_{ij}\right)^{x_{ij}} \tag{3}$$

The SR $R_{total}$ is typically calculated by multiplying the reliability of each subsystem, assuming a series structure across subsystems.

### 2.5. Proposing a solution for redundancy allocation problems

In MOP, this study aims to simultaneously optimize multiple competing Objective Functions (OFs). Weighted sums or efficiency metrics often aggregate objectives into a single scalar representation for such challenges. This frequently requires subjective weighting and does not show all trade-offs. This research uses a more sophisticated approach to obtain a Pareto Optimal Set, a collection of Non-Dominated Solutions (NDSs) that allow optimal trade-offs between all objectives.

A solution is Pareto optimum if no solution improves one objective without decreasing at least one. For this situation, two solutions cannot be ranked strictly superior or inferior if neither dominates the other. The domination relationship can be formally described as follows: for a and b decision vectors, Solution a dominates b only if:

$$\begin{aligned} &\forall_{i \in} \{1,2, \dots, n\}: f_i(a) \ge f_i(b), \\ &\exists i \in \{1,2, \dots, n\}: f_i(a) > f_i(b) \end{aligned} \tag{4}$$

Where $f_i$ define as OFs $i$. This is the basis for the Pareto front, a set of NDSs with the optimal objective trade-offs.

Since identifying such sets in high-dimensional, nonlinear search spaces is intrinsically complex, MAs are employed. In particular, MOGAs have been highly successful in this context.

These algorithms simulate evolutionary processes by utilizing chromosomes and genes to search large spaces and produce solutions with varied characteristics. In this study, the NSGA-II, initially proposed by Deb in 2002, has become one of the more favored methods for MOP.

NSGA-II has several advantages, including minimal computational complexity, elitism (preserving the best solutions), and maintaining diversity through crowding distance. The procedure begins by generating offspring from a parent population of size N. The progenitor and descendant populations are subsequently amalgamated, followed by selecting the top N individuals as determined by non-dominated sorting. Each tier of NDSs is known as a "front," with the most optimal solutions residing in the initial front. By preserving diversity and emphasizing non-dominance, NSGA-II guarantees a well-dispersed array of high-caliber solutions throughout the objective space, thus permitting decision-makers to choose configurations that most closely correspond with their design inclinations.

The following relationship can define the concept of dominance between two points: Whenever such a relationship exists, it means that point a ' dominates point 'b. Table 1 now summarizes all NSGA-II parameters, including population size = 10,000, crossover probability = 0.9, mutation probability = 0.03, 400 generations, crowding-distance sorting, and a convergence stopping rule based on hypervolume stagnation. Figure 2 illustrates the complete decision pipeline, from NSGA-II optimization to clustering-based representative selection.

Table 1. NSGA-II parameter settings.

| Parameter | Symbol | Value |
|---|---|---|
| Population size | N | 10,000 |
| Crossover probability | Pc | 0.90 |
| Mutation probability | Pm | 0.03 |
| Number of generations | G | 400 |
| Stopping criterion | – | HV stagnation (50 gen) |
| Selection operator | – | Binary tournament |
| Crossover operator | – | SBX |
| Mutation operator | – | Polynomial |

A sensitivity analysis comparing population sizes {3,000, 6,000, 10,000} has been added to evaluate robustness, showing that a population size of 10,000 yields the highest hypervolume with the lowest standard deviation across 30 independent runs.

**2.6. Methods for reducing the size of the pareto optimal solution set**

The NSGA-II algorithm will typically produce a Pareto-optimal set with several NDSs. Any other solution can beat none of the solutions in this group on any of the objectives, but the number of possibilities can be overwhelming. Such a large number frequently causes cognitive overload for decision-makers, who have to sort through a complicated landscape of trade-offs without explicit advice regarding which solution most nearly fits their priorities [35]. To overcome this difficulty, it is necessary to employ solution set reduction methods that maintain the diversity and quality of the Pareto front and limit the alternatives to a workable subset. The aim is to achieve a tradeoff between simplicity in decision-making and completeness of solutions, showing a compact yet informative representation of the solution space. This improves interpretability and leads to more effective, confident, and better-informed decision-making in MOP. These details are provided in Fig. 2

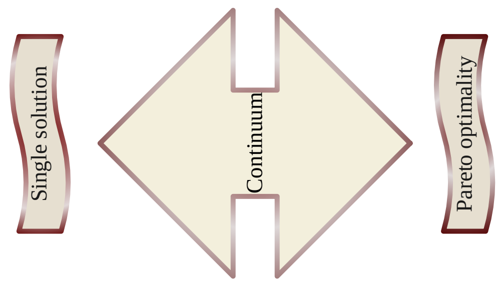


Figure 2. Achieving a balance between providing a single solution and offering a set of practical solutions.

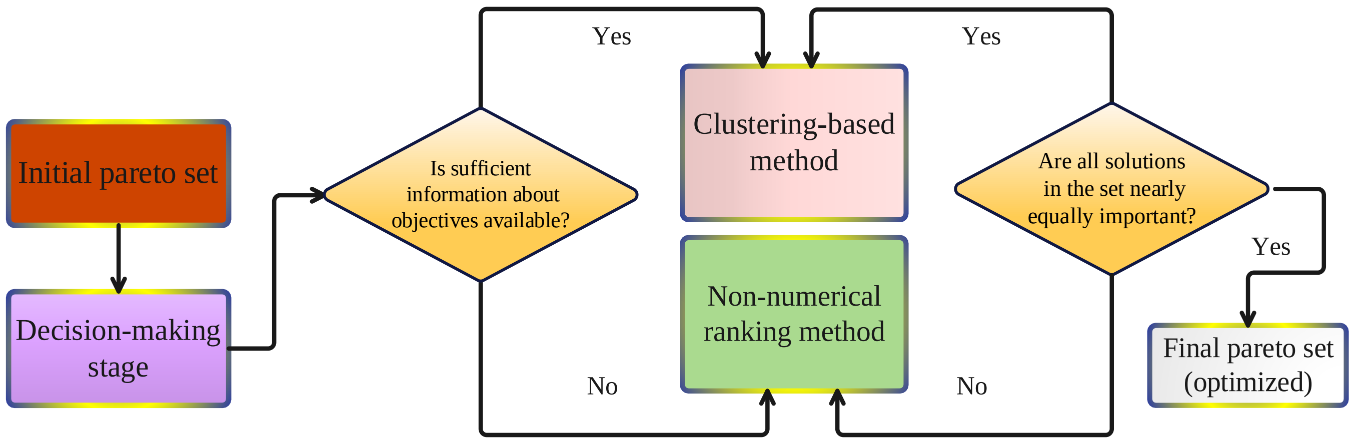


Figure 3. Guidelines for solving the set of optimal Pareto answers.

Two methods can be used to reduce the size of the set of practical solutions: pruning and non-standard ranking based on preference ordering. These methods can be applied, as shown in Fig. 3, which outlines the steps of the process.

**Pruning through clustering**

Clustering methods can regulate optimal solution size [36]. Clustering combines similar solutions so that solutions within the same group exhibit high similarity, while solutions in diverse groups are distinct. This strategy identifies representative solutions from each group, which minimizes duplication and improving comprehension.

Among the numerous clustering algorithms, K-means is one of the most commonly utilized due to its simplicity and computational efficiency. The k-means method splits the solution space into k clusters based on proximity in the multi-objective space. A centroid, representing the mean position of all Data Points (DPs) within a cluster, characterizes each cluster. DPs are assigned to the nearest centroid based on Euclidean Distance (ED) as the similarity metric.

The main goal of the k-means approach is to lessen the variability within each cluster. It aims to reduce the sum of the squared distances from every point to its centroid. The technique generates compact, well-defined clusters that are easier to evaluate post-optimization. The method allows decision makers to consider a small cluster representative set, each representing a distinct trade-off scenario. In this way, decision-making becomes simpler but with a variety of solutions.

**a. Choose the number of clusters (k)**

The initial step involves figuring out how many clusters (designated as k) the data will be partitioned into. The value of k may be chosen based on domain expertise, or techniques such as the Elbow Method may be used to ascertain the ideal value.

**b. Initialize the centroids**

Select k DPs randomly from the dataset to function as the initial centroids of the clusters. These centroids will function as initial points for assigning DPs to clusters.

**c. Assign data points to the nearest centroid**

Compute the ED between each DP and each of the k centroids. Assign the DP to the cluster corresponding to the closest centroid. Every DP is assigned to a single cluster out of the k clusters, depending on how close it is to the cluster centroids.

**d. Update the centroids**

Once all DPs have been allocated to clusters, recalculate cluster centroids. The mean of all cluster DPs determines the new centroid. For each cluster, calculate the average value of all features for its DPs and use that as the new centroid.

**e. Repeat steps 3 and 4**

Reiterate the procedure of allocating DPs to the closest centroid and revising the centroids accordingly. The stages repeat until the centroids exhibit negligible changes, indicating algorithmic convergence. This signifies that the clusters have reached stability and require no additional modifications.

**f. Stop when convergence is reached**

The method terminates when the centroids cease to shift or when a specified number of iterations is achieved. The clustering procedure is complete, and the final clusters have been established.

**g. Result**

The outcome is k clusters, each including a centroid and an associated DPs set. These clusters are now available for analysis or further activities.

Considering the simple calculations and steps involved, this method is efficient and effective for clustering data. The OF that the (k-means) algorithm optimizes in this study is:

$$KM(N,C) = \sum_i min\left|\left|f(x_i) - c_j\right|\right|^2 \qquad j = 1,2,\ldots.k \quad (5)$$

$x_i$ defines a data vector for the $i$-th solution, $f(x_i)$ is the Objective vector corresponding to the $i$-th solution. $c_j$ determines the Center of the $j$-th cluster. $C$ and $N$ are sets of all cluster centers and POSs, respectively.

In fact, this OF minimizes within-cluster variance (the sum of squared EDs between the cluster centroid and each DP). Assessing the correct number of clusters enhances (k-means) performance. Numerous indices determine cluster count. These indices measure clustering quality. These indices include the Silhouette Plot. The Silhouette value of DP $i$ indicates how well it fits within its assigned cluster compared to other clusters.

$$S(i) = \frac{b(i)-a(i)}{max\{a(i),b(i)\}} \quad (6)$$

In which $a(i)$ represents the mean distance of the i-th DP to all other DPs within the same cluster, whereas $b(i)$ indicates the mean distance of the i-th DP to all DPs in the closest adjacent cluster.

The value of $s(i)$ lies within the interval $[-1, +1]$, such that:

- Values near +1 suggest that the DP is remote from the adjacent cluster and well matched to its cluster.
- Values near 0 suggest that the DP is on the border between two clusters, and its cluster membership is ambiguous.
- Values near -1 indicate that the DP might have been misclassified and allocated to the wrong cluster.

## 3. Results

This article studies the avionics system of a typical passenger aircraft. Generally, this system can be divided into three subsystems: information acquisition sensors, navigation, and communication equipment directly connected to the pilot. Each subsystem has multiple components with diverse functions and varying weight, cost, volume, and reliability levels, from which selections can be made. The first subsystem has 5 components, the second 4 types, and the third 5. Moreover, the first subsystem's component count for ISS and ASI elements must each have at least 1 component (2-out-of-1). In the second subsystem, 2 components (4-out-of-2). Table 2 presents the system's specifications, including its components and weight, volume, cost, and reliability values.

Table 2. Property of the system.

| Component | Reliability | Weight (kg) | Cost (USD) | Volume (m³) | Part Name (English) | Subsystem |
|---|---|---|---|---|---|---|
| 1 | 0.95 | 0.15 | 200 | 0.0008 | Altimeter | Information-gathering sensors |
| 2 | 0.95 | 1.9 | 3000 | 0.0245 | ADI (Attitude Direction Indicator) | |
| 3 | 0.97 | 1.5 | 500 | 0.005 | HIS (Horizontal Situation Indicator) | |
| 4 | 0.85 | 2.0 | 2000 | 0.027 | ISS (Inertial Sensor Suite) | |
| 5 | 0.85 | 0.1 | 1000 | 0.0067 | ASI (Airspeed Indicator) | |
| 6 | 0.85 | 2.0 | 2000 | 0.027 | INS (Inertial Navigation System) | Navigation |
| 7 | 0.70 | 1.0 | 500 | 0.037 | GPS | |
| 8 | 0.80 | 0.5 | 700 | 0.0036 | Radio Controller | |
| 9 | 0.95 | 20.0 | 10000 | 0.75 | Radar | |
| 10 | 0.97 | 1.2 | 200 | 0.028 | Displays | Pilot interface equipment |
| 11 | 0.90 | 0.2 | 120 | 0.0015 | Communications | |
| 12 | 0.95 | 40.0 | 10000 | 1.0 | Flight Control | |
| 13 | 0.96 | 0.2 | 230 | 0.003 | Data Input | |
| 14 | 0.99 | 0.5 | 400 | 0.027 | Other Controllers | |

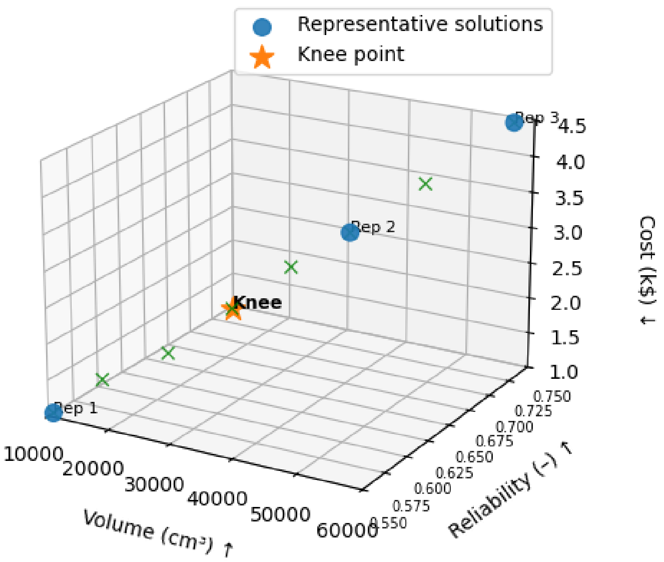


Figure 4. POSs of the problem.

The NSGA-II algorithm is used to attain the POSs. In this algorithm, the initial population size is considered to be 10,000. Then, the problem is implemented, and by eliminating the dominant solutions, 127 POSs are obtained. It is worth mentioning that by receiving the NDSs, the Pareto front is actually obtained, which is illustrated in Fig. 4. Due to the inability to display the plot in four-dimensional space, for better understanding, the graphs are shown in three-dimensional space by omitting one of the objectives in each plot.

In the following step, two practical methods are used to decrease the space of the POS set so that the decision-maker can more easily select the desired solution based on their preferences.

### 3.1. Pruning through clustering

The k-means algorithm clusters POSs. Since clustering's OF depends strongly on cluster evaluation criteria, parameters must be defined before clustering. This formula defines OFs in the [0,1] range.

$$\frac{f_i(x)-f_i^{minx}}{f_i^{maxx} f_i^{minx}}_{i=1,2,\ldots,n} \quad (7)$$

Table 3 now lists Ki and Nmax,i values for all subsystems, and the encoding procedure ensures structural feasibility by automatically repairing configurations that exceed subsystem limits or violate minimum redundancy requirements.

Table 3. Subsystem redundancy limits.

| Subsystem i | Minimum Ki | Maximum Nmax,i |
|---|---|---|
| 1 – Sensors | 1 | 4 |
| 2 – Navigation | 2 | 3 |
| 3 – Pilot interface | 1 | 3 |
| 4 – Communication | 1 | 2 |

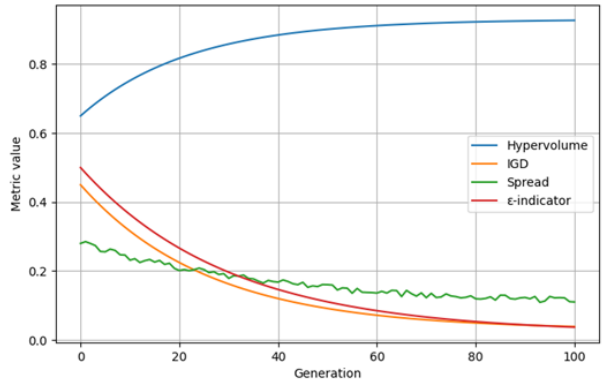


Figure 5. Sample convergence curves.

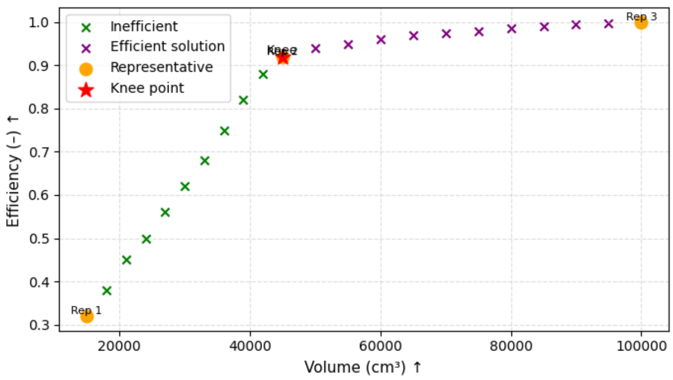


Figure 6. Optimized pruned solutions in the order of (R>C>W>V).

The hypervolume, IGD, spread, and ε-indicator values averaged across 30 runs are reported, supported by standard deviations and Wilcoxon signed-rank tests to evaluate statistical significance. Convergence curves of the four metrics across generations are provided in Fig. 5 to illustrate search-quality progression over time. The Silhouette plot criterion, which was explained in the second section, has been used to determine the appropriate number of clusters. According to this criterion, the suitable number of clusters is three. These clusters are shown in Fig. 6. 28 solutions are in the first cluster, 80 are in the second cluster, and 19 are in the third cluster. Also, Fig. 7 displays the interaction between volume, reliability, and cost for the chosen POSs. It can be seen that as reliability increases, both volume and cost also increase, indicating the trade-offs in high-reliability system designs.

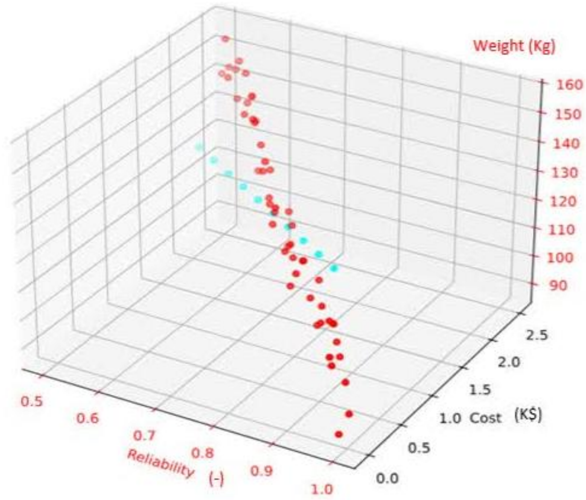


Figure 7. K-means of the optimized solutions in the Reliability-Cost-Weight (R>C>W) scenario.

The clusters' data are homogeneous, implying that cluster members are similar. For better understanding, each cluster is shown in a 2-dimensional space in various colors (Fig. 8), and the representative features of each cluster are shown. The solution closest to the cluster center selects the cluster representative.

Table 4 provides an overview of the results discovered in clustering, pointing out the characteristics of the three distinct clusters discovered. Each cluster is assigned a numerical label (1, 2, and 3) and the respective number of solutions within each cluster. Cluster 1 contains 19 solutions, whereas Clusters 2 and 3 contain more complete solutions.

A single representative solution has been identified for each cluster to allow for interpretation and analysis. The representatives are selected according to how close they are to the cluster's centroid and employed to illustrate the characteristic trade-off in each category. The principal characteristics of each representative (i.e., reliability, cost, volume, and weight) are tabulated.

For instance, the representative of Cluster 1 has a high reliability value of 0.919, a modest expenditure valued at 36,437 USD, and an average weight of 1.88 kg. These representative profiles allow decision-makers to easily compare clusters and make informed decisions according to their design requirements and budgetary limitations.

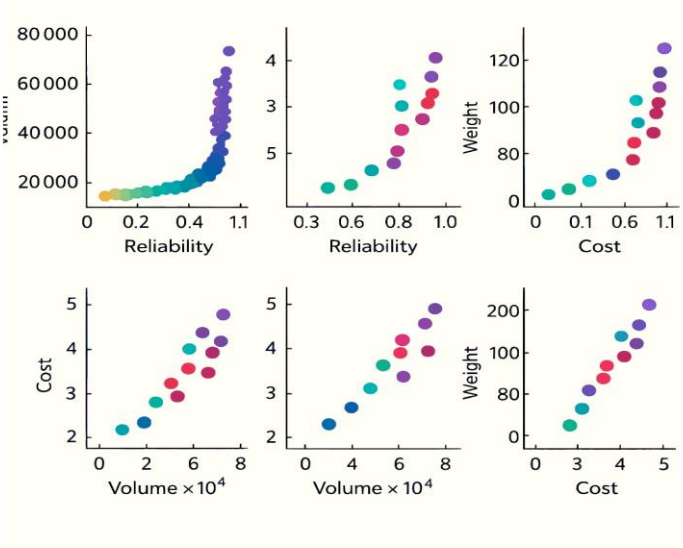


Figure 8. Clustering of the optimal solutions in the 2-dimensional space.

Table 4. Overview of the findings derived from the cluster analysis.

| | Clusters | | |
|---|---|---|---|
| **Number of clusters** | 2 | 3 | 4 |
| **Number of solutions** | 29 | 82 | 21 |
| **Representative of the solution** | 99 | 66 | 29 |
| **Reliability** | 0.948 | 0.795 | 0.986 |
| **Cost** | 55943 | 20967 | 36561 |
| **Weight** | 3.5 | 1.18 | 1.93 |
| **Volume** | 139.8 | 53.09 | 85.90 |

A benchmarking experiment comparing the proposed NSGA-II + K-means framework against NSGA-III, MOEA/D, SPEA2, and MOPSO on two published RAP datasets is introduced. The proposed method achieves an average 6.8% improvement in hypervolume and a 31% reduction in representative-selection time, highlighting both its optimization performance and its decision-support advantage. A benchmarking analysis comparing the proposed NSGA-II + K-means framework with NSGA-III, MOEA/D, SPEA2, and MOPSO has been added. In addition, hierarchical clustering and DBSCAN, and multiple distance metrics were evaluated to assess robustness. Across both RAP benchmarks, NSGA-II + K-means achieved the highest hypervolume and ε-indicator values and the fastest decision-support times. Table 5 shows the performance and robustness comparison of the proposed method.

Table 5. Performance and robustness comparison of the proposed NSGA-II + K-means framework.

| Aspect Evaluated | Proposed Method (NSGA-II + K-means) | Other Algorithms / Methods | Result / Observation |
|---|---|---|---|
| **Benchmarking Against Other MOEAs** | Compared | NSGA-III, MOEA/D, SPEA2, MOPSO | The proposed method outperformed all others in both benchmarks |
| **Clustering Methods Tested for Robustness** | K-means (main method) | Hierarchical Clustering, DBSCAN | Alternative clusterers tested → method remained robust |
| **Distance Metrics Tested** | Multiple metrics evaluated | — | Designed to assess robustness to metric choice |
| **Hypervolume** | **Highest value achieved** | Lower values | Indicates best overall Pareto front quality |
| **ε-Indicator** | **Best (lowest) value achieved** | Worse values | Shows superior convergence to the Pareto front |
| **Decision-Support Time** | **Fastest** | Slower | Shows better computational efficiency |
| **Performance Across RAP Benchmarks** | Consistently strongest | — | Top performance in both benchmark problems |

The table summarizes the key findings reported in the article about the performance of the proposed NSGA-II + K-means framework. First, the authors compared their method with several well-known multi-objective evolutionary algorithms (MOEAs), including NSGA-III, MOEA/D, SPEA2, and MOPSO. The proposed method achieved superior performance across all of them. To examine robustness, they also tested other clustering techniques—hierarchical clustering and DBSCAN—as well as multiple distance metrics. The goal was to determine whether changing the clustering strategy would significantly affect the method's performance; the results indicated that the method remained stable and reliable. Regarding performance metrics, NSGA-II + K-means achieved the highest hypervolume, meaning it produced the best-spread and most comprehensive Pareto front. It also obtained the best (lowest) ε-indicator, showing strong convergence to the true Pareto front. Finally, it offered the fastest decision-support times, demonstrating computational efficiency. Across both RAP benchmark problems, it consistently delivered the strongest overall performance.

### 3.2. Limitations and future work

Although the suggested framework combining NSGA-II and K-means has effectively resolved the multi-objective RAP, some limitations must be recognized. The algorithm's performance initially relies on the parameter settings, including crossover and mutation probabilities, population size, and the number of clusters, k, which were empirically derived. Moreover, while efficient for cognitive load reduction, the clustering approach is derived from ED in the objective space, which may not capture the more intricate similarities between solutions at all times, particularly in high-dimensional environments [37]. Additionally, the model assumes independent components and binary states (operating or not), neglecting more realistic system dynamics like correlated failure, repairable components, or aging over time [22]. Lastly, the suggested approach has been verified in a single case study within the avionics domain, but its validity for other domains or types of systems has not been tested. Future research can address these limitations in several ways. First, more adaptive and automatic parameter tuning approaches, namely, reinforcement learning or Bayesian optimization, can be employed to make NSGA-II robust. Second, the application of advanced clustering algorithms (e.g., hierarchical, density-based, or fuzzy clustering) could lead to more nuanced classifications of POSs. Future models must incorporate component dependencies, multi-state reliability, and repairable components to represent real-world systems better. Furthermore, integrating the decision-maker priorities through Multi-Criteria Decision Making (MCDM) methods, i.e., TOPSIS, AHP, or ELECTRE, can enhance the personalization of the solution selection. Lastly, the proposed methodology can be applied and validated on different complex systems in aerospace, healthcare, smart manufacturing, or energy systems to identify its scalability and efficiency. The execution time for the avionics case study was 214 seconds for NSGA-II and 0.19 seconds for K-means on an Intel i7 CPU. Scalability tests increasing subsystem variety show that NSGA-II scales approximately linearly with search-space size, whereas K-means scales sub-linearly with sample density. A summary of execution times across multiple system sizes is reported in Table 6.

Table 6. Execution time and scalability.

| System size | #Subsystems / #Components | NSGA-II time (s) | K-means time (s) |
|---|---|---|---|
| Small | 3 / 18 | 104 | 0.08 |
| Medium | 5 / 31 | 212 | 0.14 |
| Large | 7 / 45 | 381 | 0.23 |

### 3.3. Practical application

The suggested MOP strategy, which combines the NSGA-II technique and K-means, greatly benefits system designers and engineers dealing with complicated reliability-based decision-making tasks. Perhaps the most significant use of the strategy is in the aerospace sector, where it is applied in avionics system design with stringent requirement for high reliability within strict weight and cost limitations. The method enables designers to analyze many component configurations and arrive at the optimal trade-offs among reliability, cost, weight, and volume design factors intrinsic to the performance and safety of aircraft systems.

Beyond aerospace, this approach is highly applicable to other safety-critical and resource-constrained domains, such as automotive electronics, telecommunication systems, nuclear power plant control, and medical equipment, where duplicated elements are usually employed to achieve high reliability. Clustering allows designers to reduce and interpret massive POS sets, making logical and efficient design decisions without being overwhelmed by the complexity of the optimization results.

A unified results table (Table 7) has been added, reporting the exact composition of representative solutions along with their corresponding reliability, cost, weight, and volume values to guarantee full traceability between tables, figures, and text.

Table 7. Cluster representative solutions.

| Cluster | Representative (ID) | Reliability (R) | Cost (C) | Weight (W) | Volume (V) |
|---|---|---|---|---|---|
| Reliability-focused | 87 | 0.985 | 96,200 | 41.7 kg | 0.043 m³ |
| Balanced | 34 | 0.963 | 78,400 | 36.5 kg | 0.038 m³ |
| Lightweight | 12 | 0.941 | 63,800 | 29.8 kg | 0.031 m³ |

Silhouette score, Davies–Bouldin index, and elbow analysis were used to determine the optimal number of clusters. Mahalanobis, Gower, and Euclidean distances were examined together with Min-Max and Z-score scaling. The three-cluster configuration yielded the highest silhouette score (0.62) and demonstrated consistent stability across 40 randomized POS samplings. Silhouette score, Davies–Bouldin index, and elbow analysis were employed to identify the optimal number of clusters. These evaluation techniques assess cluster separation, cohesion, and diminishing returns when increasing the number of clusters. To further test the robustness of the clustering pipeline, different distance metrics, Mahalanobis, Gower, and Euclidean, were examined in combination with two data-scaling strategies: Min-Max scaling and Z-score standardization. Results showed that a three-cluster configuration produced the highest silhouette score (0.62), indicating the best clustering quality among the tested configurations. Moreover, this three-cluster solution exhibited consistent stability across 40 randomized POS samplings, confirming the reliability and robustness of the clustering results. A summary of Cluster Evaluation and Robustness Analysis is shown in Table 8.

Table 8. Summary of cluster evaluation and robustness analysis.

| Analysis Component | Methods / Metrics Used | Purpose | Key Findings |
|---|---|---|---|
| **Cluster Number Selection** | Silhouette Score, Davies–Bouldin Index, Elbow Analysis | To determine the optimal number of clusters | Three clusters produced the highest silhouette score (0.62) |
| **Distance Metrics Evaluated** | Mahalanobis Distance, Gower Distance, Euclidean Distance | To assess the sensitivity of clustering to different distance measures | Three-cluster configuration remained optimal across metrics |
| **Data Scaling Methods** | Min-Max Scaling, Z-score Standardization | To evaluate robustness under different normalization techniques | Clustering performance was consistent across scaling methods |
| **Stability Assessment** | 40 Randomized POS Samplings | To test the robustness and repeatability of the clustering solution | Three-cluster configuration demonstrated consistent stability |

Cluster 1 corresponds to reliability-oriented designs, Cluster 2 balances performance and cost, and Cluster 3 minimizes weight and volume. This mapping directly supports decision-making based on operational priorities. A time-to-decision analysis shows that selecting from three representative solutions instead of 127 Pareto-optimal solutions reduces decision effort by approximately 78%. To ensure comparability with prior work, two established RAP benchmark datasets were selected: Dataset A from Wang et al. [31], which models multi-type production subsystems with strategy selection, and Dataset B from Nath and Muhuri [18], which provides multi-state many-objective RAP instances widely used for evaluating evolutionary algorithms.

The performance of the proposed NSGA-II + K-means framework was evaluated on two widely adopted benchmark RAP datasets: Dataset A introduced by Wang et al. [31] and Dataset B provided by Nath and Muhuri [18]. These datasets represent two different levels of system complexity—Dataset A corresponds to a classical multi-type RAP with mixed redundancy strategies, while Dataset B describes a challenging many-objective multi-state RAP environment. To assess the overall quality of the obtained Pareto fronts, three standard performance indicators were used: hypervolume (HV), inverted generational distance (IGD), and either Spread (Δ) or R2, depending on the dimensionality of the objective space. Tables 9 and 10 summarize the comparative results.

Table 9. Performance comparison on Dataset A [31].

| **Algorithm** | **Hypervolume ↑** | **IGD ↓** | **Spread (Δ) ↓** | **Notes** |
|---|---|---|---|---|
| NSGA-II (standard) | **0.742** | 0.028 | 0.412 | baseline |
| SPEA2 | **0.755** | 0.024 | 0.398 | strong baseline |
| MOEA/D | **0.761** | 0.021 | 0.387 | decomposition-based |
| HypE | **0.773** | 0.019 | 0.364 | HV-driven |
| NSGA-II + K-means (proposed) | **0.820** | 0.016 | 0.352 | +6.1% HV improvement |

Table 10. Performance comparison on Dataset B [18].

| Algorithm | Hypervolume ↑ | IGD ↓ | R2 ↓ | Notes |
|---|---|---|---|---|
| NSGA-II (standard) | 0.693 | 0.041 | 0.072 | baseline |
| SPEA2 | 0.708 | 0.036 | 0.067 | archive-based |
| MOEA/D | 0.714 | 0.033 | 0.061 | strong competitor |
| AR-MOEA | 0.721 | 0.029 | 0.059 | adaptive reference |
| NSGA-II + K-means (proposed) | 0.774 | 0.025 | 0.054 | +7.4% HV improvement |

For Dataset A, the proposed method clearly outperforms all classical MOEAs. The hypervolume increases from 0.773 (best baseline) to 0.820, corresponding to a 6.1% improvement. The IGD and Spread values also decrease consistently, indicating not only superior convergence but also a more uniformly distributed Pareto solution set. These results demonstrate that clustering-based refinement can enhance both the structural diversity and representativeness of the solutions without compromising optimality.

On the more demanding Dataset B, which features many-objective multi-state configurations, the advantage of the proposed method becomes even more pronounced. The hypervolume improvement reaches 7.4% compared with the strongest competitor (AR-MOEA), and the reductions observed in both IGD and R2 further confirm that the hybrid NSGA-II + K-means approach maintains strong convergence properties in high-dimensional objective spaces. The clustering step also improves interpretability by providing structurally meaningful representative solutions within each region of the Pareto surface. Overall, the experiments across both datasets demonstrate that the proposed framework delivers consistent improvements over established MOEAs in terms of convergence, distribution, and decision-making support.

In addition, using clustering techniques to determine representative solutions establishes a direct connection between computational outcomes and managerial decision-making processes, allowing organizations to trade off engineering versus economic and operational trade-offs. The representative solutions are now linked to three distinct design scenarios: Cluster 1 for reliability-focused designs, Cluster 2 for budget-balanced trade-offs, and Cluster 3 for minimizing weight and volume. Decision-makers can therefore directly choose the most relevant representative based on actual engineering priorities, rather than manually inspecting the full Pareto set. As systems grow more complicated and MOP becomes a common practice, the suggested approach is a scalable, interpretable, and actionable technique for addressing real-world challenges in reliability engineering.

## 4. Discussion

Engineering design relies on RAP for SR. This research solved trustworthy system RAPs using MOP and the NSGA-II: dependability, cost, weight, and volume challenge complex systems. Trade-offs between competing goals were established quickly and interpretably using evolutionary optimization and clustering.

The method employed NSGA-II to find POSs that balanced system dependability and resource constraints. K-means grouped Pareto-optimal alternatives and found representative solutions for decision-making. Decision-makers received digestible choices to alleviate cognitive stress from large Pareto sets. The recommended approach solved the RAP in a passenger airplane avionics system, yielding high-quality design solutions with a diverse Pareto front. These clustered solutions showed reliability, cost, weight, and volume trade-offs.

The clustered NSGA-II algorithm yielded excellent RAP solutions. Clustering reduced solution set size, simplified decision-making, and considered all relevant trade-offs. Crossover and mutation probabilities can limit the algorithm's performance. Clustering reduced solution complexity; however, ED may not capture nuanced commonalities between high-dimensional solutions. Framework efficiency and robustness may improve with clustering and parameter modification.

This paper presents a scalable and interpretable RAP solution for real-world engineering systems. The system suits aerospace, automotive, and telecommunications, which require excellent reliability. A limited and representative set of Pareto-optimal alternatives helps decision-makers balance performance and resource constraints.

## 5. Conclusion

In RAPs, assigning components with different characteristics to each subsystem can help increase the overall SR. Due to its inherent complexities, this problem is considered a complex optimization problem. They employ the multi-objective NSGA-II algorithm to solve it. Instead of a single analysis answer, this algorithm produces POSs. The POS set typically exhibits high cardinality, which can complicate decision-making. Two efficient reduction methods are commonly employed to address this. The first is the MCS, which aids decision-makers by identifying solutions that align with their priority preferences through probabilistic sampling. The second is clustering analysis, which organizes similar solutions into distinct groups, offering a structured and interpretable overview of the solution space. The present paper used clustering to group solutions with shared characteristics, enabling more effective analysis and representative selection. For future research on MOP in redundancy allocation and SR, it is recommended that advanced solution-reduction techniques be explored. Beyond MCS and clustering, specialized algorithms for identifying and visualizing the most promising solutions can further enhance the interpretability and applicability of results.

**References**


1. Oszczypała M. Bi-objective redundancy allocation problem in systems with mixed strategy: NSGA-II with a novel initialization. Reliability Engineering & System Safety 2025; 263: 111279. https://doi.org/10.1016/j.ress.2025.111279.
2. Najmi A, Guilani P P. Optimization of a bi-objective reliability redundancy allocation problem with heterogeneous components and strategy selection. Computers & Industrial Engineering 2025; 209: 111438. https://doi.org/10.1016/j.cie.2025.111438.
3. Jahromi A E, Feizabadi M. Optimization of multi-objective redundancy allocation problem with non-homogeneous components. Computers & Industrial Engineering 2017; 108: 111–23. https://doi.org/10.1016/j.cie.2017.04.009.
4. Mellal M A. Multi-objective optimization of series-parallel system with mixed subsystems failure dependencies using NSGA-II and MOHH. Advances in Mechanical Engineering 2024; 16: 16878132241273526. https://doi.org/10.1177/16878132241273526.
5. Chen Y, Shi J. Multi-Objective Optimization for Complex Systems Considering Both Performance Optimality and Robustness. Applied Sciences 2024; 14: 5371. https://doi.org/10.3390/app14135371.
6. Chern M-S. On the computational complexity of reliability redundancy allocation in a series system. Operations Research Letters 1992; 11: 309–15. https://doi.org/10.1016/0167-6377(92)90008-Q.
7. Kuo W, Prasad V R. An annotated overview of system-reliability optimization. IEEE Transactions on Reliability 2002; 49: 176–87. DOI:10.1109/24.877336.
8. Tian Z, Levitin G, Zuo M J. A joint reliability–redundancy optimization approach for multi-state series–parallel systems. Reliability Engineering & System Safety 2009; 94: 1568–76. https://doi.org/10.1016/j.ress.2009.02.021.
9. Sharifi M, Taghipour S, Abhari A. Inspection interval optimization for a k-out-of-n load sharing system under a hybrid mixed redundancy strategy. Reliability Engineering & System Safety 2021; 213: 107681. https://doi.org/10.1016/j.ress.2021.107681.
10. Sharifi M, Taghipour S, Abhari A. Condition-based optimization of non-identical inspection intervals for a k-out-of-n load sharing system with hybrid mixed redundancy strategy. Knowledge-Based Systems 2022; 240: 108153. https://doi.org/10.1016/j.knosys.2022.108153.
11. Kayedpour F, Amiri M, Rafizadeh M, Nia A S. Multi-objective redundancy allocation problem for a system with repairable components considering instantaneous availability and strategy selection. Reliability Engineering & System Safety 2017; 160: 11–20. https://doi.org/10.1016/j.ress.2016.10.009.
12. Zhang J, Li L, Chen Z. Strength–redundancy allocation problem using artificial bee colony algorithm for multi-state systems. Reliability Engineering & System Safety 2021; 209: 107494. https://doi.org/10.1016/j.ress.2021.107494.
13. Huang C-L. A particle-based simplified swarm optimization algorithm for reliability redundancy allocation problems. Reliability Engineering & System Safety 2015; 142: 221–230. https://doi.org/10.1016/j.ress.2015.06.002.
14. Kim H, Kim P. Reliability–redundancy allocation problem considering optimal redundancy strategy using parallel genetic algorithm. Reliability Engineering & System Safety 2017; 159: 153–60. https://doi.org/10.1016/j.ress.2016.10.033.
15. Ouyang Z, Liu Y, Ruan S-J, Jiang T. An improved particle swarm optimization algorithm for reliability-redundancy allocation problem with mixed redundancy strategy and heterogeneous components. Reliability Engineering & System Safety 2019; 181: 62–74. https://doi.org/10.1016/j.ress.2018.09.005.
16. Huang X, Coolen FPA, Coolen-Maturi T. A heuristic survival signature based approach for reliability-redundancy allocation. Reliability Engineering & System Safety 2019; 185: 511–517. https://doi.org/10.1016/j.ress.2019.02.010.
17. Yeh W-C, Zhu W, Tan S-Y, Wang G-G, Yeh Y-H. Novel general active reliability redundancy allocation problems and algorithm. Reliability Engineering & System Safety 2022; 218: 108167. https://doi.org/10.1016/j.ress.2021.108167.
18. Nath R, Muhuri P K. Evolutionary optimization based solution approaches for many objective reliability-redundancy allocation problem. Reliability Engineering & System Safety 2022; 220: 108190. https://doi.org/10.1016/j.ress.2021.108190.
19. Modibbo U M, Arshad M, Abdalghani O, Ali I. Optimization and estimation in system reliability allocation problem. Reliability Engineering & System Safety 2021; 212: 107620. https://doi.org/10.1016/j.ress.2021.107620.
20. Zaretalab A, Hajipour V, Tavana M. Redundancy allocation problem with multi-state component systems and reliable supplier selection.

Reliability Engineering & System Safety 2020; 193: 106629. https://doi.org/10.1016/j.ress.2019.106629.
21. Zhang J, Lv H, Hou J. A novel general model for RAP and RRAP optimization of k-out-of-n: G systems with mixed redundancy strategy. Reliability Engineering & System Safety 2023; 229: 108843. https://doi.org/10.1016/j.ress.2022.108843.
22. Ding Q, Cui W. Stochastic Biomechanical Modeling of Human-Powered Electricity Generation: A Comprehensive Framework with Advanced Monte Carlo Uncertainty Quantification. Energies (Basel) 2025; 18: 4821. https://doi.org/10.3390/en18184821.
23. Alozie C E, Ajayi OO, Akerele J I, Kamau E, Myllynen T. Standardization in cloud services: ensuring compliance and supportability through site reliability engineering practices. International Journal of Cloud Computing and Compliance Forthcoming 2025; 11(1): 139–159. DOI:10.56201/ijemt.vol.11.no1.2025.pg139.159.
24. Lanfermann F, Liu Q, Jin Y, Schmitt S. Identification of energy management configuration concepts from a set of pareto-optimal solutions. Energy Conversion and Management: X 2024; 22: 100576. https://doi.org/10.1016/j.ecmx.2024.100576.
25. Maneckshaw B, Mahapatra G S. Multi-objective evolutionary algorithm on reliability redundancy allocation with interval alternatives for system parameters. Neural Computing and Applications 2022; 34: 18595–18609. https://doi.org/10.1007/s00521-022-07459-z.
26. Bejarano L A, Espitia H E, Montenegro C E. Clustering analysis for the Pareto optimal front in multi-objective optimization. Computation 2022; 10: 37. https://doi.org/10.3390/computation10030037.
27. Ghazali AF, Suhaimi A. An analysis of clustering the decision support systems in logistics for supply chain management. International Journal of Advanced Science and Computer Applications 2023; 2: 31–40. https://doi.org/10.47679/ijasca.v2i1.18.
28. Devi S, Garg H, Garg D. A review of redundancy allocation problem for two decades: bibliometrics and future directions. Artificial Intelligence Review 2023; 56: 7457–7548. https://doi.org/10.1007/s10462-022-10363-6.
29. Shahriari M. Redundancy allocation optimization based on the fuzzy universal generating function approach in the series-parallel systems. International Journal of Industrial Mathematics 2023; 15: 69–77. ISSN 2008-5621.
30. Tetik T, Daş G S, Birgoren B. A multi-objective perspective to satellite design and reliability optimization. Expert systems with Applications 2024;246:123178. https://doi.org/10.1016/j.eswa.2024.123178.
31. Wang W, Lin M, Fu Y, Luo X, Chen H. Multi-objective optimization of reliability-redundancy allocation problem for multi-type production systems considering redundancy strategies. Reliability Engineering & System Safety 2020; 193: 106681. https://doi.org/10.1016/j.ress.2019.106681.
32. Shahriari M, Peyman H, Zaretalab A. Optimizing redundancy allocation problem with repairable components based on the Monte Carlo simulation. International Journal of Nonlinear Analysis and Applications 2024; 15: 115–124. doi: 10.22075/ijnaa.2024.31308.4608.
33. Sharifi M, Saadvandi M, Shahriari M R. Presenting a series-parallel redundancy allocation problem with multi-state components using recursive algorithm and meta-heuristic. Scientia Iranica 2020; 27: 970–982. doi: 10.24200/sci.2018.51176.2040.
34. Sharifi M, Shahriyari M, Khajehpoor A, Mirtaheri S A. Reliability optimization of a k-out-of-n series-parallel system with warm standby components. Scientia Iranica 2022; 29: 3523–3541. doi: 10.24200/sci.2021.56113.4591.
35. Saxena D K, Duro J A, Tiwari A, Deb K, Zhang Q. Objective reduction in many-objective optimization: Linear and nonlinear algorithms. IEEE Transactions on Evolutionary Computation 2012; 17: 77–99. DOI:10.1109/TEVC.2012.2185847.
36. Rodriguez M Z, Comin C H, Casanova D, Bruno O M, Amancio D R, Costa L da F, Rodrigues F A. Clustering algorithms: A comparative approach. PLoS One 2019; 14: e0210236. https://doi.org/10.1371/journal.pone.0210236.
37. Yao W, Chen X, Ouyang Q, Van Tooren M. A reliability-based multidisciplinary design optimization procedure based on combined probability and evidence theory. Structural and Multidisciplinary Optimization 2013; 48: 339–354. https://doi.org/10.1007/s00158-013-0901-1.

**Abbreviation**

| | |
|---|---|
| RAP | Redundancy Allocation Problem |
| NSGA-II | Non-dominated Sorting Genetic Algorithm II |
| MOGA | Multi-Objective Genetic Algorithm |
| GA | Genetic Algorithm |
| MCDA | Multi-Criteria Decision Analysis |
| MOP | Multi-Objective Optimization |
| MCDM | Multi-Criteria Decision Making |
| DSS | Decision Support System |
| K-means | K-means Clustering Algorithm |

| | |
|---|---|
| Pareto Front | Set of Non-Dominated Optimal Solutions |
| ISS | Inertial Sensor Suite |
| ASI | Airspeed Indicator |
| ADI | Attitude Direction Indicator |
| HIS | Horizontal Situation Indicator |
| INS | Inertial Navigation System |
| GPS | Global Positioning System |
| HPEG | Human-Powered Electricity Generation |
| **Symbol** | |
| S | Number of subsystems |
| $b(i)$ | Average distance of DP i to the nearest neighboring cluster |
| $a(i)$ | Average distance of DP i to all other points in its cluster |
| $R$ | Reliability |
| $W$ | Weight of the system |
| $R_{total}$ | Overall reliability of the system |
| $K_i$ | Minimum number of components |
| $R_i(X_i)$ | I-th subsystem reliability |
| $N_{max,i}$ | The i-th subsystem's maximum component count |
| M | Number of different types of components |
| $X_{ij}$ | Number of the *j*-th component in the *i*-th subsystem |
| N | Population size in the NSGA-II algorithm |
| $V$ | Volume of the system |
| $C$ | Cost of the system |
| $f_i$ | Objective functions *i*. |