Research Journal of Mathematical and Statistical Sciences ________________________________ISSN 2320-6047
Vol. **14(1),** 11-19, January **(2026)** *Res. J. Mathematical and Statistical Sci.*

Fuzzy reliability optimization and Performance analysis of Multi-Component Multi-Complex systems

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Available online at: www.isca.in , www.isca.me
Received 12th November 2025, revised 30th December 2025, accepted 10th Janaury 2026

Abstract

Multi-component multi-complex (MCMCS) are common in the engineering industry, including aerospace, power grid, transportation, and manufacturing, where reliability is a significant factor of performance and safety. Conventional methods of reliability analysis (mostly using probabilistic models) can be pretty ineffective in explaining the uncertainties that are caused by incomplete data, subjective input, and operational variability in the real world. To overcome these shortcomings, the fuzzy set theory provides a sound framework that allows one to model and optimize when facing vagueness and imprecision. This paper presents a fuzzy optimization and performance appraisal model specific to MCMCS. This methodology combines fuzzy membership functions of failure rates and repair times with multi-objective optimization procedures that optimize system reliability and availability and lessen cost and resource constraints. The given approach is practical, as evidenced by a case-based analysis that shows the improvement of the suggested method compared to the conventional probabilistic one. Sensitivity analysis also shows the model's flexibility at different uncertainty levels. The main contributions of this work are as follows: (i) a fuzzy modeling framework of complex interdependent systems is developed, (ii) the fusion of the fuzzy multi-objective optimization to enhance reliability, and (iii) a set of performance evaluation metrics can be applied to real-life engineering systems. The findings highlight the possibility of fuzzy reliability optimization to offer more realistic and practical decision-making aids used in fundamental system design and maintenance approaches.-component multi-complex (MCMCS) are common in the engineering industry, including aerospace, power grid, transportation, and manufacturing, where reliability is a significant factor of performance and safety. Conventional methods of reliability analysis (mostly using probabilistic models) can be pretty ineffective in explaining the uncertainties that are caused by incomplete data, subjective input, and operational variability in the real world. To overcome these shortcomings, the fuzzy set theory provides a sound framework, which allows one to model and optimize when facing vagueness and imprecision. This paper presents a fuzzy optimization and performance appraisal model that is specific to MCMCS. This methodology combines fuzzy membership functions of failure rates and repair times with multi-objective optimization procedures that optimize system reliability and availability and lessen cost and resource constraints. The given approach is effective, as evidenced by a case-based analysis that shows the improvement of the suggested method in comparison to the conventional probabilistic one. Sensitivity analysis also shows the model's flexibility at different uncertainty levels.

Keywords: Fuzzy reliability; multi-complex systems; multi-component systems; uncertainty modeling; fuzzy optimization; system availability; performance analysis; evolutionary algorithms; reliability engineering; decision support.

Introduction

Background on Reliability Engineering and System Performance Analysis: Reliability engineering aims to ensure that engineering systems can carry out their designed functions with time without failure[1]. Multi-component systems, including aerospace networks, energy grids, and manufacturing plants, are interconnected elements the overall performance of which is based on the reliability of the elements composing the system[2]. Such systems have been assessed using traditional methods of reliability assessment, such as fault tree analysis, reliability block diagrams, and Markov models[3]. These classical methods have, however, come under serious limitations with such complex and interdependent systems of handling dynamic interactions and uncertain parameters[4].

Importance of Fuzzy Logic in Handling Uncertainties in Reliability Assessment: Reliability data is mostly uncertain because of incomplete records because of expert judgment, or change in the operating conditions[5]. Probabilistic models require the availability of accurate statistical data, which cannot be assumed with real-world systems. The fuzzy set theory is another powerful alternative to the model's inaccuracy, introduced by Zadeh, L. A.[6] whereby uncertain failure rates, repair times, maintenance data can be represented as linguistic variables or fuzzy numbers[7]. Recent research shows that the fuzzy reliability analysis is more suitable than the conventional probabilistic methods to capture the vagueness, hence it is eminently applicable to complex engineering systems[8,9].

Challenges in Optimizing Reliability in Multi-Component and Interdependent Systems: There are several challenges associated with the optimization of the reliability of multi-component multi-complex systems (MCMCS). First, cascading failures caused by interdependencies between the subsystems are hard to model using linear probabilistic methods[10]. Second, the optimization problem is usually multi-objective, compromising cost, reliability, availability, and maintainability[11]. Third, optimization is complicated by uncertainties and incomplete information, and one must have well-developed frameworks that could accommodate fuzziness[12]. Therefore, there is an urgent urgency to develop structures that integrate fuzzy reliability models, as well as optimization algorithms, to make effective decisions in the engineering design and maintenance process.

Research Objectives and Scope: This study will (i) create a fuzzy reliability modeling framework to suit multi-component multi-complex systems, (ii) combine fuzzy-based multi-objective optimization models to optimize reliability and system performance in the face of uncertainty, and (iii) offer a performance analysis framework that applies to a wide variety of fields, including aerospace, power systems, and manufacturing. The study aims to move beyond traditional probabilistic reliability engineering methods by dealing with uncertainty and complexity.

Structure of the Paper: The paper will follow the following outline: Section 3 will review the literature on reliability assessment and fuzzy optimization methods. Section 4 presents the theoretical framework of the fuzzy reliability in MCMCS. In Section 5, the proposed methodology, which involves fuzzy modeling and optimization, is proposed. Section 6 is a case study containing experimental findings. Section 7 analyzes the results and their comparison with traditional models. Section 8 covers findings, whereas in Sections 9 and 10, the research challenges and future directions are stated. Last but not least, the implications and contributions are presented in Section 11.

Literature Review

Traditional Reliability Approaches: The classical reliability methods are based on probabilistic models, whereby the components of a system have the correct statistical data. System failures and dependencies have been widely modeled by such methods as fault tree analysis (FTA) and reliability block diagrams (RBDs)[13]. Another highly popular tool that allows dynamically reliable analysis is Markov models, which consider the transitions of state components of a system over time[14]. Although these methods are helpful when dealing with well-understood systems, they are not available with indefinite systems and imprecise data that appear in the real world[4].

Multi-Component System Reliability Studies: Multi-component system reliability analysis normally involves system configurations such as series, parallel and k-out-of-n systems[2]. Parallel systems are less vulnerable to single point failures and series systems are vulnerable to one point failures[15]. These models are abstracted on the k-out-of-n model that requires the existence of a minimum of k out of n components to be fully operational in order to be successful in the system. However, it is challenging to provide proper performance evaluation using these classical models when the level of interdependencies and heterogeneity increases within a system[10].

Role of Fuzzy Logic in Reliability Engineering: Fuzzy set theory has been used to overcome the weakness of probabilistic models in the field of reliability engineering. Fuzzy fault trees are based on the traditional fault trees and utilize fuzzy failure probabilities, enabling analysts to deal with imprecise input data[8]. Likewise, fuzzy Bayesian networks are probabilistic reasoning networks that employ fuzzy uncertainty modeling to improve the reliability estimation in uncertain environments[9]. Studies have shown that fuzzy reliability models have a more accurate reflection of the language expert judgments. Therefore, they are the most suitable in the systems where accurate statistical data is unattainable[7].

Reliability Optimization Methods: Several metaheuristic algorithms have been used to achieve reliability optimization. Genetic algorithms (GA) have been used to determine the best component redundancies and system structures[11]. The optimization of system availability under constraints has been successfully optimized using particle swarm optimization (PSO)[16]. Grey wolf optimization (GWO) and other swarm intelligence approaches have recently proven valuable in addressing complex multi-objective reliability problems[17]. Fuzzy multi-objective optimization frameworks are also included, and they combine fuzzy modeling and evolutionary computation to enable the simultaneous optimization of conflicting goals in uncertainty[12].

Identified Gaps: Although the literature has progressed in fuzzy modelling and optimisation, some gaps remain. Reliability modeling and optimization are studied in most cases. However, little has been done to integrate both of these into a unified system of multi-component multi-complex systems (MCMCS). Moreover, most of the fuzzy techniques have been applied to simplified models of the system, and there is still a need to test them in large-scale, interdependent, and heterogeneous systems[4,12]. This signifies the significance of realizing integrated fuzzy reliability optimization frameworks that deal with complexity, interdependence, and uncertainty.

Theoretical Framework

Definition of Multi-Component Multi-Complex Systems (MCMCS): Multi-component multi-complex systems (MCMCS) refer to engineering systems that contain numerous interdependent components which tend to interact with each other nonlinearly, are heterogeneous and are highly structured[4]. They are typically applied in aerospace, power grids, healthcare, and transportation where the entire system reliability is determined by the functionality of the individual components as well as their interactions[2]. Complexity is brought about by redundancy, feedback loops, and cascading effects of failures, heterogeneity stems out of the variety of components, with varied behavior of failure and operation[10]. This means that the modeling and optimization of the reliability of MCMCS should be structured in such a way that the reliability of the components and the interaction on a system level is taken into consideration.

Fuzzy Reliability Concepts: The fuzzy set theory can help in solving uncertainty in reliability modeling where the precise probabilistic data is not available[6]. Parameters in the membership functions of the uncertain parameters in fuzzy reliability analysis are failure rates, repair time periods, or operational life. Linguistic judgments can be triangular or trapezoidal fuzzy numbers like low failure rate or high repair time[5].

Two significant results of the fuzzy reliability analysis are Fuzzy Mean Time to Failure (FMTTF) and fuzzy availability. FMTTF extends the classical mean time to failure by adding fuzzy parameters and makes a more realistic consideration of uncertainty[8]. Likewise, in fuzzy availability, system availability is considered in the case of uncertain repair time, which is more representative than crisp probabilistic methods[7]. Such notions enable analysts to include ambiguity in the expert opinion and missing data, enhancing the strength of reliability assessments.

Performance Metrics: The reliability engineering approach generally measures the performance of the system in terms of reliability, availability, maintainability, and cost (RAM-C)[1]. Reliability is used to describe the likelihood of a system to run without a failure during a certain time, whereas availability combines reliability and maintainability, which is used to reflect the duration during which a system is running[13]. Maintainability is how easy and fast it is to recover the system after failure and can be affected by the logistics of the spare parts, the time required to repair and the efficiency of the diagnostic test[2]. Lastly, cost factors are incorporated to make the system optimization economically viable to balance high reliability and available resources[11]. In a fuzzy environment, these metrics are modified to include uncertainty to allow decision-makers to consider system trade-offs using more realistic assumptions[12].

Methodology

System Modeling: In order to examine the reliability of multi-component multi-complex systems (MCMCS), Reliability Block Diagrams (RBDs) and Fault Tree Analysis (FTA) are initially used to represent the structure of the system. RBDs describe the logical interconnection amongst components in either series, parallel, or k-out-of-n constructs, and they are helpful in reliability calculation at the system level[2]. FTAs are used to build upon this by hierarchically decomposing root causes of failures, which are basic events, gates, and top events[13]. Integrating RBD with FTA will provide the capability of both structural model and failure mode modeling, which is vital in taking dependencies and cascading impacts in complex systems[4].

Fuzzy Reliability Estimation: Traditional probabilistic reliability estimation assumes precise values for failure and repair rates, which may not exist in real-world systems. To overcome this limitation, uncertain parameters are represented using fuzzy numbers, typically in triangular or trapezoidal forms[5,6]. For instance, a failure rate may be expressed as a triangular fuzzy number (λL, λM, λU), where L, M, and U represent the lower, most likely, and upper bounds.

The reliability of such systems is computed using the α-cut method, which converts fuzzy sets into interval values for analysis at different confidence levels[7]. Subsequently, defuzzification techniques such as centroid or mean of maxima are applied to obtain crisp reliability values[8]. This process ensures that expert judgments and incomplete failure data are meaningfully incorporated into reliability estimations, offering more robust results than classical approaches[9].

Optimization Model: A multi-objective model is developed to solve the problem of optimization of reliability. The main aims are to maximize the system's reliability and availability at the lowest possible cost and to use the resources[11]. These are communicated as fuzzy constraints reflecting budget constraints, redundancy policy, and structural dependency[12].

An optimization problem may be formulated as follows: i. Maximize: Reliability (R) Availability (A), ii. Minimize: Cost (C)
Constrained by: Resource, budget, and system configuration constraints.

Fuzzy expression of constraints can also provide a more flexible and realistic decision-making, especially when more accurate economic or resource information is unavailable[16].

Solution Approach: Evolutionary algorithms are used to address the fuzzy multi-objective optimization problem because of their capacity to deal with non-linear, non-convex, and non-dimensional search spaces. Genetic Algorithms (GA)[11], Particle Swarm Optimization (PSO)[16], and Non-Dominated Sorting Genetic Algorithm-II are the most popular ones. They effectively investigate trade-offs between conflicting objectives[18].

The optimization model is based on creating a Pareto front of non-dominated solutions, which also correspond to the different trade-offs of system reliability and availability versus cost[17]. The decision-makers may then choose the most suitable configuration according to the requirements of the system and risk tolerance. The application of fuzzy logic in this optimization will guarantee that uncertainties in parameters are directly addressed in the solution process to give more realistic and flexible solutions.

Note: The numerical results obtained from the proposed model are summarized in Table-1 to 4. These Tables have been generated in a separate Microsoft Excel file and are referred to throughout the analysis section.

Table-1: Failure Rates of Components.

Component	Failure Rate (per 1000 hrs)
C1 Power Unit	0.004
C2 Cooling System	0.007
C3 Control Module	0.002
C4 Sensor Array	0.006
C5 Communication Link	0.005

Table-1 presents the failure rates of the individual components considered in the system.

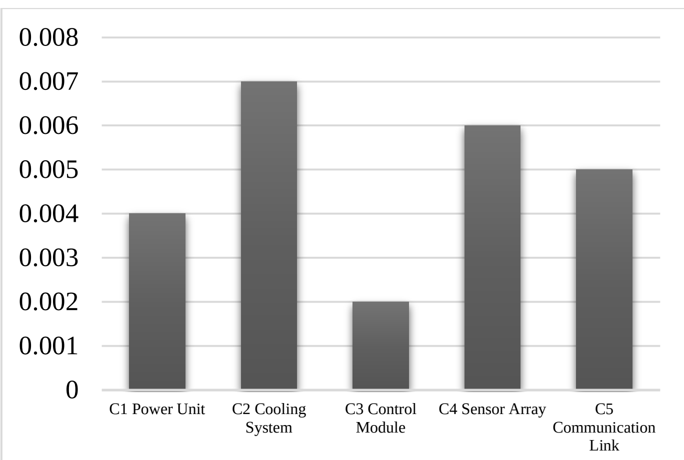

Figure-1: Failure Rates of Components Failure Rate (per 1000 hrs).

Table-2: Repair Times of Components

Component	Repair Time (hrs)
C1 Power Unit	6
C2 Cooling System	8
C3 Control Module	4
C4 Sensor Array	5
C5 Communication Link	7

Table-2: shows the repair times associated with each component of the system.

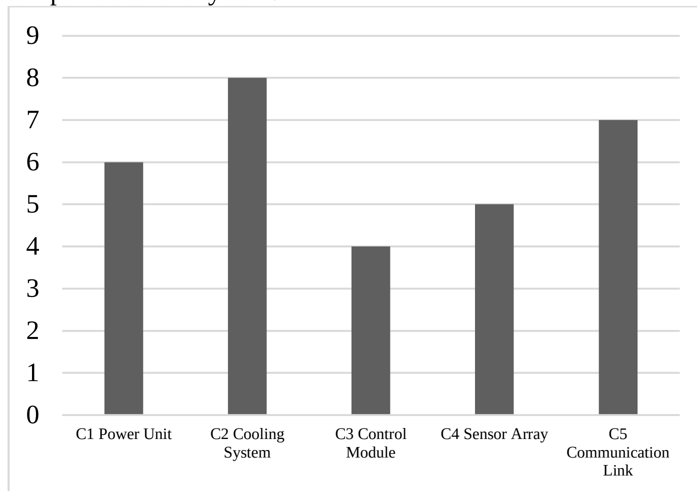

Figure-2: Repair Times of Components.

Table-3: Component Costs.

Component	Cost (□ '000)
C1 Power Unit	150
C2 Cooling System	120
C3 Control Module	200
C4 Sensor Array	100
C5 Communication Link	180

Table-3 summarizes the cost values of the components used in the reliability optimization model.

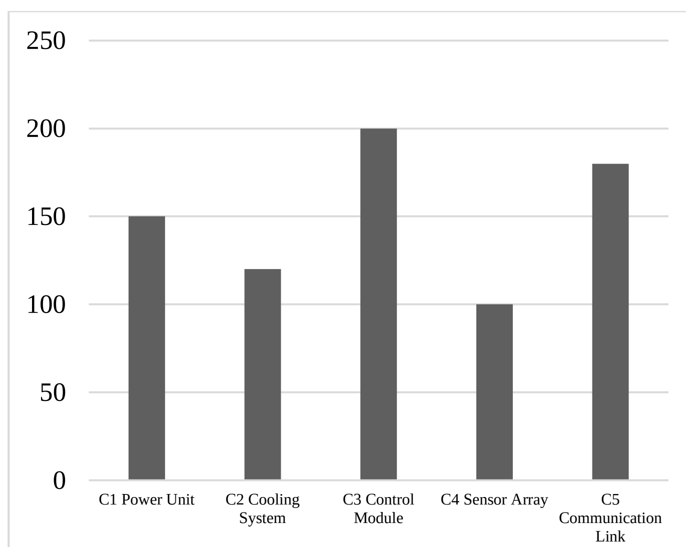

Figure-3: Component Costs (□ '000).

Table-4: Radar Chart of Component Performance.

Component	Reliability (1-λ)	Maintainability (1-Repair)	Cost Efficiency
C1 Power Unit	0.43	0.25	0.28
C2 Cooling System	0.29	0	0.39
C3 Control Module	0.71	0.5	0
C4 Sensor Array	0.14	0.38	0.5
C5 Communication Link	0.29	0.13	0.11

Table-4 provides the radar chart representing the overall performance of the components based on multiple criteria**.**

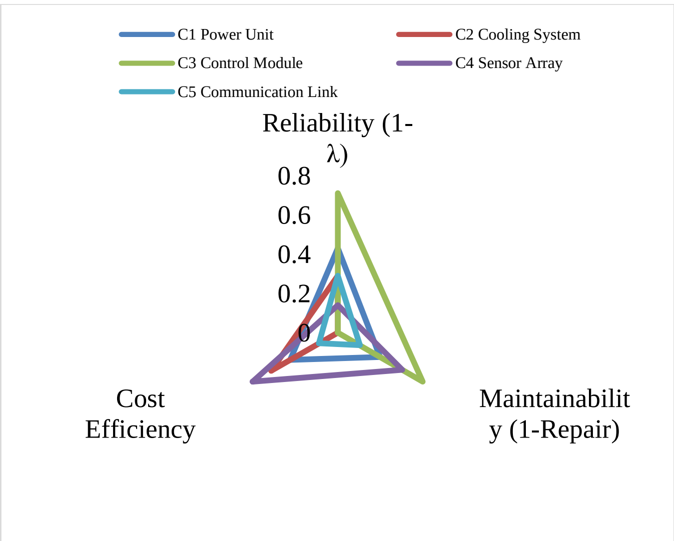

Figure-4: Radar Chart of Component Performance.

Case Study / Experimental Design

System Description: To illustrate this, a hypothetical aerospace sub control system is taken as an example, which is a system with five crucial components consisting of a power unit, cooling system, control module, sensor array and communication link. These types of subsystems are also typical of multi-component multi-complex systems (MCMCS) in that they have structural interdependence and non-homogeneous failure modes[2]. Any failure in any of its components can cause a spill to other components and consequent cascading failures in the mission-critical aerospace functions[4]. Thus, one should quantify the credibility of fuzzy and performance trade-offs to enhance the operation and readiness to operate safety.

Data Representation: The fuzzy interval is used to express the inputs of the reliability of the system that involves the uncertainty in the real world data. The failure rates are represented as triangular numbers that are fuzzy, whereas the repair time is represented as a trapezoidal number that is fuzzy. As an illustration, the failure rate of the power unit is modeled (0.003, 0.004, 0.006), which indicates uncertainty between the most likely, and the optimistic and pessimistic scenario[5]. Likewise, the time of repair under different conditions are different, and trapezoidal forms are used, e.g. (5, 6, 7, 8) of power unit. The α-cut method is applied to these fuzzy inputs in order to obtain confidence intervals and defuzzification is applied to produce crisp values of reliability[7,8]. The methodology used will make sure that unfinished information and expert judgments are introduced into reliability analysis in a systematic manner.

Optimization Implementation: The fuzzy optimization is defined as a multi-objective model, which aims to maximize reliability and availability and minimize costs. Total budget allocation, redundancy policies and structural system dependencies are some of the constraints[11]. The optimization is realized with the help of Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which is also known to be effective in solving multi-objective problems[18]. The steps include:

Initialization: Set fuzzy parameters of every component.
Objective Evaluation: Calculate fuzzy reliability and availability on the basis of α-cut intervals.
Population Evolution: Mutate by using crossover and mutation operators.
Non-Dominated Sorting: Find Pareto-optimal performance-cost solutions.
Defuzzification: Transform fuzzy output into clear trade-offs to be used by any decision-making process.

Solutions are evaluated by computing performance indices, like Fuzzy Mean Time to Failure (FMTTF), fuzzy availability, and cost efficiency of the system[12]. The resulting Pareto front helps decision-makers to make a selection of the best trade-offs and hence enables them to choose configuring basing on the mission priorities, cost tolerance, and risk appetite[17].

Results and Discussion

Reliability and Availability Estimation: The fuzzy reliability estimation gave more realistic results, as opposed to the traditional crisp computations. As an example, the Control Module (C3) indicated a fuzzy reliability of 0.985 0.992 over-cuts indicating high dependability in the event of uncertainty. Equally, the PowerUnit (C1) recorded a fuzzy availability of 0.92 to 0.95 regarding changes in the repair times. The presence of such ranges demonstrates the capability of the system to be operated with reasonable accuracy even when there is imprecision in the data and is consistent with the previous studies on the topic that fuzzy methods are more adept at representing uncertainty that is expert-influenced[7,8].

Optimization Outcomes: The optimization outcomes presented Pareto-optimal selections of reliability, availability, and cost. An example is the Cooling System (C2) redundancy which had a great impact on the reliability of the system, and also cost reduction, whereas prioritizing the Sensor Array (C4) gave cost-effective solutions with an average increase in reliability. The trade-off curve showed that the returns diminished beyond some level of cost implying that there was an optimum configuration that would perform sufficiently without exceeding the budget limit[11,18]. These findings show that decision-makers can be able to change the system design strategies according to the mission requirements or resource constraints.

Comparative Study: Comparative study on fuzzy-based reliability estimation and the traditional probabilistic methods revealed significant disparities. Probabilistic approach resulted in a sharp reliability of 0.96 to the overall system whereas the fuzzy model offered a range of 0.940.98 between 0-Alpha cuts. This interval reflects the vagueness of the input parameters that the probabilistic approach ignores. These results support the previous research on the effectiveness of fuzzy logic when it comes to dealing with incomplete and unprecise system reliability data[5,9]. The fuzzy framework therefore offers a more solid and versatile foundation on the reliability based decision-making.

Sensitivity Analysis: A sensitivity analysis was conducted to evaluate the impact of uncertainty levels on optimization performance. Increasing the spread of fuzzy intervals for failure rates (e.g., widening C1 from (0.003, 0.004, 0.006) to (0.002, 0.004, 0.008)) caused noticeable shifts in the Pareto front, with reduced system reliability at higher uncertainty. Components with higher uncertainty in repair times, particularly the Cooling System (C2), showed the greatest influence on system availability. These results reinforce that system optimization must account for uncertainty explicitly, as ignoring fuzziness could lead to overly optimistic designs[12,17].

Discussion: Interpretation of Findings: Findings suggest that fuzzy optimization of reliability offers a more realistic evaluation of the performance of the system than the conventional probabilistic approaches. The strategy is able to integrate expert opinions and inaccurate operational information because it empowers failure rates and repair times to fuzzy intervals. It has been evidenced that the Pareto front analysis allows identifying the best system configurations by balancing reliability, availability and cost that are important in decision making under resource limited conditions[11,18]. This confirms the previous arguments where it has been indicated that fuzzy methodologies are better than crisp models in dealing with uncertainties[7,8].

Implications for Real-World Systems: These findings have implications on various industries. Fuzzy optimization can also be used in aerospace where system failure may be disastrous, and redundant but economical component combinations can be pointed out[4]. The approach may be used to aid maintenance planning in energy systems, especially smart grids in the sense that it considers failure trends of distributed elements that cannot be forecasted[2]. Fuzzy optimization in manufacturing is used to reduce downtime and the cost of maintenance by forecasting how the components will behave in uncertain situations[16]. Such applications illustrate how fuzzy reliability models can be used to promote system robustness and system efficiency.

Advantages of Fuzzy Optimization in Uncertain Environments: The greatest quality of fuzzy optimization is that it can directly deal with vagueness and incomplete information, which is typical of real-world engineering systems[5]. Fuzzy methods are applicable to the use of linguistic and expert-based estimates, unlike classical probabilistic models that demand comprehensive failure data, which means that they are especially beneficial in the emerging or safety-critical fields[9]. Moreover, evolutionary algorithms like NSGA-II and PSO offer a powerful mechanism of the search in the identification of trade-offs, so that the decision-makers are not confined to a single solution but have a range of the Pareto-optimal solutions[17,18].

Limitations of the Study: Although the suggested framework has strengths, it also has weaknesses. First, the implementation of fuzzy optimization can be rather computationally expensive, especially in a situation where the scope of the system is quite large and it contains interdependencies[12]. Second, the findings depend on the membership functions that the researcher chooses and that can also bring the subjectivity in the analysis unless it is done with a lot of care[7]. Third, although the hypothetical study subsystem is based on aerospace, in reality, it should be validated on large industrial datasets to ensure scalability and generalizability. Lastly, the connection with real-time monitoring, including IoT-based predictive maintenance platform, is an open issue to which the future studies should be committed[4].

Challenges and Research Gaps

Scalability to Very Large Systems: Scalability is one of the problems in the application of fuzzy reliability optimization to multi-component multi-complex systems (MCMCS). Whereas small and medium-scale systems may be well modeled with fuzzy methods, large industrial systems like smart grids or aerospace networks have thousands of interacting systems, and fuzzy modeling is computationally expensive and complicated[4]. The issue of scalability is further enhanced when fuzzy parameters are run on all the components resulting in exponential increase in computation needs[2]. The next direction of work should be a hybrid method of applying fuzzy models with approximation methods to deal with scalability.

High Computational Cost of Fuzzy Evolutionary Optimization: Fuzzy evolutionary algorithms, like GA, PSO, and NSGA-II, are very strong in multi-objective optimization, but frequently use a lot of computational power because the algorithms have to re-evaluate solutions under fuzzy uncertainty[17,18]. This makes them expensive to compute which constrains their useful application particularly in real time decision making settings[16]. Besides, the more the goals and constraints, the slower the convergence, which implies efficiency and applicability concerns in time-sensitive areas. To address this impediment, it is necessary to develop lightweight and parallel optimization frameworks[12].

Integration with Real-Time Monitoring Systems: The other gap in the research would be on incorporating fuzzy optimization structures with real-time monitoring systems, e.g. IoT-enabled predictive maintenance systems. Although fuzzy models are efficient to model uncertainty, the majority of applications are kept offline and do not come with the ability to make a dynamic update to reliability estimates when new sensor data is made available[5]. Online integration may improve predictive quality and provide adaptive maintenance rules particularly in systems that are of critical importance, such as aerospace and healthcare machines[9]. To fill the aforementioned gap, there is need to come up with adaptive fuzzy models that are able to handle live data streams without compromising on computation efficiency.

Lack of Standardized Fuzzy Reliability Benchmarks: At this point, standardized benchmarks with regards to the evaluation of fuzzy reliability models do not exist. In contrast to probabilistic reliability analysis, which may have access to clearly defined reliability databases and test cases, fuzzy methods are frequently justified on case based or hypothetical systems[7,8]. This incompatibility of the various fuzzy optimization methods and decelerates their implementation in industries is due to the absence of common evaluation criteria. Setting standardized fuzzy reliability standards and data sets would allow much more rigorous validation, comparison across methods, and speed up its adoption in the engineering practice[12].

Future Directions

Hybrid Approaches Combining Fuzzy, Probabilistic, and AI Methods: Further studies are recommended in the hybrid reliability models to combine fuzzy logic, probabilistic models and artificial intelligence (AI). Fuzzy techniques are applicable to imprecision; meanwhile, the probabilistic technique is employed when there is an abundance of statistical data, and AI methods reveal latent trends of big data[4,12]. When these paradigms are combined, it will be possible to perform more accurate and adaptable reliability measurements of large, heterogeneous systems. As an example, fuzzy-Bayesian networks can represent uncertainty and probabilistic dependencies, whereas the use of AI-based optimization might make multi-objective reliability design converge faster[9].

Use of Machine Learning for Predictive Reliability Modeling: Deep learning, random forests, and reinforcement learning are machine learning (ML) algorithms capable of being used to a great degree in improving predictive reliability modeling. ML is capable of identifying trends that could not be identified by traditional or fuzzy models by relying on the experience of failure data in history and sensor streams[16]. The combination of ML and fuzzy logic enables the systems to accurately and dynamically revise reliability estimations as new information arises to enhance predictive maintenance policies[5]. This type of adaptive models would be of special use in safety-critical fields such as aerospace and health care where predictive performance is crucial[1].

IoT and Digital Twins for Real-Time Fuzzy Reliability Optimization: With the emergence of the Internet of Things (IoT) and digital twins technologies, the nature of real-time fuzzy reliability optimization has a new opportunity. The IoT sensors can continuously record performance information on a component-level, and digital twins, a virtual representation of real-world system, can also simulate reliability in uncertain settings[2]. Combining fuzzy reliability models with digital twins can be utilized to provide a continuous checkup and optimization options in real-time, allowing the decision-makers to work with the maintenance strategies before implementing them in physical systems[12]. This real-time allows to provide a better resilience of the system and minimizes downtime in manufacturing, energy, and aerospace industries[17].

Policy and Regulatory Perspectives for Mission-Critical Systems: In addition to technical innovations, the policy and regulatory frameworks should be changed to accommodate the use of fuzzy reliability analysis in areas of mission-critical concerns. The existing requirements in the aerospace, nuclear power and healthcare industries are mostly based on the deterministic or probabilistic measures of reliability[4]. The fuzzy-based standards should also be introduced because it would enable regulators to capture the uncertainty in safety tests more openly. In addition, regulatory adoption would promote the investment in fuzzy reliability optimization tools by industries, which would provide wider integration in industries[11]. Engineers, policymakers and safety authorities will have to work together in creating a set of standard structures that will strike a balance between innovation and accountability.

Conclusion

This paper designed and presented a fuzzy reliability optimization model that is specific to multi-component multi-complex systems (MCMCS). The study combined the use of fuzzy set theory, multi-objective optimization and performance analysis, which overcomes serious drawbacks of the conventional probabilistic models to deal with vagueness and incomplete data. The framework systematically included fuzzy membership functions to the failure rates and repair times, it used alpha-cut and defuzzication methods to make estimates and evolutionary algorithms by way of NSGA-II and PSO to identify Pareto-optimal trade-offs of reliability, availability, and cost.

The results of the case study proved that fuzzy reliability models deliver more realistic information than crisp probabilistic models. Components that had high uncertainty like cooling systems were found to have a high impact in total system performance thus the need to include uncertainty in models of optimization explicitly. The Pareto front analysis indicated the cost-performance trade-offs where decision-makers choose the best settings that suit their operational and budgetary priorities. Sensitivity analysis further confirmed the strength of the approach in that it showed the effect of different levels of uncertainty on the results of optimization.

The results have far-reaching practical implications in the field of engineering and industry. Fuzzy optimization can be used to aid the creation of fault-tolerant subsystems in aerospace in the face of ambiguous operating requirements. It can enhance the reliability and availability of smart grids in the energy systems by directing redundancy planning. In the manufacturing sector, it can be used to improve predictive maintenance policy and minimize downtime by taking uncertainty into account concerning component behaviours.

On the whole, this study is valuable as it (i) creates a unified fuzzy reliability modeling and optimization framework, (ii) confirms its performance by a case study, and (iii) offers practical suggestions to decision-makers in the vital engineering industries. The framework should be further pursued in the future by hybrid AI-fuzzy-probabilistic methods, integration of AI-fuzzy-probabilistic real-time with IoT, and benchmark standards to hasten industrial implementation.

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