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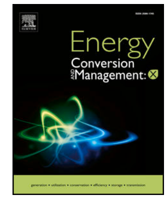

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Enhancing Risk Assessment in Net Zero Energy Building Design through the Integration of Decision-Making Frameworks and Failure Modes Analysis

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Highlights

Comprehensive identifying potential failures in NZEB design

Propose strategies to enhance the performance and sustainability of NZEB through innovative design and construction

Proposing the group decision-making framework based on fuzzy sets and fuzzy ZE-numbers.

Comparison of the results obtained by the proposed approach with other approaches.

Abstract – Failures in Net Zero Energy Buildings (NZEBs) can undermine energy efficiency and environmental sustainability, often increasing reliance on conventional energy sources and elevating carbon emissions. Such failures impair system operation, reduce performance efficiency, and compromise long-term economic benefits. To uncover root causes and enhance NZEB performance, effective failure analysis is essential. Traditionally, Failure Mode and Effects Analysis (FMEA) has been the standard tool for identifying and ranking potential faults in design and operation. This study proposes an extended FMEA based on ZE-number that considers group reliability, and also by incorporating cost alongside severity, occurrence, and detection, it improves the Risk Priority Number (RPN), thereby providing a more comprehensive and effective risk assessment. The proposed framework proceeds in three stages: (i) calculation of the extended RPN, (ii) weighting of sixteen evaluation criteria using Step-Wise Weight Assessment Ratio Analysis under Fuzzy ZE numbers (ZE-SWARA), and (iii) ranking of failure modes using the Combined Compromise Solution under Fuzzy ZE numbers (ZE-COCOSO). Compared with the traditional FMEA, the proposed approach yields greater discrimination among failure modes; for example, poor air sealing and insufficient insulation are prioritized significantly higher once cost impacts are considered. The results identify poor air sealing as the most critical issue, followed by suboptimal insulation practices and inadequate sizing of renewable energy systems. These findings highlight the added value of integrating economic factors and fuzzy multi-criteria decision-making into failure analysis. The proposed framework offers practical guidance for designers and engineers, supporting more reliable decision-making, preventive strategies, and resource allocation in NZEB projects.

Keywords: Net zero energy; Energy Efficiency, Failure Mode and Effects Analysis; Uncertainty environment; renewable energy systems, Multi-Criteria Decision-Making, Risk Assessment

Abbreviation

NZEB, Net Zero Energy Building

FMEA, Failure Mode and Effects Analysis

RPN, Risk Priority Number

MCDM, Multi-Criteria Decision-Making

SWARA, Step-Wise Weight Assessment Ratio Analysis

CoCoSo, Combined Compromise Solution

IFSs, Intuitionistic Fuzzy Sets

IVFSs, Interval-Valued Fuzzy Sets

NSS, Neutrosophic Sets

FST, Fuzzy Set Theory

PFS, Pythagorean Fuzzy Set

CO_2, Carbon dioxide

TFN, Triangular Fuzzy Number

ZE, Z-Number with Expert Evaluation

S, Severity (FMEA criterion)

O, Occurrence (FMEA criterion)

D, Detection (FMEA criterion)

C, Cost (proposed additional criterion)

1. Introduction

The ongoing global energy crisis, intensified by the rapid adoption of electric vehicles (EVs), rising load demand, and the depletion of fossil fuel resources, has created an urgent need for innovative and sustainable energy solutions. Increasing electricity consumption across industrial, commercial, and residential sectors continues to strain existing energy infrastructures, which often rely on limited and unsustainable energy sources[1, 2]. In response, hybrid energy systems—integrating multiple renewable and conventional energy sources such as solar, wind, and battery storage—have emerged as a vital strategy to enhance energy security, reliability, and efficiency[3-5]. These systems can balance fluctuations in supply and demand while reducing dependence on fossil fuels and mitigating greenhouse gas emissions. Maximizing renewable energy generation—particularly solar and wind—and minimizing power losses are critical strategies in hybrid energy systems to reduce the mismatch between supply and demand[6]. Techniques such as Maximum Power Point Tracking (MPPT)[7, 8], demand response programs, environment , corrosion mitigation[9], and lightning protection systems play essential roles in enhancing system reliability and efficiency.. Within this context, the concept of autonomous [10] and NZEBs has gained increasing importance, as buildings can function not only as consumers but also as active contributors to the energy grid. By incorporating advanced energy design strategies, hybrid generation, and smart management systems, NZEBs represent a practical pathway toward achieving sustainability goals, minimizing operational costs, and ensuring resilience in the face of growing environmental and energy challenges.

Zero-energy buildings are considered to be an efficient solution for the world, which is getting warmer day by day due to the excessive consumption of fossil fuels and neglecting the use of renewable energy sources[11-14]. The world must be purified and remain pure for the survival of its inhabitants. Considering that a significant part of the share of energy consumption among consumer sectors is related to the domestic and commercial sectors, and this share is still increasing, research in energy consumption management and the investigation of effective indicators in the construction industry to optimize energy consumption seem vital. One of the most appropriate ways of optimizing fuel consumption in the construction and housing sector is the implementation of ZEB, which is considered to be the main solution in the world[15]. The concept of zero net energy consumption has attracted particular attention due to the use of renewable energy sources in order to reduce pollutants and greenhouse gases[16, 17]. Due to the high cost of fossil fuels, their harmful effects on the environment, as well as a negative impact on the ecological balance, the construction industry has come up with an alternative to the production and construction method. The most important advantage of the ZEB concept is the use of low-cost energy sources, renewable energy sources and the absence of pollution[18, 19]. It is possible that ZEB are not connected to existing energy supply networks in the city. In this case, they are equipped with facilities capable of storing a large amount of energy through special batteries.

Failure analysis is of utmost importance in the design of net-zero energy buildings. It plays a critical role in identifying and rectifying weaknesses or failures within the system[20-24]. By comprehending the causes behind failures, designers can enhance the overall performance and efficiency of the building, resulting in improved energy savings and reduced environmental impact. Failure analysis allows designers to optimize performance by identifying and addressing gaps or deficiencies in building systems. It also helps to reduce costs by pinpointing failures that may lead to increased operational and maintenance expenses. Moreover, failure analysis contributes to improving energy efficiency by identifying areas where energy is wasted and implementing appropriate solutions. By rectifying such issues during the design phase, net-zero energy buildings can achieve maximum energy efficiency. Additionally, failure analysis enhances the reliability and resilience of building systems by identifying potential failures and malfunctions. This ensures uninterrupted operation and reduces the risk of energy supply disruptions. In terms of environmental impact, failure analysis helps identify areas where the building's environmental footprint can be minimized. Furthermore, failure analysis provides valuable insights for future design improvements. By learning from failures and their causes, designers can continuously improve net-zero energy building design practices. In conclusion, failure analysis is vital in net-zero energy building design as it enables the identification and rectification of weaknesses and failures in the system, resulting in optimized performance, reduced costs, improved energy efficiency, enhanced reliability, mitigated environmental impact, and informed future design improvements.

There is a lack of research on failure analysis in NZEB design and performance, highlighting the need for further investigation in this area. One example of research conducted in the field of renewable energy is in study the analysis focused on identifying the components and sub-components of the photovoltaic system. A comprehensive FMEA was conducted, including ranking scales and final results. The benefits and limitations of the approach were discussed, with limited open-source information on failure probabilities for the photovoltaic system parts being a notable limitation. In another study [26]analyzes the performance, failure, and reliability of a 15-turbine wind farm in South India. It examines parameters such as availability and capacity factor, and discusses Pareto analysis, reliability assessment, spare parts optimization, and financial implications of failure. In study[27] presents a method for comprehensive hazard and risk analysis of a multi-modal local energy system. The method identifies trends in critical risks and the impact of system structure on failure modes. Decentralization reduces the impact of failures but introduces new failure modes.

This research aims to define appropriate sustainability criteria for evaluating sustainable NZEBs by incorporating both active and passive design strategies. The goal is to achieve environmentally friendly construction, decrease air pollution, and cut CO_2 emissions. Going beyond the conventional sustainability triad—environment, economy, and society—the study introduces three more primary criteria: sustainability, resilience, and social responsibility, alongside sixteen sub-criteria to support a more comprehensive evaluation. Expert input plays a vital role, focusing on framing the issue from a decision-making standpoint. In complex systems, reliability analysis is key for detecting and mitigating potential failures, which can affect the safety and dependability of processes. FMEA serves as a tool to proactively identify and assess potential issues using the RPN, which considers severity, occurrence, and detection.[28].

A failure mode with a high RPN indicates greater severity and demands corrective action to lower the risk. Although FMEA is used widely, it has been criticized for its limitations, such as vagueness and potential subjectivity in assigning values, which may affect decision quality. Multi-Criteria Decision-Making (MCDM) methods focus on analyzing and selecting alternatives in situations where multiple—often conflicting—criteria must be considered simultaneously. The primary purpose of these methods is to provide effective tools that assist decision-makers in addressing complex and multidimensional problems. In such contexts, there is rarely a single definitive answer; instead, the decision-making process requires approaches that enable the selection of the most appropriate or optimal option among several possible alternatives. However, different MCDM methods may yield varying outcomes for the same problem. Such discrepancies can cause uncertainty and confusion among decision-makers regarding which method provides the most reliable result. In other words, inconsistency among results is one of the main criticisms directed at this family of methods. The variability in outcomes is primarily due to differences in criteria weighting, algorithmic structures, the quantification of qualitative indicators, and the unique parameters applied in each approach. According to Dason, the process of selecting a suitable MCDM method involves a series of systematic steps, including:

1. Defining the objectives and reasons for employing MCDM methods;
2. Selecting evaluation criteria for assessing the capability and performance of the techniques;
3. Listing the candidate methods as viable options;
4. Determining the feasibility and effectiveness of each technique; and
5. Constructing a decision matrix based on the evaluation of methods against the relevant problem criteria to ultimately identify the most suitable approach.

In practice, most real-world decision-making problems occur under uncertain and unreliable conditions. Indeed, decision-making in a completely certain environment is considered unrealistic . Furthermore, the multi-attribute nature of many problems increases their complexity. Therefore, decision-making systems must be capable of addressing uncertainties arising from incomplete data, lack of knowledge, or imprecise information sources [29]. These factors—often referred to as uncertainty parameters—cause deviations between estimated and actual information values [30]. Managing uncertainty in decision-making has long been recognized as a classical and challenging issue. Nevertheless, numerous theories and methods have been proposed to mitigate its impact [31, 32]. In situations where available data are imprecise or ambiguous, Fuzzy Set Theory (FST)—first introduced by [33] has been widely utilized as a powerful framework for modeling vagueness and uncertainty across diverse domains. In recent decades, several extensions of fuzzy set theory have been developed for use in decision-making problems, such as Intuitionistic Fuzzy Sets (IFSs), Interval-Valued Fuzzy Sets (IVFSs) [34] and Neutrosophic Sets (NSS)

Furthermore, [35] expanded the concept of fuzzy sets by introducing the Z-number theory, which incorporates a reliability component into the fuzzy representation. Subsequently, Seiti et al. proposed a new concept called R-numbers, designed to more accurately model fuzzy risks and errors in MCDM applications. In addition, [36] introduced the notions of importance and necessity within the framework of G-numbers**,** further enhancing decision-making under uncertainty. By comparing the methods and concepts summarized in Table 1, it becomes evident that various fuzzy-based approaches have been developed to manage uncertainty and achieve more precise results, primarily through the use of fuzzy membership functions for representing vagueness [37]. Interval and boundary-based methods have also been employed to reduce uncertainty by defining upper and lower bounds for the membership functions. Typically, decision-makers assign a reliability value to each fuzzy number based on past experience and existing knowledge [38]. In this regard, ZE-numbers—an enhanced version of fuzzy Z-numbers—combine reliability and uncertainty to improve the decision-making process. Each ZE-number consists of two fuzzy components: one representing the decision variable and the other expressing the reliability of that decision. This dual-structure framework allows for a more precise assessment of uncertainty, particularly in group decision-making contexts where expert opinions may vary. By simultaneously considering both reliability and uncertainty, ZE-numbers provide a more comprehensive evaluation of decision variables. Unlike traditional fuzzy numbers, which often struggle to reach consensus in group settings, ZE-numbers efficiently integrate diverse expert opinions into the decision-making process. Moreover, by evaluating decision-makers and experts separately, ZE-numbers reduce the ambiguity inherent in conventional fuzzy numbers, thereby producing more consistent and reliable outcomes. Overall, ZE-numbers can represent a broader range of preferences and enable more accurate judgments in evaluations. They have demonstrated higher stability and robustness, as evidenced by stronger correlation coefficients compared to traditional fuzzy approaches. Their ability to improve the accuracy of evaluations under uncertainty makes them a valuable and dependable tool in MCDM frameworks, particularly when precise judgments and reliable decisions are essential.

1.1 Research Gaps

Previous studies on NZEB performance and failure analysis have primarily focused on technical issues such as thermal insulation, HVAC efficiency, or renewable energy integration. However, three key research gaps remain. First, most studies have applied traditional FMEA approaches that neglect economic impacts, despite the fact that cost is a critical driver of design and operational decisions. Second, existing works often treat all evaluation criteria equally, without a structured method for assigning weights based on expert knowledge, which can bias prioritization outcomes. Third, uncertainty in expert judgments is typically not addressed, reducing the reliability of results. This study addresses these gaps by (i) extending the RPN formula to incorporate cost, (ii) applying fuzzy ZE-SWARA to derive systematic and reliable weights for evaluation criteria, and (iii) employing fuzzy ZE-COCOSO to prioritize NZEB design failures while explicitly accounting for uncertainty. In this way, the proposed framework contributes both methodological innovation and practical value to the body of knowledge on NZEB risk assessment."

1.2 Aim and Objective

The primary aim of this study is to develop a comprehensive and reliable decision-making framework for risk assessment in NZEB design by integrating FMEA with MCDM methods under a fuzzy ZE-number environment. The framework is designed to enhance the accuracy, reliability, and interpretability of risk prioritization under uncertainty, addressing both technical and economic factors that influence NZEB performance and safety.To achieve this aim, the study pursues the following specific objectives:

1. To enhance the traditional FMEA approach by introducing *cost* as a fourth evaluation criterion in the Risk Priority Number (RPN) formulation—alongside severity, occurrence, and detection—to reflect the economic impact of potential failures.
2. To apply the ZE-SWARA method to determine systematic and uncertainty-aware weights for the FMEA criteria, allowing expert opinions to be expressed with both value and reliability components.

3. To employ the ZE-CoCoSo method to prioritize failure modes based on the weighted evaluations, providing a robust and balanced ranking that accounts for uncertainty in expert judgments.
4. To demonstrate the proposed framework's effectiveness through a practical NZEB case study, validating its ability to improve decision accuracy, reduce ambiguity, and support cost-efficient maintenance and design strategies.

1.3 The Main Contributions of The Study

This work addresses crisis management in NZEB design by offering practical strategies. The primary aim is to explore alternative NZEB solutions that can mitigate the crisis through focused investment and structured development. What sets this study apart is its broad evaluation of different criteria and factors during the selection of the most suitable NZEB design. A novel framework is introduced that combines evaluations from decision-makers and expert insights at multiple phases to ensure dependable decision-making. Fuzzy logic is utilized to capture uncertainty in expert assessments. One of the core innovations of this study is the development of a collaborative decision-making model that functions effectively in uncertain environments while maintaining consistency and reliability. The proposed method supports better decision-making in NZEB planning by using fuzzy ZE-numbers along with the SWARA and CoCoSo techniques to assess both expert and stakeholder input in parallel. These characteristics make the approach particularly strong in handling complex decision scenarios. Key contributions of the study include:

- Recognizing essential evaluation criteria and influencing elements for NZEB investment and planning.
- Designing a collaborative decision-making structure using fuzzy logic and ZE-number principles.
- Enhancing SWARA and CoCoSo techniques with fuzzy ZE-number integration for improved NZEB design selection.

The structure of the paper is as follows: Section 2 presents a literature review on hybrid FMEA–MCDM approaches. Section 3 introduces the fundamentals of fuzzy ZE-number theory and outlines the proposed FMEA–ZE-SWARA–ZE-CoCoSo methodology. Section 4 applies the framework through a case study to demonstrate its effectiveness. Finally, Section 5 summarizes the main findings and outlines future research directions.

2. Literature Review

The literature on NZEBs highlights a growing emphasis on optimizing energy efficiency through advanced design, material selection, and renewable integration strategies. However, numerous studies reveal persistent gaps between theoretical energy models and actual performance outcomes, underscoring the importance of identifying and mitigating design and operational failures. This section first reviews the main causes of performance shortfalls in NZEBs, emphasizing technical, economic, and behavioral factors that contribute to energy inefficiency. Following this, the review examines the evolution of FMEA and its hybrid adaptations—particularly those integrating fuzzy logic and MCDM methods such as SWARA and CoCoSo—which provide structured and quantitative tools for assessing and prioritizing risks under uncertainty. Together, these reviews establish the theoretical foundation for the proposed framework that combines failure analysis and decision-making techniques to enhance the reliability and sustainability of NZEB design.

2.1 Failures in NZEB Design and Performance

Achieving net-zero energy performance in buildings requires a delicate integration of architectural, mechanical, and operational systems, yet numerous studies demonstrate that inefficiencies and failures persist across these domains. The energy efficiency of NZEBs largely depends on the quality of their building envelope, renewable energy system integration, and operational management; failures in any of these aspects can critically undermine performance outcomes [18, 39]. For example, inadequate insulation and poor air sealing have been repeatedly identified as major contributors to energy loss, thermal discomfort, and excessive HVAC demand. [40] emphasize that such envelope-related deficiencies often stem from inadequate material selection, poor installation quality, and insufficient thermal bridging control. Similarly, [41] argue that design oversights in airtightness compromise both the building's energy balance and indoor air quality, leading to higher heating and cooling loads that prevent NZEBs from meeting their intended performance targets.

Beyond the envelope, improper sizing and integration of renewable energy systems represent another recurring failure category. Studies by [18]and [42] reveal that miscalculations in load estimation, inaccurate modeling of solar generation, and insufficient energy storage planning often result in renewable energy systems that either underperform or generate excess energy without efficient utilization. This mismatch between supply and demand reduces overall system efficiency and can increase reliance on grid-supplied electricity. In [43]further highlight that region-specific climatic factors, such as solar irradiation variability and shading conditions, significantly affect PV system output. However, these factors are frequently neglected during the early design stages, resulting in performance gaps between simulated and actual energy production. In [44]add that structural and aesthetic constraints often limit optimal PV placement and orientation, compromising energy yield. Consequently, failures in renewable system design not only affect technical outcomes but also impose long-term economic and operational burdens on NZEB projects. HVAC and mechanical systems also play a pivotal role in maintaining NZEB energy efficiency. Inefficient or oversized HVAC systems are among the most common causes of performance deviation, as identified by researchers. Oversizing typically occurs due to conservative design assumptions that aim to mitigate uncertainty but ultimately result in suboptimal operation and increased energy use. Inadequate ventilation further exacerbates these issues, leading to poor indoor air quality and occupant discomfort [39]. Moreover, ineffective commissioning and calibration during the post-construction phase often cause system controls to operate improperly, leading to persistent inefficiencies in temperature regulation and airflow distribution [45]. These operational deficiencies underscore the importance of integrating performance-based design and rigorous commissioning protocols throughout the building's lifecycle.

From an economic perspective, the integration of advanced energy systems and high-performance materials often leads to elevated upfront costs, which may prompt developers to compromise on essential efficiency features during construction [46]. This trade-off between cost and performance has been widely documented as a recurring failure mechanism in NZEB projects. Additionally, fragmented project delivery and insufficient coordination among multiple stakeholders can result in inconsistent application of energy-efficient measures [45]. The absence of mandatory performance verification and post-occupancy evaluation further allows such inefficiencies to persist undetected. Lastly, occupant behavior remains a significant determinant of NZEB energy efficiency. Even in technically sound buildings, deviations from expected user behavior—such as frequent window opening, thermostat adjustments, or misuse of mechanical ventilation—can lead to substantial variations in actual energy performance. Studies have shown that occupant engagement and feedback systems are often overlooked in NZEB design, resulting in a lack of user awareness about energy-efficient operation [39]. Consequently, behavioral inconsistencies contribute to a widening performance gap between predicted and measured outcomes. In summary, literature on NZEB performance failures consistently identifies recurring technical and operational issues, including inadequate insulation and air sealing, inefficient HVAC design, suboptimal renewable system integration, and limited occupant engagement. These failures collectively undermine the energy efficiency objectives of NZEBs, highlighting the need for integrated design frameworks that align technical rigor, cost-effectiveness, and user behavior. The present study builds upon these insights by systematically ranking NZEB design failures through an improved Failure Mode and Effects Analysis framework that explicitly accounts for both technical and economic dimensions.

The following section focuses on FMEA as a valuable tool for ensuring the reliability and safety of net-zero energy systems, particularly in the context of photovoltaic applications. While FMEA provides significant advantages in identifying and mitigating potential failures, its effectiveness can be further enhanced through the integration of advanced analytical techniques and improved data availability. Implementing FMEA in NZEB systems can therefore lead to more robust and reliable energy solutions, supporting the broader objective of achieving true net-zero energy performance[25]. This section is divided into three parts to review the relevant literature. The first part discusses the use of the FMEA method and its hybrid applications across multiple areas. The second and third parts highlight studies involving existing research related to the SWARA and CoCoSo methodologies.

2.2 Hybrid FMEA Approach

FMEA is a structured method commonly applied in numerous industries and research domains to evaluate potential failures in product design and processes[47, 48]. Given the limitations of conventional FMEA, researchers have increasingly integrated it with MCDM techniques to improve its accuracy and usefulness. For instance, Wang et al. [49] proposed an enhanced FMEA model that combines interval-valued intuitionistic fuzzy ANP with IVIF-COPRAS to identify and rank risks in hospital services. Similarly, Lo et al.[50] developed a framework for risk assessment utilizing the Best-Worst Method (BWM) to assign weights to RPN factors and integrated grey interval linguistic variables to handle uncertainty. In another study, they introduced a combined MCDM-FMEA approach aimed at detecting key failure points in manufacturing processes. This was done by determining weights through DEMATEL and applying SAW, GRA, VIKOR, and COPRAS for prioritization, with TOPSIS employed to resolve any inconsistencies in the rankings [51]. Ghoushchi et al. [52] applied fuzzy BWM to determine RPN factor weights and used Z-MOORA grounded in Z-number theory to rank failure modes. In a subsequent study, Ghoshchi et al [53] extended this approach by combining fuzzy BWM with Z-MOORA, again leveraging Z-number theory, to prioritize failure modes. Another study proposed a hybrid method incorporating Z-SWARA, Z-MOORA, and an enhanced FMEA model to assess risk in an automotive parts supplier. Additionally, Boral et al.[54] introduced a methodology based on IT2F-MCDM for identifying and ranking potential failure causes in CNC machinery related to human error. Their model employed IT2F-AHP to compute risk weights and IT2F-DEMATEL to analyze interrelationships between error types. They then applied an extended IT2F-MARCOS method to rank the identified risks. Wang et al. [55] addressed uncertainty using Probabilistic Hesitant Fuzzy Linguistic Term Sets,(PHFLTS), applied SNA, MCM, and BWM for weight determination, and utilized TOPSIS for final rankings. Rahmati et al. [56] developed a hybrid method combining Z-SWARA, Z-WASPAS, and FMEA to prioritize risk factors in financial control within manufacturing management. Additionally, Ghoushchi et al. [57] proposed an extended FMEA framework that integrates BWM-COPRAS and G-number theory to evaluate health, safety, and environmental risks in uncertain conditions.

2.3 SWARA Method

KerLsuliene et al [58] introduced the SWARA method to determine the relative importance of criteria by assigning appropriate weights. Expert judgment plays a central role in this process. In SWARA, experts initially rank the criteria from highest to lowest importance based on their experience and insight. The final ranking is derived by calculating the median of these expert assessments. A core feature of the method is its ability to determine weight ratios during the evaluation process. Due to its simplicity, SWARA is frequently applied in a wide range of MCDM tasks, including supplier selection, machine tool selection, product design, personnel recruitment, reverse logistics, occupational health and safety risk analysis, manufacturing decisions, and waste reduction efforts. SWARA proves especially beneficial when decision priorities have already been defined by policies or organizational frameworks, eliminating the need for additional criteria weighting. Unlike methods such as AHP and ANP, SWARA places less emphasis on direct criteria comparisons [59]. Zolfani et al [60] introduced a SWARA-COPRAS combination to prioritize investments in high-tech industries. An integrated SWARA-WASPAS framework was used for selecting suitable locations for marine energy production in Turkey [61]. To handle the ambiguity in expert assessments, researchers have applied SWARA within fuzzy environments [62]. Zarbakh et al. [63] developed a hybrid fuzzy SWARA-COPRAS approach to evaluate and rank third-party providers in reverse logistics. In another study, a Pythagorean fuzzy SWARA-VIKOR technique was adopted to assess the efficiency of solar panels [64]. He et al. [65] proposed an interval-valued Pythagorean fuzzy SWARAMULTIMOORA method to support tourism-related decisions in the Indian Himalayas. Additionally, Ghoushchi et al. [66] employed a SWARA-WASPAS hybrid model within a spherical fuzzy framework to select optimal landfill sites in the context of healthcare waste management.

2.4 CoCoSo Method

Yazdani et al. [67] introduced the CoCoSo method in 2019 as a new approach in MCDM. It integrates simple additive weighting with an exponentially weighted product model. CoCoSo offers a modern compromise-based strategy for ranking and selecting optimal alternatives. It has gained attention as a reliable tool for improving result consistency in MCDM scenarios, which are often criticized for inconsistent outcomes. In the context of sustainable supplier evaluation, S.HZol et al. [68] introduced a framework integrating BWM and CoCoSo for evaluating sustainable suppliers. Another hybrid model that combines fuzzy SWARA and CoCoSo was presented by A.ETork et al. [69]. later proposed a hybrid model combining fuzzy SWARA and CoCoSo, which was applied to assess healthcare systems using both the best-worst method (BWM) and level-based weight assessment (LBWA) [70]. In addition, the integration of AHP and CoCoSo has been explored to identify optimal locations for distribution centers of perishable agricultural products [71]. In a separate study, Adar et al. [72] used AHP-CoCoSo to rank criteria for industrial wastewater management. CoCoSo has also been incorporated into fuzzy decision-making environments to manage uncertainty more effectively. A recent study combined PF-SWARA with PF-CoCoSo to assess alternatives in the manufacturing industry[73]. M.Yazdani et al. [67] introduced a combined F-FMEA–CoCoSo approach utilizing triangular fuzzy hesitant sets (TFHS) to address risks linked to outsourcing decisions. Similarly. P.Liu et al. [74] presented Pythagorean fuzzy CoCoSo framework to evaluate technologies for medical waste treatment. Similarly, Lahane et al.[75] applied PF-AHP in conjunction with PF-CoCoSo to analyze performance metrics within the context of a circular supply chain.

In summary, the reviewed literature reveals that while FMEA remains a fundamental tool for reliability and failure assessment, its conventional form often overlooks economic considerations and depends on deterministic weighting schemes. SWARA and CoCoSo methods, on the other hand, provide structured and effective means of weighting and ranking; however, they are limited in handling uncertainty and expert reliability in complex decision-making environments. Therefore, integrating these methods under the fuzzy ZE-number framework provides a more robust and comprehensive solution. This integration not only manages uncertainty more effectively but also ensures that cost, reliability, and expert confidence are simultaneously considered in evaluating and prioritizing NZEB design failures.

3. Research Methodology

This section outlines the implementation of the proposed framework for evaluating and ranking failure modes in NZEB design. To address uncertainty in expert assessments, the study applies an integrated decision-making approach under a Z-number environment. The methodology consists of three stages: (1) applying an improved FMEA, where the RPN is extended by adding cost as a fourth criterion alongside severity, occurrence, and detection; (2) determining the relative importance of the criteria using the ZE-SWARA method, which incorporates expert input expressed through linguistic terms converted into Z-numbers; and (3) aggregating the weighted evaluations through the ZE-COCOSO method to obtain the final ranking of failure modes. The results of the ZE-SWARA weighting and ZE-COCOSO ranking are presented and analyzed, while Figure 1 provides a visual summary of the three main phases: improved RPN calculation, criteria weighting, and prioritization of alternatives.

3.1 Problem definitions

NZEB design experts emphasize the importance of sustainable building practices to ensure a clean, efficient, and healthy environment for urban populations. Promoting sustainable NZEBs is essential for addressing climate-related challenges and decreasing greenhouse gas emissions. In this work, sixteen NZEB-related design failures were identified with support from three FMEA specialists. The assessment focused on four primary criteria: Severity(S), Occurrence(O), Detection(D) and Cost(C), as presented in Table 1. The expert panel for this study was formed using specific selection criteria to ensure reliability and relevance of judgments. Experts were required to have: (i) at least 7 years of professional or academic experience in building design, sustainable construction, or energy management; (ii) demonstrated familiarity with NZEB concepts and practical implementation; (iii) multidisciplinary backgrounds covering architecture, HVAC systems, renewable energy integration, and building performance evaluation; and (iv) willingness to participate in multiple rounds of consultation. Based on these criteria, a panel of X experts was selected to provide linguistic evaluations, which were then processed using the fuzzy ZE-SWARA and ZE-COCOSO methods (see Figure 1). An additional classification level has been introduced to enhance clarity. Failure modes are grouped into broader categories such as *Building Envelope*, *Lighting & Daylighting*, *Renewable Energy Systems*, *HVAC & Mechanical Systems*, *Energy Management & Modeling*, and *Energy Storage & Management*. The analysis remains based on the individual failure modes, but this classification improves readability and highlights the relative influence of different domains on NZEB performance.

As illustrated in Figure 2**,** the conceptual framework of NZEB design failures encompasses the interaction between key system domains, including the building envelope, renewable energy systems, HVAC and mechanical components, lighting and daylighting, and energy management systems. This conceptual map outlines how deficiencies in design, integration, or control within these domains can contribute to overall performance degradation. It serves as the foundation for identifying the sixteen specific failure modes evaluated in this study, which are summarized in Table 1.

3.2 Improved FMEA

The conventional FMEA evaluates risks using the Risk Priority Number (RPN), calculated as follows :

$$RPN=S\times O\times D$$

Although widely applied, this approach does not account for the economic consequences of failures, which can be particularly significant in NZEB projects. To address this limitation, the present study introduces cost (C) as an additional criterion, resulting in an improved formulation:

$$RPN* = S \times O \times D \times C$$

This modification ensures that failure modes with high economic impact are prioritized alongside those that are severe, frequent, or difficult to detect, thereby supporting more informed decision-making in NZEB design. The improved FMEA provides the foundation for assessing NZEB failure modes by incorporating cost into the conventional RPN model. However, to ensure that the criteria (severity, occurrence, detection, and cost) are evaluated according to their relative importance, a systematic weighting procedure is required. For this purpose, the Fuzzy ZE-SWARA method is applied to determine the priority of the criteria based on expert judgments. Once the criteria weights are established, the Fuzzy ZE-COCOSO method is employed to integrate these weights into the overall assessment and generate the final ranking of failure modes.

3.3 Fuzzy ZE-numbers

Fuzzy set theory provides a robust and effective tool for handling imprecise data and subjective evaluations. Within this framework, each element is associated with a membership value ranging from zero to one. Fuzzy numbers—particularly triangular fuzzy numbers (TFNs)—are commonly applied in fuzzy systems. In hierarchical models, TFNs help determine the relative importance of individual elements. Each TFN is typically represented by three parameters: the lower bound (l), the central value (m), and the upper bound (u) [76]. The membership values of TFNs are provided in Equation (1).

$$\tilde{\mu}_s(x) = \begin{cases} 0; & x < l \\ \frac{x-l}{m-l}; & l \le x \le m \\ \frac{u-x}{u-m}; & m \le x \le u \\ 0; & x > u \end{cases} \quad (1)$$

Let $\tilde{S}_1$ = (l1, m1, u1) and $\tilde{S}_2$ = (l2, m2, u2) be two TFNs. Guo et al [77] offered additional insights into deriving crisp values from TFNs.

Fuzzy Z-numbers, a concept first introduced by Zadeh[35], have emerged as a powerful tool in uncertainty modeling, particularly within the field of reliability analysis. A Z-number consists of a pair of fuzzy numbers, denoted as Z = (A, B). In this representation, component A signifies the fuzzy constraint applied to variable X, while B reflects the degree of confidence in that constraint. The fuzzy restriction R(X): X is A can be interpreted as a probabilistic condition describing the distribution over X [78]. This concept can also be formulated mathematically, as shown in Equation (2).

$$R(X): X is\ A \rightarrow \text{Poss}\ (X = u) = u_A(u) \quad (2)$$

In Eq (3), the variable u and $u_A(u)$ are denotes to a general value of X and the membership function of fuzzy number A. The set membership $u_A(u)$ is a constraint linked to the fuzzy restriction R(X). For u to be satisfied, it must correspond to $u_A(u)$. Thus, under a probability distribution R(X), the random variable X can impose certain constraints on itself. The equation captures the essence of the probability distribution of the random variable.

$$R(X){:}Xisp \rightarrow \text{Prob}\ (u \leq x \leq u + du) = p(u)du \tag{3}$$

Also, Eq (4) is employed to determine the precise reliability values for fuzzy Z-numbers.

$$\alpha = \frac{\int x\mu_B(x)dx}{\int \mu_B(x)dx} \tag{4}$$

As shown in Equation (5), a concealed probability function links the fuzzy numbers A and B in the context of fuzzy Z-numbers.

$$\sum_{i=1}^{n} \mu_A(x_i) \cdot p_{x_A}(x_i) \rightarrow b_i \tag{5}$$

$$ZE = ((A,B),E) \tag{6}$$

Tian et al. [79] extended the idea of fuzzy Z-numbers to evaluate reliability in group decision-making. They introduced fuzzy ZE-numbers for this purpose. To determine how reliable group decisions are, a voting approach is used, as outlined in Equation (7).

$$\text{Evaluation - number} = (Y,N,\theta) \tag{7}$$

Experts indicate agreement with decision-maker (DM) assessments using 'Y', while 'N' denotes disagreement, aligning with the voting process. The symbol θ signifies instances where experts abstain from voting. The confidence in the decisions is quantified by aggregating expert opinions using Equation (8). Based on the voting outcomes, fuzzy Z-numbers are converted into fuzzy ZE-numbers, following the procedures in Equations (8–9).

$$R = \frac{Y-N}{n-\theta} \tag{8}$$

$$M = \begin{cases} b_i^* = b_i^{**}\ (1+R)\cdot R < 0 \\ b_i^* = b_i \cdot R = 0 \\ b_i^* = 1 - (1-b_i)^*(1-R)\cdot R > 0 \end{cases} \tag{9}$$

While b_i^* displays the corrected value of b_i and b_i is b of B Fuzzy number in the fuzzy Z-numbers.

3.4 Fuzzy ZE-SWARA

The SWARA (Step-wise Weight Assessment Ratio Analysis) method, proposed by Stanujkic et al. [7] addresses decision-making challenges in contexts involving incomplete data, uncertainty, and qualitative expert input. Traditional MCDM techniques may not always be effective in such fuzzy environments [43]. To enhance its capability, this paper introduces ZE-SWARA—a more advanced approach that incorporates fuzzy Z-numbers. Below is a concise summary of how ZE-SWARA works:

Stage 1. Experts assess and arrange the criteria based on their perceived level of importance, beginning with the highest priority.

Stage 2. Following this, they assign appropriate linguistic values to express how important each criterion jjj is relative to the ones previously ranked (j−1).

At this point, linguistic terms used for pairwise comparison—outlined in Table 2—are generated using Triangular Fuzzy Numbers (TFNs). The Z-number approach focuses on incorporating reliable variables, as shown in Table 3, allowing experts to evaluate the credibility of the provided inputs. The computation of the fuzzy Z value is conducted using mathematical equation (10). Furthermore, the process for determining the value of α is detailed in equation (13). The linguistic variables, membership functions, and reliability level are listed in following table 2 and table 3 that are utilized in evaluating the decision makers' judgments.

$$z-number(l_{Z(ij)}.m_{Z(ij)}.u_{Z(ij)}) = (l_j \times \sqrt{\alpha} m_j \times \sqrt{\alpha} u_j \times \sqrt{\alpha}) \tag{10}$$

In the Z number method, the base criterion is compared with other criteria using a pairwise comparison matrix, as described by equation (11).

$$\tilde{A}_B = ((l_{Z(B1)}.m_{Z(B1)}.u_{Z(B1)}).(l_{Z(B2)}.m_{Z(B2)}.u_{Z(B2)}).\ldots.(l_{Z(Bn)}.m_{Z(Bn)}.u_{Z(Bn)})) \tag{11}$$

Within the framework of Z-numbers, the triplet $(l_{Z(Bj)}.m_{Z(Bj)}.u_{Z(Bj)})$, indicates the comparative significance of a reference element relative to element *j*. To establish these relative importance values for pairwise comparisons among criteria, equation (12) is applied. This equation not only facilitates the efficient management of inputs but also addresses and resolves any inconsistencies that may arise, ensuring the accuracy and reliability of the comparison process.

$$(l_{(ij)}.m_{(ij)}.u_{(ij)}) = \frac{(l_{(Bj)}.m_{(Bj)}.u_{(Bj)})}{(l_{(Bj)}.m_{(Bj)}.u_{(Bj)})} \tag{12}$$

$$(8.9.9) \le (l_{(ij)}.m_{(ij)}.u_{(ij)}) \le (1/9.1/9.1/8) \tag{13}$$

Stage 3. Expert judgments, conveyed through pairwise comparison matrices, are utilized to formulate fuzzy ZE numbers. During this stage, experts contribute by expressing preferences over the decision-makers' comparison vectors. The fuzzy ZE value is subsequently determined through Equations (8) and (9), which categorize three distinct states for R. Using aggregated input, the appropriate state of R is identified and used to calculate the corresponding updated figures. Ultimately, the application of ZE fuzzy logic to the refined preferences allows for ranking the criteria in order of significance.

$$(l_{ZE(Bj)}.m_{ZE(Bj)}.u_{ZE(Bj)}) = \begin{cases} ZE = ((l_{B1}.m_{B1}.u_{B1}).(l_R.m_R.u_R).E_1) \\ ZE = ((l_{B2}.m_{B2}.u_{B2}).(l_R.m_R.u_R).E_2) \\ ZE = ((l_{B3}.m_{B3}.u_{B3}).(l_R.m_R.u_R).E_3) \\ \text{L} \\ ZE = ((l_{Bn}.m_{Bn}.u_{Bn}).(l_R.m_R.u_R).E_n) \end{cases} \tag{14}$$

Stage 4. Utilizing the outcomes from Stage 3, the parameter $\tilde{q}_j$ is introduced and interpreted as the fuzzy weighting factor, which is determined as follows:

$$\tilde{q}_j = \frac{\tilde{q}_j - 1}{\tilde{z_j}'} (15)$$

Stage 5. Finally, for a set of n criteria, the normalized weight of the jth criterion is determined using the following calculation:

$$\widetilde{W}_j = \frac{\tilde{q}_j}{\sum_{j=1}^{n} \tilde{q}_j} (16)$$

where $\tilde{w}_j$, is the TFN.

3.5 Fuzzy ZE - CoCoSo

Yazdani et al. [13] introduced the CoCoSo method as an innovative ranking strategy in the field of MCDM. This method combines principles from several established approaches, including SAW (Simple Additive Weighting), MEW (Multiplicative Exponential Weighting) and WASPAS (Weighted Aggregated Sum Product Assessment). The CoCoSo technique has been further developed by incorporating different fuzzy logic models to handle uncertainty, such as fuzzy Bonferroni sets [45], neutrosophic fuzzy sets [46], hesitant fuzzy sets [47], and interval-valued fuzzy sets [48]. This method has proven effective in addressing complex decision-making issues, particularly in industrial applications. The fuzzy ZE-CoCoSo variant builds on this by structuring the process into a set of clearly defined steps. By integrating fuzzy logic into the CoCoSo model, the method gains improved flexibility and reliability. It has shown value in tackling diverse decision-making scenarios within the industry, as it accounts for ambiguity through various fuzzy set types.

Step 1: Create the initial matrix using the DM's evaluations.

$$Y = \begin{cases} (l_{MF(11)}, m_{MF(11)}, u_{MF(11)})(l_{RF(11)}, m_{RF(11)}, u_{RF(11)}) & \cdots & (l_{MF(1n)}, m_{MF(1n)}, u_{MF(1n)})(l_{RF(1n)}, m_{RF(1n)}, u_{RF(1n)}) \\ (l_{MF(21)}, m_{MF(21)}, u_{MF(21)})(l_{RF(21)}, m_{RF(21)}, u_{RF(21)}) & \cdots & (l_{MF(2n)}, m_{MF(2n)}, u_{MF(2n)})(l_{RF(2n)}, m_{RF(2n)}, u_{RF(2n)}) \\ \vdots & \cdots & \vdots \\ (l_{MF(mn)}, m_{MF(mn)}, u_{MF(mn)})(l_{RF(mn)}, m_{RF(mn)}, u_{RF(mn)}) & \cdots & (l_{MF(mn)}, m_{MF(mn)}, u_{MF(mn)})(l_{RF(mn)}, m_{RF(mn)}, u_{RF(mn)}) \end{cases}$$
(17)

Where Y refers to the decision matrix for n criteria and m alternatives. The TFNs define both the membership function values $(l_{MF(mn)}, m_{MF(mn)}, u_{MF(mn)})$ and the Reliability values $(l_{RF(mn)}, m_{RF(mn)}, u_{RF(mn)})$. of the elements of the initial matrix are.

Step 2: Calculate the fuzzy ZE-numbers for each alternative row based on the experts' votes. In this process, experts cast their votes for each alternative row, and the fuzzy ZE-numbers are determined using Equations (8–9). The fuzzy ZE-numbers decision matrix, based on the experts' inputs, is presented as follows.

Step 3: Apply normalization to the decision matrix constructed with fuzzy-ZE-numbers. The resulting normalized matrix (N) consists of elements expressed as triplets $(l_{ZE(ij)}, m_{ZE(ij)}, u_{ZE(ij)})$ which are derived using the following equation[80]:

$$\text{Normalize } (l_{ZE(ij)}, m_{ZE(ij)}, u_{ZE(ij)}) = \begin{cases} Nl_{ZE(ij)} = \frac{l_{ZE(ij)}}{max(u_{ZE(j)})}; Nm_{ZE(ij)} = \frac{m_{ZE(ij)}}{max(u_{ZE(j)})}; Nu_{ZE(ij)} = \frac{u_{ZE(ij)}}{max(u_{ZE(j)})} \\ Nl_{ZE(ij)} = \frac{min(l_{ZE(j)})}{u_{ZE(ij)}}; Nm_{ZE(ij)} = \frac{min(l_{ZE(j)})}{m_{ZE(jj)}}; Nu_{ZE(ij)} = \frac{min(l_{ZE(j)})}{l_{ZE(ij)}} \end{cases} (18)$$

Step 4: To determine the weighted normalization of the fuzzy-ZE-numbers decision matrix, we multiply each normalized fuzzy ZE-number by its corresponding weight derived from the fuzzy ZE-SWARA method. Using the Weighted Sum Model (WSM) and Weighted Product Model (WPM), we calculate both the fully compensatory performance values for the ith alternative ($S_{i(ZE)}$) and partially compensatory performance values ($P_{i(ZE)}$), for the ith alternative, as outlined in Equations (19) and (20).

$$S_{i(ZE)} = \sum_{j=1}^{n} ((l_{ZE(j)}, m_{ZE(j)}, u_{ZE(j)}) \times N(l_{ZE(ij)}, m_{ZE(ij)}, u_{ZE(ij)}))(19)$$

$$P_{i(ZE)} = \sum_{j=1}^{n} (N(l_{ZE(ij)}, m_{ZE(ij)}, u_{ZE(ij)})^{(l_{ZE(j)}, m_{ZE(j)}, u_{ZE(j)})})(20)$$

Step 5: Determine the alternative weights by combining the scores from the three evaluations.

$$M_{ia(ZE)} = \frac{P_{i(ZE)} + S_{i(ZE)}}{\sum_{i=1}^{m}(P_{i(ZE)} + S_{i(ZE)})}(21)$$

$$M_{ib(ZB)} = \frac{S_{i(ZE)}}{MinS_{i(ZE)}} + \frac{P_{i(ZE)}}{MinP_{i(ZE)}}(22)$$

$M_{ic(ZE)} = \frac{\lambda(S_{i(ZE)}) + (1-\lambda)(P_{i(ZE)})}{\lambda maxS_{i(ZE)} + (1-\lambda) maxP_{i(ZE)}}; 0 \leq \lambda \leq 1$(23)

In the CoCoSo method, $M_{ia(ZE)}$ and $M_{ib(ZB)}$are respectively denotes the arithmetic mean of the sums and the sum of relative scores compared to the best alternative. Furthermore, $M_{ic(ZE)}$ indicates the balanced compromise score. While the default value for λ in $M_{ic(ZE)}$ is set at 0.5, CoCoSo offers flexibility by allowing λ to vary between 0 and 1.

Step 6: Rank the alternatives according to the values calculated in Equation (24).

$$M_{i(ZE)} = (M_{ia(ZE)} * M_{ib(ZE)} * M_{ic(ZE)})^{1/3} + 1/3(M_{ia(ZE)} + M_{ib(ZE)} + M_{ic(ZE)}) \quad (24)$$

4. Results and Discussion

This section presents the outcomes of applying the proposed framework to the evaluation of NZEB failure modes. The results are structured in three parts. First, the weights of the evaluation criteria are determined using the Fuzzy ZE-SWARA method, reflecting the relative importance of severity, occurrence, detection, and cost. Next, the Fuzzy ZE-COCOSO method is applied to integrate these weights and produce the final ranking of failure modes. Finally, a sensitivity analysis is conducted to examine the robustness of the rankings under different parameter settings. The following subsection begins with the weight of criteria, which forms the basis for the subsequent ranking of failure modes.

4.1 Weight of Criteria

This section outlines the findings of the weight coefficient assessment performed using the SWARA approach, integrated within the fuzzy ZE-number framework. According to this methodology, experts determined the most and least significant criteria. Next, criteria were compared in pairs using linguistic scales, with values assigned through membership functions and certainty levels, as detailed in Tables 4 and 5. A panel of twelve experts contributed their evaluations for each decision. A "Yes" vote indicated agreement with the decision-maker's opinion, a "No" vote indicated disagreement, and a "θ" vote indicated uncertainty. The following table summarizes the decision-makers' evaluations and the experts' judgments for the criteria. It is clear the DM1 reports the weight of cost as moderately less important, but reliability high important, followed by severity and then detection. In DM2 shows that weight of severity s less important but the reliability is very high, and for DM3again the weight of cost is moderate less important, and the reliability high important.

In the fuzzy ZE-numbers framework, the reliability coefficient R is defined as a measure of the level of agreement between experts and decision-makers. According to the original formulation by Tian et al [58] and later applied by [80], the Rvalue can be positive, zero, or negative, representing respectively high consensus, neutrality, or disagreement among evaluators. Therefore, the negative value of $R = -0.221$observed for DM2 does not indicate an error in data or computation; rather, it reflects a lower level of confidence and consistency in that expert's judgments. This property is inherent to the ZE-number model and is retained in the present study to accurately capture variability in human reliability. In the ZE-SWARA procedure, the weighting process is first conducted individually for each decision-maker (DM), and then the obtained weights are integrated and averaged to derive the final aggregated (Crisp) weights representing the group decision. As a result, while certain criteria such as *Occurrence* or *Severity* received the highest weights for some individual DMs, the Cost criterion obtained the highest overall weight after aggregation, indicating its dominant importance from a collective perspective. Furthermore, the order of criteria in Tables 4 and 5 varies among decision-makers because each DM independently evaluates and prioritizes the criteria based on their own experience, perception, and professional focus. This variation is natural and reflects the diversity of expert opinions rather than inconsistency in data presentation. Following section, ZE scores were determined for the specified criteria, followed by the computation of final fuzzy weights using the ZE-SWARA method. The corresponding table presents the derived fuzzy weight values. As shown in Table 5, each criterion's relative importance was established using the fuzzy ZE-SWARA approach. These fuzzy weights encapsulate the aggregated expert assessments and reflect the prioritization process within the decision framework. These fuzzy numbers reflect the collective input of decision-makers throughout the process. From the weight values obtained through ZE-SWARA, it was found that the cost criterion holds the highest weighting. This indicates that cost is perceived as the most influential factor when evaluating and implementing NZEB strategies. The ZE-SWARA outcomes underscore the crucial role of financial considerations in NZEB initiatives. Assigning a high weight to cost highlights the importance of affordability and economic feasibility in facilitating the widespread adoption and successful realization of sustainable building practices.

4.2 Strategies Rank

This section presents the procedure used to rank various strategic alternatives by integrating insights from decision-makers and subject matter experts. Through the ZE-COCOSO approach, participants assessed the alternatives using a fuzzy decision matrix, which incorporated linguistic membership values drawn from Tables 2 and 3. In this matrix, "A" represents the degree of membership, while "B" indicates the certainty level. Experts provided judgments based on their evaluation of different strategies, contributing to the decision-making process. Tables 6 through 8 display the results from the previous phases, including the evaluation of 16 barriers and 4 criteria for the first and third sets of decision-makers. These aggregated evaluations were then used to finalize the ranking of strategic choices. The ZE-COCOSO method employed in this analysis is a valuable tool for multi-criteria decision-making, particularly in the context of NZEBs. By incorporating input from both decision-makers and subject matter experts, the method ensures a comprehensive and well-informed evaluation of the various barriers and criteria associated with NZEB implementation. The fuzzy decision matrix allows for the capture of uncertainty and ambiguity in the assessments, reflecting the complex and often subjective nature of the decision-making process. The linguistic membership functions provide a flexible and intuitive way for decision-makers to express their preferences, accommodating the inherent vagueness and imprecision that can arise when evaluating complex scenarios. The incorporation of expert judgments further enhances the reliability and validity of the analysis, as it taps into the specialized knowledge and experience of individuals who are deeply familiar with the NZEB field. This integration of decision-maker and expert inputs helps to ensure that the final rankings and conclusions are based on a well-rounded and informed perspective.

Based on the assessment of design for NZEBs and defining a set of criteria to examine these barriers, strategies can be provided to improve the implementation of NZEBs. Giving to the outcomes of the ZE-COCOSO ranking technique, poor air sealing (FM2) is the most significant design failure for NZEBs. This is caused by improper insulation material selection, inadequate insulation thickness or coverage, or poor installation techniques, which can impact increased energy consumption for heating and cooling, thermal discomfort for occupants, and potential moisture and mold issues. The second most important failures are inappropriate sizing or design of renewable energy systems (FM10), which is due to inaccurate assessment of energy loads and demand, improper selection or sizing of renewable energy components, or lack of integration with building energy systems. This can lead to an inability to meet energy generation targets and reduced overall energy efficiency and self-sufficiency. Thirdly, insufficient insulation (FM1) can also be a cause of design failure, stemming from improper insulation material selection, inadequate insulation thickness or coverage, and poor installation techniques. Finally, the least important among the obstacles is insufficient control of lighting and automation (FM7), which can be caused by a lack of occupancy sensors, timers, or dimming controls, improper programming or configuration of lighting controls, or insufficient integration of lighting controls with building management systems. This can impact increased energy consumption for lighting and inefficient use of lighting based on occupancy and daylight availability.

This study highlights the enhanced efficiency and performance of the latest ZE-COCOSO variant when compared to earlier models that lacked fuzzy ZE-number integration. To assess its effectiveness, a comparative analysis was conducted using two widely recognized fuzzy COCOSO approaches: fuzzy COCOSO and fuzzy Z-COCOSO, both of which have been thoroughly examined in prior studies. The results of this evaluation are presented in Table 11. Notably, the weighting values obtained from ZE-COCOSO show a reduced tolerance range, reflecting its capacity to incorporate a wider spectrum of preferences in decision-making. This section presents a comparative evaluation of obstacle prioritization using multiple MCDM techniques. Table 11 provides a comparative evaluation of failure-mode rankings derived from four distinct approaches—classical RPN, Fuzzy-CoCoSo, Z-CoCoSo, and the proposed ZE-CoCoSo. The purpose of this comparison is to demonstrate how the inclusion of *uncertainty modeling* and *multi-level reliability* affects the prioritization of potential failures.Under the conventional RPN approach, FM2 (RPN=2352)**,** FM1(RPN=2016), and FM10(RPN=1400) occupy the top three ranks. When the fuzzy CoCoSo and Z-CoCoSo methods are applied, the ranking order changes slightly due to the incorporation of fuzzy parameters and the individual reliability dimension (B) of each decision-maker. However, in the ZE-CoCoSo model, a further advancement is achieved by introducing a group-reliability mechanism, in which not only the three decision-makers but also a panel of external experts contribute reliability feedback on each decision-maker's evaluation. This dual-layer reliability structure—combining *individual confidence* and *collective endorsement*—creates a more robust and socially validated weighting of the decision data. As a result, the ZE-CoCoSo model refines the ranking outcomes: while FM2 remains the most critical failure mode (rank 1), the relative positions of FM10 and FM1 are adjusted based on the aggregated reliability feedback, leading to a more balanced and credible prioritization. Overall, the ZE-CoCoSo framework demonstrates superior stability, interpretive accuracy, and representativeness of group consensus compared with the Z-CoCoSo and classical RPN methods. It effectively integrates both quantitative uncertainty and qualitative reliability judgments, offering a comprehensive tool for decision-making in uncertain and multi-expert environments.

Table 11: Comparison of ranking obtained from four methodsSensitivity analysis

The proposed method determines the final rankings using a parameter sourced from the CoCoSo technique. To assess how this parameter influences the ranking outcomes, we performed a sensitivity analysis by altering its value across several distinct scenarios. Figure 3 presents the variations in λ values and the associated changes in ranking results. The results of this analysis reveal that modifying the λ parameter does not lead to noticeable differences in the rankings. Across all tested scenarios, the rankings remain consistent, indicating that changes in λ have minimal influence on the final outcomes. In particular, FM2 consistently holds a top-ranked position, regardless of the scenario, suggesting that the ranking process is stable and resilient to fluctuations in this parameter. However, it's important to note that the significance of the λ can vary depending on the specific data and context. experts may need to carefully consider the value of the λ. based on the nature of their application

To evaluate the dependability, precision, and overall performance of the obtained outcomes, a comprehensive sensitivity analysis of the criteria was carried out. Sensitivity analysis plays a pivotal role in experimental modeling, offering insights into how model behavior shifts under different conditions. It is often employed to assess the impact of parameter changes on model performance through various scenarios[81]. In this study, the final ranking was derived using the CoCoSo method, which depends on the parameter λ. To analyze how changes in λ influence the rankings, multiple scenarios were tested by varying λ. Within the CoCoSo method, λ values significantly affect how weights are distributed among criteria. These values reflect the relative significance of each criterion in the decision-making process. Similarly, the SFWASPAS method uses λ to encapsulate the priorities and preferences of decision-makers, allowing the weighting to adapt accordingly. By adjusting λ, certain criteria can be emphasized or downplayed, depending on their importance. This dynamic approach enables decision-makers to tailor the decision framework to align with specific goals and requirements. The clarity and interpretability of the CoCoSo method are further enhanced through this parameterization, enabling a better understanding of each criterion's influence on the final ranking. This, in turn, facilitates more logical and data-driven decision-making[82, 83]. To assess how variations in weighting schemes impact the ranking outcomes, ten distinct scenarios were formulated, each employing a unique set of weights. These scenarios allowed for a detailed investigation into how shifts in criteria importance affect overall outcomes. By comparing ranking results across scenarios, it was possible to gain a deeper understanding of how λ variations affect model output.

Figure 3 visually represents the outcomes of the sensitivity analysis, emphasizing how ranking results fluctuate under different conditions (X-axis: failure modes, and Y-axis: ranking results). The figure demonstrates that varying the weighting schemes affects the prioritization of failure modes in NZEB evaluations. This analysis validates the stability and dependability of the proposed framework, indicating its capacity to deliver reliable and insightful results across multiple scenarios. Notably, the approach maintains its consistency even when the criteria weights are modified. This enhances the credibility of the findings and underlines the method's utility in systematically identifying and ranking failure modes in the context of NZEB design.

4.3 Comparative analysis

This section compares the ranking of strategies using different MCDM methods: WASPAS, COPRAS, and MABAC. Table 13 presents the prioritization results obtained from CoCoSo and these other methods for selecting the most significant risks. The CoCoSo results align with the other methods in identifying the most important risk. We chose CoCoSo for this study because it is more intuitive for decision-makers and emphasizes compromise solutions. CoCoSo is a valuable tool for evaluating multiple conflicting criteria, as it provides a balanced perspective on alternatives by focusing on compromise solution.

4.4 Discussion

The extended fuzzy ZE-FMEA framework proposed in this study provides a richer and more discriminative understanding of failure behavior in NZEBs than the classical FMEA formulation. By incorporating cost as a fourth factor and embedding expert reliability through ZE-numbers, the analysis redefines risk from a purely technical probability into a multidimensional construct that links economic, environmental, and epistemic aspects of design. The combined ZE-SWARA and ZE-COCOSO procedures expose how the perceived importance of each failure mode changes once uncertainty and financial impact are accounted for, thereby yielding a more credible prioritization of preventive actions. The results identify poor air sealing (FM2) as the most critical failure mode across all weighting and sensitivity scenarios. This dominance reflects the central role of the building envelope as both an energy and information interface between indoor and outdoor environments. Air leakage simultaneously undermines thermal comfort, increases HVAC load, and erodes the building's ability to maintain its designed energy balance. From an economic perspective, each unit of uncontrolled airflow represents an invisible cost stream that accumulates throughout the building's life cycle. The ZE-FMEA model captures this duality precisely because the cost criterion amplifies the significance of small but persistent inefficiencies. In this way, the framework translates physical leakage into economic leakage, transforming an engineering detail into a systemic risk signal.

The second-ranked failure—improper sizing or design of renewable-energy systems (FM10)—highlights a recurring challenge in NZEB implementation. Oversizing increases embodied cost and resource use, while undersizing forces greater reliance on grid power, reducing the building's self-sufficiency. The fuzzy reliability analysis reveals notable divergence among expert judgments for this criterion, indicating that sizing decisions remain one of the most uncertain aspects of NZEB design. By quantifying that divergence rather than suppressing it, the ZE-number approach converts disagreement into measurable reliability information, offering designers a structured awareness of where expert consensus is weakest and further data collection is most needed. Insufficient insulation (FM1) ranks third, confirming that thermal-envelope performance remains a foundational determinant of NZEB success. Although insulation has long been recognized as a key factor, its persistent appearance among top failures suggests that the problem lies less in material science than in execution—installation quality, site supervision, and workforce training. In this respect, the fuzzy reliability weighting functions as an indirect indicator of organizational reliability: variability in expert confidence mirrors variability in construction practice. Thus, the ZE-FMEA framework not only ranks technical vulnerabilities but also reveals the social dimensions of reliability within sustainable building projects.

A comparative assessment among classical RPN, fuzzy CoCoSo, Z-CoCoSo, and the proposed ZE-CoCoSo models demonstrates the advantages of the hybrid structure. The ZE-based results show narrower tolerance ranges and higher stability, confirming that the inclusion of group-reliability feedback improves both the interpretive accuracy and the credibility of the ranking outcomes. By embedding expert reliability within the decision matrix, the method mitigates one of FMEA's long-standing weaknesses—the implicit assumption of equal confidence among evaluators. This advancement produces risk rankings that are not only numerically precise but also socially validated through multi-expert consensus. The sensitivity analysis further supports the robustness of the framework. Variations in the λ-parameter within the CoCoSo aggregation step did not significantly affect the hierarchy of critical failures; FM2 consistently retained its leading position. This invariance demonstrates that the ranking structure is not an artifact of parameter tuning but a stable reflection of the underlying relationships among severity, occurrence, detection, and cost. Such robustness is essential for decision contexts where datasets are sparse and expert judgments dominate quantitative inputs.

The broader implications of these findings extend beyond the immediate case study. Integrating cost into FMEA reframes reliability analysis as a tool for systemic performance management rather than fault detection. Economic feasibility becomes an intrinsic reliability attribute, encouraging design teams to approach NZEB projects as interdependent ecosystems in which technical and financial parameters co-evolve. At the regulatory level, the consistent prominence of envelope-related failures underscores the need for mandatory airtightness diagnostics and envelope-performance verification within NZEB certification protocols. Policy frameworks that currently emphasize energy-balance calculations should therefore expand to include empirical leakage testing as a standard compliance metric. Finally, from a methodological standpoint, the study demonstrates that uncertainty is not a defect to be eliminated but a dimension to be organized. The ZE-based hybrid model transforms ambiguity into structured knowledge, enabling a more transparent negotiation between expert intuition and data-driven reasoning. In a broader philosophical sense, every NZEB can be viewed as a living system learning to breathe through its envelope. When that breath leaks, energy and understanding leak with it. The ZE-FMEA framework listens to that breath—it quantifies doubt, disciplines intuition, and transforms uncertainty into awareness. Within this paradigm, reliability is redefined not as the mere absence of failure but as the continual capacity to perceive how failure begins and to respond before it propagates. This synthesis of analytical precision and ecological sensitivity positions the proposed framework as both a scientific and a reflective contribution to the evolving discipline of sustainable building design.

5. Conclusion

This study developed an integrated decision-making framework to assess and rank design failures in NZEBs by combining an improved Failure Mode and Effects Analysis (FMEA) with fuzzy MCDM methods. The improved FMEA introduced cost as a fourth factor in the Risk Priority Number (RPN), thereby strengthening the ability to capture both technical and economic impacts of failures. To address uncertainty in expert judgments, the ZE-SWARA method was applied to derive the relative importance of criteria, and the ZE-COCOSO method was used to aggregate results and generate robust rankings of failure modes.

The analysis revealed several key findings:

- Poor air sealing (FM2) was identified as the most critical failure mode, leading to significant increases in heating and cooling energy consumption, occupant discomfort, and moisture-related risks.

- Inadequate sizing or design of renewable energy systems (FM10) ranked as the second most influential issue, highlighting the importance of accurate energy demand estimation and proper component selection.

- Insufficient insulation (FM1) emerged as another high-priority concern, reflecting the sensitivity of NZEB performance to envelope design decisions.

- In contrast, inadequate lighting controls and automation (FM7) was found to be the least critical, although still relevant for efficiency improvements.

The findings emphasize that building envelope quality and renewable energy system design are decisive factors in achieving NZEB performance. This aligns with other research in sustainable construction, where passive design features and energy system integration are often the main determinants of success. By explicitly incorporating cost into the failure assessment, this study provides practical insights for balancing economic feasibility and energy efficiency in NZEB design.

It is important to note that in decision-making frameworks such as FMEA, expert judgment inherently plays a central role, as this approach is designed to identify and prevent potential failures and risks before they occur. Therefore, it relies on the experience and perception of experts to evaluate uncertain or probabilistic conditions that cannot yet be measured empirically. The main purpose of our study is to reduce the uncertainty typically associated with expert-based evaluations by introducing the ZE-CoCoSo method, which incorporates both fuzzy modeling and multi-level reliability assessment. This framework not only accounts for the preferences of decision-makers but also integrates the reliability feedback from additional experts, providing a more realistic and credible reflection of group consensus. Although FMEA-based analyses are inherently qualitative and preventive, this approach strengthens their analytical rigor by quantifying uncertainty and expert confidence. The aim of this proposed approach of this study is not post-event validation, but rather risk prevention and reliability enhancement through structured expert reasoning. For future research, several directions are recommended:

- Expanding the analysis to include dynamic interactions among criteria using advanced tools such as fuzzy cognitive maps, DEMATEL, or the Choquet integral.
- Investigating the applicability of other emerging MCDM techniques (VIKOR, MARCOS, OPA, BWM, SECA, or WASPAS) under fuzzy or Z-number environments to benchmark and validate results.
- Conducting empirical case studies across diverse climates and building types to better understand context-specific failures and refine prioritization strategies.
- Incorporating real operational data from existing NZEB projects to validate expert-based assessments and improve the practical reliability of findings.

In summary, the proposed framework enhances the accuracy and clarity of NZEB failure analysis, supporting designers and decision-makers in prioritizing interventions that yield the greatest improvements in energy efficiency, resilience, and cost-effectiveness.

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Figure 1. The Methodology framework.

Figure 2. NZEB Design Failure concept.

Figure 3. Failure mode ranking comparison with different $\boldsymbol{\lambda}$

Table 1. NZEB design most common evaluation criteria.

Failure	Failure Type	Impact	Cause	Categories
FM1	Inadequate insulation	↑ energy consumption for heating & cooling - Thermal discomfort for occupants - Potential moisture and mold issues	- Improper insulation material selection - Inadequate insulation thickness or coverage - Poor installation techniques	Building Envelope
FM2	Poor air sealing	↑energy consumption for heating and cooling - ↓ indoor air quality - Potential moisture and mold issues	- Gaps and cracks in the building envelope - Inadequate caulking and weatherstripping - Improper installation of air barriers	Building Envelope
FM3	Lack of proper vapor barrier	Moisture buildup &potential for mold growth - ↓ insulation effectiveness - Potential structural damage	- Omission of vapor barrier in the building envelope - Improper placement or installation of the vapor barrier - Inadequate vapor barrier material selection	Building Envelope

FM4	Thermal bridging	↑ energy consumption for heating & cooling - Localized areas of thermal discomfort - Potential for condensation and mold growth	- Inadequate insulation around structural elements - Lack of thermal breaks in the building envelope - Improper design and detailing of building components	Building Envelope
FM5	Inefficient lighting systems	↑ energy consumption for lighting - Inadequate illumination levels - Poor lighting quality and distribution	- Use of outdated or inefficient lighting technologies - Improper lighting fixture selection or layout - Lack of energy-efficient lighting controls & automation	Lighting & Daylighting
FM6	Insufficient daylighting design & utilization	↑ energy consumption for artificial lighting - Lack of natural lighting & visual comfort for occupants	- Inadequate window size, placement, or orientation - Lack of shading devices or blinds -Insufficient integration of daylighting with artificial lighting	Lighting & Daylighting
FM7	Inadequate lighting controls & automation	↑energy consumption for lighting - Inefficient use of lighting based on occupancy and daylight availability	- Lack of occupancy sensors, timers, or dimming controls - Improper programming or configuration of lighting controls - Insufficient integration of lighting controls	Lighting & Daylighting

			with building management systems	
FM8	Overestimation or underestimation of energy consumption	Oversizing or undersizing of building systems - ↑ energy costs or reduced energy efficiency	- Inaccurate assumptions or data used in energy modeling - Lack of detailed energy analysis or simulation - Failure to account for actual occupancy & usage patterns	Energy Management & Modeling
FM9	Failure to account for site-specific factors (e.g., climate, shading)	Suboptimal building performance & energy efficiency - ↑ energy consumption for heating &cooling	- Insufficient site analysis & consideration of local climate conditions - Lack of shading analysis & integration of passive solar strategies - Inadequate adaptation of building design to site-specific factors	Energy Management & Modeling
FM10	Inadequate sizing or design of RE systems	Inability to meet energy generation targets - Reduced overall energy efficiency & self-sufficiency	- Inaccurate assessment of energy loads and demand - Improper selection or sizing of RE components - Lack of integration with building energy systems	Renewable Energy Systems[20]
FM11	Poor integration of renewable energy	↓ energy efficiency and utilization of RE	- Lack of coordination between RE systems & building HVAC,	Renewable Energy Systems

	sources with building systems	- Potential compatibility issues and system failures	electrical, or control systems - Insufficient expertise or understanding of system integration requirements	
FM12	Insufficient energy storage capacity	Inability to effectively store and utilize RE - Reliance on grid-supplied energy during peak demand	- Underestimation of energy storage needs based on building loads and RE generation - Inadequate selection or sizing of energy storage systems	Energy Storage & Management
FM13	Inefficient HVAC equipment (e.g., outdated, oversized or undersized systems)	↑ energy consumption for heating and cooling - Inability to maintain comfortable indoor conditions	- Use of outdated or inefficient HVAC technologies - Improper sizing of HVAC systems based on building loads - Lack of regular maintenance and system optimization	HVAC & Mechanical Systems
FM14	Inadequate ventilation	Poor indoor air quality & occupant health issues - Potential moisture and mold problems	- Insufficient ventilation system design or capacity - Improper balancing or control of ventilation systems - Lack of integration with building automation & monitoring	HVAC & Mechanical Systems
FM15	Poor distribution of conditioned air	Uneven temperature & humidity levels within the building	- Inadequate ductwork design or installation	HVAC & Mechanical Systems

		- Occupant discomfort and dissatisfaction	- Imbalanced airflow distribution within the building - Lack of zoning and individual room-level controls	
FM16	Lack of zone control and occupancy sensing	Inefficient energy use for heating & cooling - Inability to optimize comfort & energy savings based on occupancy	- Absence of zone-level temperature & ventilation controls - Lack of occupancy sensors or integration with building automation systems - Insufficient programming & optimization of zone control strategies	HVAC & Mechanical Systems

↓=Reduce ; ↑ = Increase; RE =Renewable Energy

Table 2. Linguistic variables for weight criteria[28]

Linguistic Variables	TFNs
Equally important (E.I)	(1, 1, 1)
Moderately less important (M.O.L)	(2/3, 1, 3/2)
Less important (L.I)	(2/5, ½, 2/3)
Very less important (V.L.I)	(2/7, 1/3, 2/5)
Much less important (M.U.L)	(2/9, ¼, 2/7)

Table 3. Linguistic variables for reliability[19]

Linguistic variables	Very Weak (VW)	Weak (W)	Medium (M)	High (H)	Very High (V,H)
TFNs	(0,0,0.25)	(0.2,0.35,0.5)	(0.35,0.5,0.75)	(0.5,0.75,0.9)	(0.75,1,1)

Table 4. Evaluations of Criteria Based on DMs' and Experts' Input

DM1,	**y**	**n**	**θ**	**R**
O				

C	M.O.L - H	9	2	4	0.78
S	L.I - V,H	7	3	5	0.51
D	M.U.L - V,H	6	5.	2	0.27
DM2					
C					
S	L.I - V,H	6	3	6	0.43
D	M.O.L - H	5	7	3	-0.22
O	V.L.I - M	9	3	3	0.60
DM3					
S					
C	M.O.L - H	6	4	5	0.25
D	V.L.I - M	5	3.	7	0.33
O	M.U.L - V.H	9.	0	4	1.00

Table 5. Criteria Weights Derived from Fuzzy ZE-SWARA

DM1	ZE-Number				**K**			$\tilde{q}_j$			$\widetilde{W}_j$		
O	-	-	-	-	1.00	1.00	1.00	1.00	1.00	1.00	0.42	0.47	0.54

C	MOL-H	0.65	0.97	1.45	1.65	1.97	2.45	0.41	0.51	0.61	0.17	0.24	0.33
S	LI-VH	0.40	0.49	0.66	1.40	1.49	1.66	0.25	0.34	0.44	0.10	0.16	0.24
D	MUL-VH	0.22	0.25	0.28	1.22	1.25	1.28	0.19	0.27	0.36	0.08	0.13	0.19
							sum	1.84	2.11	2.39			
DM2			**ZE-Number**			**K**			$\tilde{q}_j$			$\widetilde{W}_j$	
C	-	-	-	-	1.00	1.00	1.00	1.00	1.00	1.00	0.39	0.43	0.48
S	LI-VH	0.40	0.49	0.66	1.40	1.49	1.66	0.60	0.67	0.72	0.23	0.29	0.34
D	MOL-H	0.51	0.77	1.15	1.51	1.77	2.15	0.28	0.38	0.47	0.11	0.16	0.23
O	VLI-M	0.26	0.30	0.36	1.26	1.30	1.36	0.21	0.29	0.38	0.08	0.12	0.18
							sum	2.08	2.34	2.56			
DM3			**ZE-Number**			**K**			$\tilde{q}_j$			$\widetilde{W}_j$	
S	-	-	-	-	1.00	1.00	1.00	1.00	1.00	1.00	0.39	0.44	0.50
C	MOL-H	0.60	0.89	1.34	1.60	1.89	2.34	0.43	0.53	0.63	0.17	0.23	0.31
D	VLI-M	0.24	0.27	0.33	1.24	1.27	1.33	0.32	0.41	0.51	0.13	0.18	0.25
O	MUL-VH	0.22	0.25	0.29	1.22	1.25	1.29	0.25	0.33	0.41	0.10	0.15	0.21

sum	1.99	2.27	2.54

Table 6. The initial decision matrix for strategic options using the judgment of the first decision-maker and the votes of the experts

Failure	S		O		D		C		Expert Decision			R
	A	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**Y**	**N**	**θ**	
1	M	H	M,G	H	M	V,H	M,G	M	7	3	2	0.4
2	M,G	M	M,G	W	M,P	H	M	H	8	3	1	0.45
3	G	M	M,G	H	M,P	H	M	W	6	5	1	0.09
4	M,G	H	M	H	M	V,H	M,G	M	3	5	4	-0.25
5	M	M	M,P	M	M,P	H	M,P	M	3	4	5	-0.14
6	MP	W	M,P	H	G	M	M,G	H	4	6	2	-0.2
7	M	H	M	H	P	M	P	H	6	4	2	0.2
8	M,G	W	M,G	M	M,P	V,H	MP	M	4	6	2	-0.2
9	M,G	M	M,P	W	M,P	M	M	H	7	4	1	0.27
10	G	M	M,P	H	M	H	VG	M	5	4	3	0.11
11	G	H	M,P	M	G	M	M,G	H	4	6	2	-0.2

12	M,G	H	P	M	P	M	G	H	7	4	1	0.27
13	M,G	H	M,P	M	M,P	M	G	M	3	5	4	-0.25
14	M	H	M,P	H	M	H	M,G	M	4	5	3	-0.11
15	M,G	H	M,P	W	M,P	V,H	M	H	5	6	1	-0.09
16	M	M	M,P	H	P	H	M,G	V,H	4	3	5	0.14

Table 7. The initial decision matrix for strategic options using the judgment of the second decision-maker and the votes of the experts

	S		O		D		C		Expert Decision			R
FM	A	B	A	B	A	B	A	B	Y	N	θ	
1	M,G	M	M,G	M	M,P	M	M	H	6	3	3	0.33
2	G	H	M	H	M	H	M	W	7	4	1	0.27
3	M	H	M	VW	M	H	M,P	M	6	5	1	0,09
4	M,G	V,H	G	M	M,P	M	M	H	4	6	2	-0,2
5	M,G	H	M	H	M,P	H	M,G	H	4	4	4	0.00
6	M	H	M,P	V,H	M,G	H	M	W	4	5	3	-0.11
7	M,P	VW	M	M	M,P	H	M,P	M	6	4	2	0.20

8	M,G	M	M,P	W	M	M	M,G	M	4	5	3	-0.11
9	M	H	M	H	M,P	H	M	V,H	8	3	1	0.45
10	M,G	H	M	W	M	M	G	H	6	4	2	0.20
11	M,G	M	M	H	M	H	G	H	3	6	3	-0.33
12	M,G	M	M,P	H	VP	W	M,G	M	5	4	3	0.11
13	G	H	M	H	M	H	M,G	V,H	5	5	2	0.00
14	M,G	M	M,P	M	M,P	M	M	H	3	7	2	-0.40
15	G	W	M,P	H	P	H	M	M	4	5	3	-0.11
16	M,P	M	P	M	P	M	G	H	4	5	3	-0,11

Table 8. The initial decision matrix for strategic options using the judgment of the third decision-maker and the votes of the experts

	S		O		D		C		Expert Decision			R
FM	A	B	A	B	A	B	A	B	Y	N	θ	
1	G	M	M	W	M	H	M	H	5	3	4	0.25
2	M,G	H	M	M	M,G	M	M,G	H	7	4	1	0.27
3	M	M	M	W	M,P	V,H	M,P	H	6	5	1	0.09

4	M	M	M,G	H	M	H	M	M	3	7	2	-0.4
5	G	M	MG	H	M	H	M	H	4	4	4	0.00
6	M	M	M	H	M	M	MG	M	4	6	2	-0.2
7	M	M	M,P	W	M,P	V,H	P	M	5	3	4	0.25
8	M	H	M	H	M	H	M	H	4	7	1	-0.27
9	G	H	M,G	H	M	W	M	H	8	2	2	0.60
10	M,G	H	M,P	M	M,P	M	M,G	V,H	6	4	2	0.20
11	G	M	M,P	W	M	M	M,G	M	4	8	0	-0.33
12	M	W	P	H	P	H	G	M	7	3	2	0.40
13	G	M	M,G	M	M,P	H	M	H	5	5	2	0.00
14	M	V,H	M,P	H	M	M	M	H	3	6	3	-0.33
15	M,G	M	M	H	P	M	M,G	M	4	6	2	-0.20
16	M,G	H	P	H	P	W	M,G	H	6	5	1	0.09

Table 9. Decision matrix including developed fuzzy ZE numbers

Failure	S	O	D	C

1	4.46	5.44	6.42	3.85	4.96	6.07	3.06	4.10	5.14	3.81	4.83	5.85
2	5.02	6.20	7.38	3.61	4.58	5.55	3.16	4.32	5.48	3.70	4.70	5.70
3	3.91	4.70	5.48	2.78	3.55	4.32	2.39	3.61	4.83	1.93	2.95	3.98
4	3.44	4.43	5.43	3.59	4.39	5.18	2.44	3.27	4.09	2.80	3.55	4.31
5	3.99	4.88	5.77	3.01	4.06	5.11	2.24	3.35	4.46	3.01	4.06	5.11
6	2.29	3.03	3.78	2.15	3.25	4.35	3.70	4.54	5.37	3.09	3.98	4.87
7	2.57	3.37	4.18	2.70	3.62	4.53	1.51	2.71	3.90	1.08	2.04	2.99
8	2.99	3.83	4.68	2.42	3.26	4.10	2.46	3.37	4.28	2.53	3.44	4.34
9	4.78	5.81	6.83	3.29	4.44	5.58	2.30	3.45	4.60	3.78	4.72	5.66
10	4.72	5.86	7.00	2.03	3.09	4.15	2.73	3.67	4.62	5.72	6.76	7.80
11	4.13	4.88	5.62	1.68	2.48	3.28	3.21	3.86	4.50	3.89	4.80	5.71
12	3.80	4.88	5.97	1.16	2.17	3.18	0.57	1.36	2.15	5.32	6.28	7.24
13	4.91	5.81	6.70	2.75	3.71	4.67	2.13	3.15	4.18	4.23	5.21	6.19
14	3.07	3.88	4.70	1.38	2.41	3.44	2.23	2.97	3.72	2.95	3.74	4.53
15	3.73	4.65	5.57	1.94	2.88	3.82	1.11	2.06	3.01	3.06	3.88	4.70
16	2.92	3.95	4.98	1.10	2.06	3.01	0.73	1.46	2.20	4.97	6.17	7.36

Table 10. Final table for ranking barriers

FM	Fuzzy Fic			Crisp Fic	Final Score Fi	Fi	Final Ranking
1	0.70	0.85	0.99	0.84	4.22	4.22	3
2	0.71	0.86	1.00	0.86	4.34	4.34	1
3	0.57	0.74	0.88	0.73	3.20	3.20	9
4	0.61	0.76	0.89	0.75	3.39	3.39	8
5	0.62	0.78	0.92	0.77	3.58	3.58	6
6	0.47	0.70	0.85	0.67	2.96	2.96	12
7	0.37	0.64	0.80	0.60	2.43	2.43	16
8	0.54	0.71	0.85	0.70	2.95	2.95	13
9	0.68	0.83	0.97	0.83	4.07	4.07	4
10	0.68	0.85	0.99	0.84	4.22	4.22	2
11	0.61	0.76	0.89	0.75	3.40	3.40	7
12	0.39	0.73	0.89	0.67	3.15	3.15	10
13	0.67	0.82	0.96	0.82	3.95	3.95	5
14	0.49	0.69	0.83	0.67	2.74	2.74	15

15	0.53	0.71	0.86	0.70	2.97	2.97	11
16	0.38	0.69	0.86	0.64	2.88	2.88	14

Table 11. Comparison of ranking obtained from four methods

			FUZZY-COCOSO		Z-COCOSO		ZE-COCOSO	
FM	RPN	Final Ranking	Fi	Final Ranking	Fi	Final Ranking	Fi	Final Ranking
1	2016	2	6.30	5	4.85	6	4.22	3
2	2352	1	6.45	4	4.96	5	4.34	1
3	1050	6	5.32	11	3.87	13	3.20	9
4	1260	5	6.24	6	5.10	4	3.39	8
5	600	9	5.73	7	4.62	8	3.58	6
6	980	7	5.30	12	4.15	11	2.96	12
7	180	15	3.61	16	2.66	16	2.43	16
8	600	9	5.65	9	4.21	9	2.95	13
9	480	11	5.73	7	4.65	7	4.07	4
10	1400	3	6.57	3	5.15	3	4.22	2

11	1344	4	6.79	1	5.21	2	3.40	7
12	288	14	5.00	14	3.64	15	3.15	10
13	980	7	6.58	2	5.27	1	3.95	5
14	360	12	5.13	13	4.18	10	2.74	15
15	360	12	5.52	10	4.11	12	2.97	11
16	180	15	4.48	15	3.67	14	2.88	14

Table 12. The rankings of the alternative based on various scenario

Alternative	SWARA weight	Fixed weight	S=0	O=0	D=0	C=0
1	3	2	1	4	3	2
2	1	1	2	2	1	1
3	9	9	10	10	12	8
4	8	8	7	11	8	7
5	6	6	6	8	6	6
6	12	10	8	13	15	12
7	16	16	16	16	16	13
8	13	11	11	15	13	10

9	4	4	4	5	4	3
10	2	3	3	1	2	5
11	7	7	9	6	9	9
12	10	13	12	7	7	15
13	5	5	5	3	5	4
14	15	14	15	14	14	14
15	11	12	14	12	11	11
16	14	15	13	9	10	16

Table 13. The prioritization results obtained from different methods

Failure	COCOSO		WASPAS		MABAC		COPRAS	
	Fi	Final Ranking	Ki	Ranking	Defuzzification of Si	Ranking	N(j)	Rank ZCOPRAS
1	4.22	3	0.73	2	0.45	3	0.97	3
2	4.34	1	0.74	1	0.46	1	0.99	2
3	3.20	9	0.55	9	0.27	10	0.74	11
4	3.39	8	0.59	8	0.30	8	0.78	9
5	3.58	6	0.62	6	0.33	6	0.83	6

6	2.96	12	0.54	11	0.25	11	0.71	12
7	2.43	16	0.44	16	0.15	16	0.59	16
8	2.95	13	0.52	12	0.23	13	0.69	14
9	4.07	4	0.70	4	0.42	4	0.94	4
10	4.22	2	0.73	3	0.45	2	1.00	1
11	3.40	7	0.59	7	0.30	7	0.80	7
12	3.15	10	0.55	10	0.28	9	0.80	8
13	3.95	5	0.68	5	0.39	5	0.92	5
14	2.74	15	0.49	15	0.20	15	0.66	15
15	2.97	11	0.52	13	0.23	14	0.71	13
16	2.88	14	0.51	14	0.24	12	0.74	10