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Enhanced FMEA for Critical Failure Mode Identification Under Uncertainty and Dependency Conditions

James J. H. Liou ¹, Bruce H. T. Guo ¹, Sun-Weng Huang ^{2,3,*} and Guo-Xuan Fan ¹

¹ Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei 10608, Taiwan; jamesjhliou@gmail.com (J.J.H.L.); hotoguo@gmail.com (B.H.T.G.); jason0860406@gmail.com (G.-X.F.)

² Department of Health Care Management, National Taipei University of Nursing and Health Sciences, Taipei 112303, Taiwan

³ Institute of Urban Planning, College of Public Affairs, National Taipei University, New Taipei City 23741, Taiwan

* Correspondence: t107379004@ntut.org.tw; Tel.: +886-2-28227101 (ext. 1268)

Abstract

Failure Mode and Effect Analysis (FMEA) is a widely applied preventive risk assessment approach to enhance product reliability and safety, yet its structural validity is frequently questioned. Existing improvement models generally overlook the interrelationships among failure modes and suffer from high uncertainty and instability in opinion aggregation, risk factor weight allocation, and Risk Priority Number (RPN) computation. To bridge these gaps, this study proposes an integrated decision-making model. First, the Decision Making and Trial Evaluation Laboratory (DEMATEL) method is employed to analyze interactions among failure modes, constructing an influential network diagram to identify critical items. Second, a Rough Dombi Aggregator is applied for opinion aggregation, minimizing data loss and handling uncertainties from experts' diverse backgrounds. Third, the Full Consistency Method (FUCOM) is utilized to determine the relative weights of risk factors. Finally, four weighted aggregation methods are developed to calculate RPNs, mitigating the instability common in traditional methods. This vehicle power system case study, alongside model comparison and sensitivity analysis, demonstrates the model's effectiveness and robustness. The results indicate that across 9 different weight fluctuation scenarios, the core high-risk item "FM₇: Generator coil burned out due to short circuit" consistently ranks 1st. This highlights the exceptional stability of the proposed model in overcoming evaluation fluctuations. Ultimately, this integrated framework not only enhances the accuracy and robustness of failure mode prioritization but also serves as a valuable practical reference for engineers formulating preventive maintenance strategies under limited resources.



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1. Introduction

Failure Mode and Effect Analysis (FMEA) serves as an analytical framework for identifying and eliminating potential failure modes. Expert teams prioritize failure modes using three factors, Severity (S), Occurrence (O), and Detection (D) ratings within the defined system boundaries. The failure modes are categorized by their severity level and assessed based on their system impact, with the goal of minimizing damage and preventing

problems before they arise. Preventive measures and improvements are implemented for failure modes receiving higher risk scores, enabling proactive problem resolution. A failure mode refers to any known or potential failure, issue, or error in components, subsystems, or assemblies that could affect customers or compromise the operation of the overall organizational system.

Additionally, a failure mode can be defined as the specific manner or way by which an item's failure occurs [1]. The analysis begins at the level of a known or potential failure mode and examines its effects on the system, as well as on both lower and higher levels [2]. However, all complex mechanical systems are composed of multiple subsystems, which can be further decomposed into modules or assemblies. Therefore, a comprehensive FMEA should encompass all hierarchical levels within the system, from the bottom up [3].

With the evolution of FMEA, several experts have recognized that evaluating failure modes and obtaining their Risk Priority Number (RPN) is conceptually similar to the Multi-Criteria Decision-Making (MCDM) approach. However, traditional FMEA has several limitations. These include the failure to consider the relative importance of risk factors (S, O, and D) [4], the potential for different combinations of S, O, and D factors to yield the same RPN value, which can result in high redundancy [5], and the limited number of risk factors considered, which undermines the comprehensiveness and effectiveness of risk assessment, thus reducing the practical value of the results [6].

The rigorous mathematical framework of MCDM can improve the shortcomings of traditional FMEA, offering more reliable and effective rankings of failure modes [5]. As a result, scholars have begun using various types of MCDM methods to establish new FMEA models, making their structure more comprehensive and effective. For example, the Fuzzy Analytical Hierarchy Process (FAHP) combined with Fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (FVIKOR) has been applied to wind turbine design [7], using fuzzy logic to address expert uncertainty, the Analytic Hierarchy Process (AHP) subjective weighting method to account for the relative importance of risk factors, and the VIKOR ranking method to prioritize alternatives. To handle expert information uncertainty, some researchers have integrated Rough Set Theory (RST) with FMEA [8]. Pawlak [9] first introduced RST, a mathematical tool capable of handling subjective and imprecise concepts. The advantage of RST lies in its ability to process subjective information without the need for any assumption set conditions. Subsequently, numerous models combining Rough Set with MCDM methods have emerged [10]. For example, Rough Number Entropy combined with the Rough Number Technique for Order Preference by Similarity to an Ideal Solution (FTOPSIS) has been applied to the design of turbine steam engines in nuclear power plants [11], using the concept of rough numbers to address the uncertainty and subjectivity arising from differences in experts' subjective awareness and experience during the risk assessment process.

As the integration of FMEA with MCDM methods has increased, experts have started to recognize that risk factors or failure modes are not independent, but instead exhibit interdependencies [12]. For example, the 2011 Fukushima Daiichi nuclear disaster was not caused by a single equipment defect, but by the cascading failure of backup power and cooling systems following an external power outage, ultimately leading to core melt-down [13,14]. This case demonstrates that assuming failure modes are independent while ignoring their interdependencies can severely underestimate overall system risk and misguide decision-making. In real-world scenarios, the dependence between factors is more reflective of reality. Therefore, methods such as Decision Making and Trial Evaluation Laboratory (DEMATEL) have been used to consider the influence between risk factors [15] or the influence between failure modes [16]. Although there are various methods for combining FMEA with MCDM, the consideration of the interdependencies between failure

modes has rarely been proposed. In traditional FMEA calculation methods, the RPN for a component (calculated by the product of S, O, and D) may result in a low value. However, if the component fails, it could cause the entire system to collapse, which is often far from the estimated value, leading to inaccurate data. Therefore, this study incorporates the influence values obtained from DEMATEL into the RPN calculation. Traditional FMEA frameworks, such as those discussed by Bowles and Peláez [4], often focus exclusively on operational or technical risks (S, O, D) while failing to account for financial impacts and resource constraints, which can limit the practical applicability of risk assessments in industrial settings. To bridge this gap, recent advancements have begun to recognize the necessity of economic evaluation in risk analysis, moving from purely technical prioritization to budget-conscious risk management. Furthermore, considering the limited resources, economic costs are also an important factor. Following the research by Lo et al. [17], this improved FMEA model introduces a risk factor for expected cost (EC). Additionally, to better align with expert opinions, the concept of rough sets is introduced to address the uncertainty in information, reducing the loss of information and thus providing a more accurate evaluation.

This study first utilizes the Full Consistency Method (FUCOM) to obtain the weights of the risk factors. Compared with the AHP, which requires $n(n-1)/2$ pairwise comparisons, FUCOM only needs $n-1$ comparisons for a problem with n criteria, enhancing consistency in expert information [18]. Moreover, due to the uncertainty and subjectivity arising from differences in experts' subjective perceptions and experiences, this study adopts the Rough Dombi aggregator to aggregate expert preferences. Compared to the arithmetic mean, this method is more objective. By using rough numbers, it effectively integrates expert information into a set of interval values, enabling the acquisition of more precise expert insights [19]. In addition to incorporating the degree of influence between failure modes into the RPN calculation using DEMATEL, this study applies four different weighted calculation methods: weighted addition RPNS (WARPN), weighted exponent RPNS (WERPN), weighted u-function RPNS (WURPN), and weighted logarithm RPNS (WLRPN). The values are then integrated to compute a comprehensive RPN, which is used to identify critical failure modes. As a result, the obtained RPN values are more stable and reasonable.

Traditional FMEA relies on the RPN for risk assessment; however, the RPN approach is highly subjective and dependent on expert judgments. This subjectivity often results in equal weighting of S, O, and D, identical RPN values arising from different score combinations, and an inability to reflect the actual relationships among risk factors and their inherent uncertainty [20]. To address these limitations, this study first employs the FUCOM to derive optimal weighting coefficients, thereby improving the consistency of expert evaluations and reducing decision-making risk. Compared with the AHP and the Best-Worst Method (BWM), FUCOM requires fewer pairwise comparisons while achieving comparable weighting results [21]. However, FUCOM only determines the relative importance of evaluation criteria and does not account for the interdependencies and interactions among risk factors. Therefore, the DEMATEL method is incorporated to analyze the causal relationships and mutual influences among risk factors. DEMATEL enables the visualization of complex causal structures, facilitating a better understanding of interdependencies and influence mechanisms among factors [22]. Nevertheless, its decision-making process heavily depends on expert judgments, and uncertainties and inconsistencies arising from differences in experts' backgrounds, experiences, and preferences may affect the reliability of the analytical results [23]. To overcome this issue, the Rough Dombi approach is further integrated. Rough Set Theory defines uncertainty boundaries through lower and upper approximations without requiring predefined membership functions, thereby providing a

fully data-driven mechanism for handling uncertainty [24]. Meanwhile, the Dombi operator effectively aggregates expert opinions and processes ambiguous information in decision-making contexts [24]. The integration of these two approaches forms the Rough Dombi method, which not only reduces the influence of extreme values on the results but also effectively integrates expert judgments to mitigate uncertainty and inconsistency issues [25], thereby enhancing the robustness of weight estimation and ranking outcomes [24].

Although the aforementioned methods address expert evaluation consistency, causal relationships among risk factors, and uncertainty in expert judgments, their analytical outcomes remain limited to a single risk assessment scenario. Considering that real-world decision-making environments involve diverse risk scenarios and varying decision preferences, this study further incorporates four weighted RPN methods for risk evaluation. Specifically, ARPN improves the consistency of failure mode risk assessment [26]; ERPN reduces duplicate values in traditional RPN calculations by assigning differentiated weights to risk factors [27]; URPN considers the relative importance of each risk parameter, thereby enhancing the discriminatory power of risk rankings [28]; and LRPN further addresses the gap and dispersion problems associated with ERPN and URPN, although it cannot resolve duplicate values or the subjectivity inherent in defining risk factors [29]. Therefore, the four weighted RPN methods are integrated to capitalize on their respective strengths while compensating for their individual limitations. Finally, the Integrated Risk Priority Number (IRPN) mechanism is employed to synthesize the results obtained from different RPN methods, producing a more comprehensive, discriminative, and robust ranking of failure mode risks [30]. Despite these individual advancements, existing FMEA models still lack a unified framework that can simultaneously account for failure mode interdependencies, weight consistency management, and expert evaluation uncertainty. In summary, this study integrates FUCOM, DEMATEL, Rough Dombi, and multiple weighted RPN methods to establish a risk assessment framework that simultaneously incorporates consistency, causality, and uncertainty-handling capabilities, thereby enhancing the reliability of weight estimation and risk prioritization and generating results that more closely reflect real-world decision-making situations.

Therefore, the main contributions of this study are as follows:

1. Formulate a FUCOM-based weight determination framework for an expanded risk parameter set (S, O, D, EC), which reduces pairwise comparisons to $n - 1$ and guarantees zero consistency deviation, outperforming traditional AHP and BWM approaches.
2. Advance uncertainty management in FMEA by utilizing a Rough Dombi aggregator that, unlike traditional fuzzy or arithmetic mean methods, robustly converts subjective judgments into objective intervals to eliminate information loss without predefined assumptions.
3. Incorporate EC as a risk factor, making the model more aligned with practical needs of industry practitioners.
4. Quantify the influence among failure modes and incorporate it into the RPN calculation, thereby providing a more accurate reflection of real-world risk scenarios.

The remainder of this paper is organized as follows: Section 2 provides a brief overview of the concept of FMEA and related studies combining it with MCDM. Section 3 explains the proposed model. Section 4 presents the case study. Section 5 discusses the results, and Section 6 concludes the paper.

2. Literature Review

This section is divided into four subsections, the details are described as follows.

2.1. Application of FMEA and MCDM

Lo and Liou [4] proposed a new model for FMEA that combines MCDM and Grey Theory. They added EC to the original RPN to reflect actual resource constraints and used the BWM to consider different weights for S, O, D, and cost in risk prioritization. The study applied Grey Relational Analysis to calculate RPN, preserving information about failure modes through interval values. This study collected expert opinions using the arithmetic mean method, which, however, is prone to information loss or being influenced by extreme values. Ghoushchi et al. [31] proposed a fuzzy MCDM-based method to improve FMEA, addressing the drawbacks of previous methods. They used the concept of Spherical Fuzzy Sets (SFS) to resolve the fuzziness and uncertainty of the information. First, SFS was applied to weight evaluation using Step-Wise Weight Assessment Ratio Analysis (SWARA) to determine the weights of risk factors. Then, the SFS-based Combined Compromise Solution (CoCoSo) method was used to rank failure modes. The model's effectiveness and practicality were demonstrated through a case study of an Iranian wind farm.

Additionally, there are several related studies from different fields. For example, Karasan and Erdogan [32] proposed a hybrid FMEA method for textile sector failure modes by using FAHP and FTOPSIS to determine which failures pose a higher risk. To better align with the experts' true perspectives, the study used triangular fuzzy numbers to account for expert evaluations. Kuchekar et al. [33] introduced an integrated MCDM-FMEA model applied to assess the critical factors leading to industrial pressure relief valve failures. They measured the impact relationships using DEMATEL and estimated risk factor weights, employing Simple Additive Weighting (SAW), VIKOR, Grey Relational Analysis (GRA), and TOPSIS for ranking. The results were integrated to identify key factors, and an improvement plan was developed to address the issues. Klarić et al. [34] proposed a new hybrid MCDM-FMEA model combining FAHP, FTOPSIS, and the Fuzzy Weighted Influence Non-linear Gauge System (FWINGS) to assess the risk of potential failure modes (PFM) and applied it to optimize production processes in a furniture manufacturing company. The results indicated that this model could calculate RPN rankings while considering chain effects, enabling more accurate risk assessments.

More recently, the integration of advanced uncertainty characterization and failure dependency analysis has become a prominent trend in the FMEA-MCDM domain. For instance, Lo et al. [11] extended the conventional FMEA model to explore potential failure modes in complex energy systems, emphasizing the need for robust risk frameworks. Regarding uncertainty modeling, Dhalmahapatra et al. [18] developed an integrated rough FUCOM (RFUCOM) and rough TOPSIS approach for FMEA in the manufacturing industry, demonstrating that rough set theory provides superior mathematical stability in preserving expert opinions without requiring prior membership functions. Furthermore, to address the intertwined relationships among failure modes, Liou et al. [35] and Lo et al. [36] proposed dependency-based FMEA models using DEMATEL for product and medical equipment risk analysis, proving that failures in complex engineering systems rarely occur in isolation and that cascading effects must be incorporated into RPN calculations. These recent advancements underscore that while the academic community recognizes the critical nature of dependency and uncertainty, a holistic framework that simultaneously addresses both through optimal expert preference aggregation remains highly desirable.

Based on the aforementioned literature on integrating FMEA with MCDM, although numerous methods and various factors have already been considered, it can be observed that to better reflect real-world scenarios, it is not only important to account for the inter-

relationships among failure modes, but also essential to adopt more effective approaches for aggregating expert opinions. To synthesize, although previous studies have advanced FMEA through various MCDM techniques, they exhibit distinct limitations. For instance, models incorporating economic constraints [4] often rely on simple arithmetic means that risk information loss, whereas frameworks addressing uncertainty [31,32] or interdependencies [33,34] frequently overlook cost factors or fail to simultaneously manage both expert ambiguity and failure mode interactions. To bridge this gap, this study proposes an integrated framework that uniquely combines Rough Dombi aggregation for robust uncertainty management, EC for economic realism, and DEMATEL-based interactions within multiple weighted RPNs, providing a more comprehensive and practical risk assessment.

2.2. Uncertainty and Rough-Based Aggregation in Group Decision-Making

One of the key characteristics of the MCDM process is the presence of uncertainty in the available information. To more accurately represent the values of decision attributes under such conditions, various approaches have been developed—often based on interval values—including fuzzy theory, grey theory, Z-numbers, and others. Aside from fuzzy theory, RST has emerged as a highly practical method for handling uncertainty [10]. In existing literature, RST has been successfully applied across diverse fields. Originally proposed by Pawlak [9], RST is a mathematical tool capable of dealing with subjective and imprecise concepts. Since then, a growing number of models have integrated RST with MCDM methods. For example, Khan et al. [37] combined RST with TOPSIS to select suitable food distribution sites. This approach provided a framework to determine appropriate locations, ultimately supporting managerial decision-making and demonstrating the predictive power of RST. The results clearly indicated that the computational rules of RST can serve as a valuable tool for site identification. Chatterjee et al. [38] applied an MCDM method to Green Supply Chain Management (GSCM), using rough numbers integrated with DEMATEL and the ANP for group decision-making. A rough DEMATEL approach was used to identify the relationships between different dimensions, constructing an influential network diagram. Based on this, a rough ANP was implemented to derive the weights of each criterion. Then, a rough Multi Attributive Ideal-Real Comparative Analysis (MAIRCA) method was used to evaluate suppliers' environmental performance. The results of the study demonstrated that employing RST significantly improved the objectivity of supplier evaluation under subjective environmental conditions.

DOMBI is an effective approach for information aggregation and has been successfully applied across various domains. For instance, Matić et al. [39] employed it to evaluate and select sustainable suppliers in the construction industry. In their study, FUCOM was applied to determine the criterion weights, and the obtained values were transformed into rough numbers. Then, Rough Dombi was used for information aggregation. Finally, a Rough Complex Proportional Assessment (COPRAS) method was applied to select sustainable suppliers. Hesami [40] proposed a hybrid approach for evaluating and selecting strategic alliance suppliers in reverse logistics. The ANP method was used to calculate the relative weights of the criteria, while DOMBI and RST were adopted to address the fuzziness and uncertainty in the decision-making process. By expanding traditional data into interval values, this approach enhanced the objectivity and applicability of the results. TOPSIS was then employed for ranking. This method effectively tackled the complexities of supplier selection and responded well to the inherent uncertainties in reverse logistics. Altogether, while existing literature has successfully utilized Rough Set Theory and Dombi aggregation to manage expert uncertainty, these applications are predominantly limited to conventional supplier selection or site identification. A distinct research gap remains in extending the Rough Dombi framework to FMEA, particularly for aggregating expert

opinions across multiple weighted RPNs. To provide an empirical foundation, the methodological superiority of our approach is firmly supported by the comprehensive comparative analysis conducted by Shao et al. [24]. Their study demonstrated that while Fuzzy BWM effectively handles vagueness and Rough BWM improves the processing of subjectivity, they both remain constrained in adapting to highly divergent expert insights. Notably, their comparative analysis explicitly proved that the Rough Dombi framework is the best-performing method among all alternatives, as it successfully balances optimistic and pessimistic expert judgments without compromising mathematical flexibility. To illustrate this proven advantage intuitively within an FMEA context, when multiple experts evaluate a specific failure mode, their risk ratings often vary widely due to differing professional backgrounds or personal optimism. While conventional fuzzy or rough methods may oversimplify or constrain these varying insights, the Rough Dombi framework captures the exact boundary intervals of individual judgments. By integrating rough set theory with the flexible Dombi operator, it seamlessly incorporates diverse expert insights into a robust interval value, validating why it stands out as the most reliable and effective approach for risk prioritization. To bridge this gap, this study applies the Rough Dombi aggregator to integrate expert judgments into objective interval values without requiring any assumption set conditions, thereby mitigating information loss and enhancing the robustness of the FMEA risk prioritization.

2.3. Criteria Weight Determination and Consistency Management in FMEA

MCDM problems involve evaluating a set of alternatives based on predefined criteria, with the goal of selecting the most acceptable option. Among these, the weights assigned to criteria play a crucial role throughout the evaluation process. Generally, weights can be categorized as either subjective or objective. Since FMEA primarily relies on the subjective opinions of experts, inconsistencies may arise in expert evaluations—especially when large volumes of data lead to unstable judgments across assessments. Pamučar et al. [21] first proposed the FUCOM, which incorporates two constraint sets: the first ensures the ranking of importance among criteria, and the second is based on mathematical transitivity conditions. The study validated FUCOM through several numerical cases and compared it with other subjective weighting models such as the BWM and AHP. The results demonstrated that, when balancing consistency and the number of comparisons required, FUCOM necessitates fewer pairwise comparisons than both BWM and AHP, while yielding comparable results. Therefore, FUCOM is more practical and user-friendly in real-world applications and better suited for achieving consistent evaluations.

The effectiveness and consistency of FUCOM have been validated across various fields. Feizi et al. [41], in their study on mineral potential in newly developed lands, pointed out that FUCOM, as a novel comparison-based method, can reduce the number of required comparisons. It significantly improves the consistency ratio, thereby making the results more reliable. In the human resources evaluation study of a transportation company conducted by Stević and Brković [42], FUCOM was applied to determine the importance of each criterion's weight, and the method achieved zero deviation from full consistency. Pamucar et al. [43] applied FUCOM to Transportation Demand Management (TDM) measures and adopted the fuzzy full consistency method–Dombi–Bonferroni model. The study also compared the results with four well-known MCDM methods to demonstrate its effectiveness and consistency. In summary, while the reviewed literature demonstrates that FUCOM can significantly reduce pairwise comparisons and achieve near-zero deviation in consistency, these validations have been largely confined to traditional MCDM, resource exploration, or transportation management. A critical research gap remains in leveraging FUCOM's efficiency within an FMEA framework to manage the consistency of

expert evaluations regarding risk factors—especially when extending S, O, and D to include economic constraints like EC. To bridge this gap, this study applies FUCOM to derive optimal weighting coefficients for the expanded FMEA risk parameters, minimizing the cognitive burden on experts while strictly ensuring evaluation consistency and reducing decision-making risk.

2.4. Modeling Interdependencies and Causal Relationships Among Failure Modes

DEMATEL was developed in 1972 by the Battelle Memorial Institute in Geneva [44]. This method is used to address complex problem groups [45]. One of the main advantages of DEMATEL lies in its ability to distinguish between cause (dispatchers) and effect (receivers) groups within a set of problems [46]. Assuming interrelationships among the criteria, DEMATEL evaluates the degree of influence among them. Factors that exert a greater influence on others are referred to as dispatchers, whereas those more influenced by others are considered receivers [47]. DEMATEL is particularly useful in visualizing complex causal structures and constructing and analyzing structural models involving interrelated factors. The use of causal diagrams makes it easier to understand interdependencies among factors and helps to investigate and resolve complex, intertwined issues [22].

From an engineering perspective, providing precise interpretations for these cause and effect groups is essential for diagnosing system vulnerabilities. In complex engineering systems, factors classified into the cause group (dispatchers) typically represent critical root-cause failure modes or primary driving faults. These failure modes possess high propagating power, meaning their occurrence is highly likely to trigger secondary issues or cross-subsystem damage across the network. Conversely, factors belonging to the effect group (receivers) represent derivative or consequential failure modes. These failures are highly susceptible to cascading effects and are frequently the end-results of interconnected faults within the system. Distinguishing between these two groups allows design engineers to trace fault propagation paths, isolate source vulnerabilities, and implement proactive technical interventions at the root level rather than merely treating the derivative symptoms.

Due to its strengths and practical applicability, DEMATEL has been widely used over the past decade in resolving complex system problems across various domains, including computer science and artificial intelligence, environmental science, operations research, management science, and business management [44]. Additionally, DEMATEL can be integrated with various fuzzy theories to support better decision-making under different circumstances, as real-world systems often involve imprecise and uncertain information. For instance, Boral and Chakraborty [16] integrated DEMATEL with Interval Type-2 Fuzzy Sets (IT2FSs) to rank human error-related risks in CNC operations based on four risk factors S, D, O, and EC. Jamali et al. [48] applied DEMATEL and ANP to determine the interrelationships among criteria, and the study utilized GIS to provide visual outputs, aiding urban planners in understanding the causal relationships among dimensions and criteria. Jalhoom and Mahjoob [49] developed a model, which integrates fuzzy logic with grey systems and DEMATEL to assess structural risks. This model simultaneously analyzes uncertainty and fuzziness, helping users examine different project stages, identify uncertainties, and evaluate risks associated with specific stakeholders. Ultimately, while the reviewed literature demonstrates DEMATEL's strong capability in visualizing causal relationships and capturing interdependencies, existing applications typically use it to analyze criteria interactions or establish structural models. A notable research gap remains in directly incorporating DEMATEL-derived influence values between failure modes into multiple weighted RPN calculations to correct traditional risk underestimations. To address this gap, this study integrates DEMATEL into the RPN formulation, successfully capturing

the cascading effects of interconnected failure modes to ensure a more accurate and stable risk prioritization.

3. Methodology

This section introduces the definition and formulas of the hybrid MCDM methods used and provides a detailed description of the research steps. The research model combines Rough Dombi-DEMATEL, Rough Dombi-FUCOM, and four weighted RPN value methods, which are applied to FMEA analysis for key failure modes. The definitions of the relevant symbols can be found in the attached Appendix A Table A1.

3.1. Execution Procedure of the Improved FMEA Model

This section introduces the definition and formulas of the improved FMEA method used and provides a detailed explanation of the research steps, as shown in Figure 1. In this study, expert opinions are consolidated using Rough Set Theory, followed by an application of the improved FMEA method to assess the system's key failure modes. Through discussions with the engineering design team, the critical components of the system are identified, and their potential failure modes are analyzed. With advancements in technology, the complexity of system design has increased, and manufacturing costs have risen year by year. Therefore, expected costs are included as a risk factor to make the analysis results more aligned with actual conditions and practical factors. Given the consideration of the influence between failure modes, this study uses DEMATEL and FUCOM to compute the degree of influence and the weights of risk factors, and through discussions with the engineering design team and recording the evaluation values of failure modes under each risk factor, the analysis of traditional FMEA is improved. For the RPN value calculation formula, since the traditional multiplication of values is controversial, this study uses four different methods to calculate the weighted RPN values. Finally, the integrated final function values are prioritized through a rigorous process to identify the failure modes with the highest risks, which need to be prioritized for improvement.

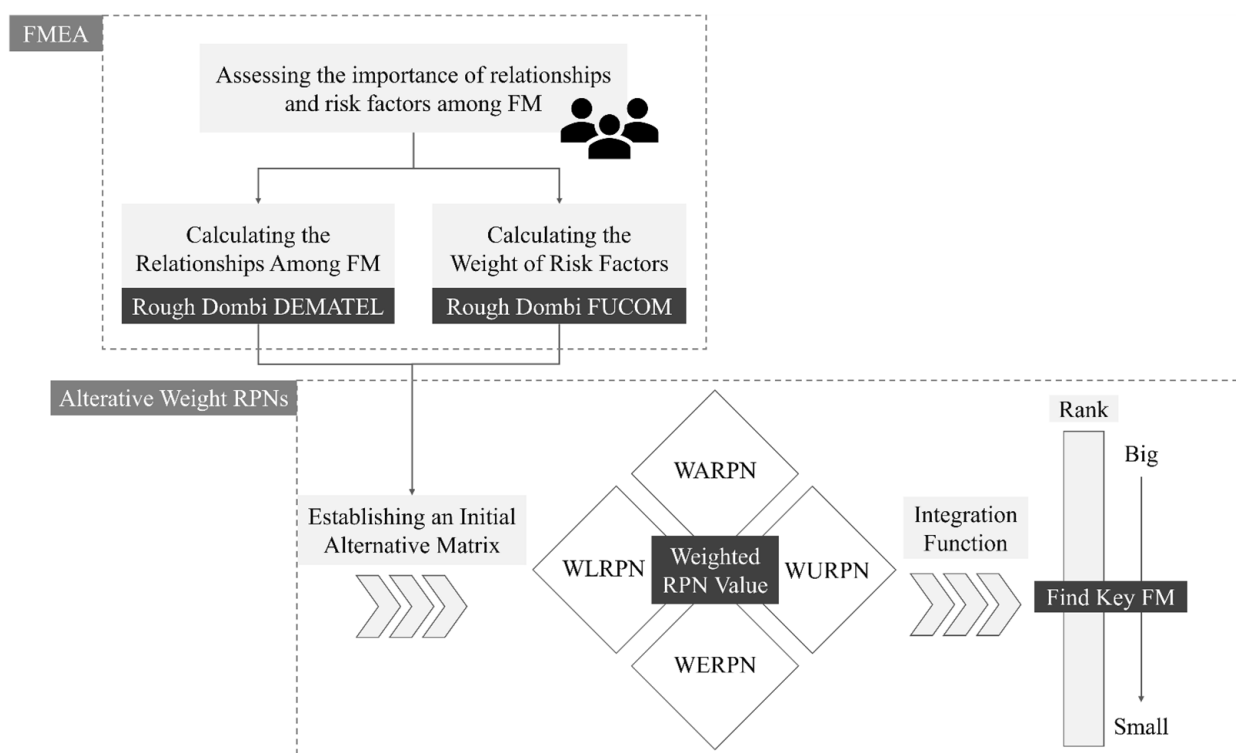


Figure 1. Research methodology flowchart.

3.2. Assessment of Critical Risk Factors of Failure Modes

In traditional FMEA methods, the primary factors considered are S, O, and D. Many scholars argue that these factors alone are insufficient for providing a comprehensive risk assessment [35,36]. To address this limitation, this study incorporates EC to better reflect real-world conditions. This approach transforms the semantic judgments of each factor under various failure modes into a 10-level scoring system, as shown in Table 1. EC is used as a semi-quantitative ordinal measure to reflect the potential economic impact of each failure mode. Each level on the 10-point scale corresponds to an increasing range of costs, from minimal expenses (level 1) to extremely high costs, such as total system replacement (level 10). A detailed explanation of each factor and its corresponding definition is presented in the next sections.

Table 1. Failure modes and definitions of powertrain systems.

Assessment	S	O	D	EC
10	Danger—No Warning	Extremely High	Almost Impossible to Detect	Extremely High Costs
9	Danger—Warning	Very High	Very Small Chance	Very Expensive
8	Extremely Serious	Repeated Failure	Small Chance	Expensive
7	Highly Serious	High	Very Low	Very High
6	Moderate to High Severity	Medium to High	Low	High
5	Moderately Severe	Middle	Moderate	Middle to High
4	Low to Medium Impact	Medium to Low	Middle to High	Middle
3	Low Severity	Low	High	Medium Low
2	Very Low Impact	Very Low	Very High	Low
1	No Impact	Close to 0	Almost Certainly	Minimal Expenses

- Severity (S): Refers to the extent of system and functional damage caused by a failure mode. Higher scores indicate more severe consequences of the failure mode;
- Occurrence (O): Refers to the likelihood or frequency of a failure mode. This can be assessed based on historical failures or similar systems. Higher scores indicate higher probability of occurrence and suggest that the item should be prioritized for improvement. Common indicators include Mean Time Between Failures (MTBF) or failure rates;
- Detection (D): Refers to the likelihood of detecting a failure mode and is closely related to its risk. A high detection probability indicates that failures can be identified early through visual inspections, regular checks, or auxiliary tools, whereas a low detection probability implies that failures are less likely to be noticed, increasing risk.

This study incorporates the EC as a risk factor, aiming to more realistically reflect real-world situations. It explores the expected costs incurred in the event of a failure mode, including repair materials, labor costs, and other expenses.

3.3. Rough Dombi Aggregator

This paper introduces a mathematical formula for Rough Dombi Weighted Geometric Averaging (RDWGA) used to aggregate rough expert preferences. RDWGA, proposed by Sremac et al. [19], was developed to aggregate rough numbers and determine the initial rough matrix for Multi-Criteria Decision-Making (MCDM), aiming to achieve more precise consensus in group decision-making. Since experts' consistency when evaluating data in group decisions is uncertain, it is preferred to evaluate using interval numbers rather than providing exact values or simply using averages. Here, we present the basic concepts and definitions related to RDWGA.

Definition 1. Assume that C_{ij} is the global set in the objective, where there are n categories within $C_{ij}^e \{e_1, e_2, \dots, e_n\}$. The lower approximation set of C_{ij}^e consists of all values in the global set that are less than or equal to X_{ij}^e .

$$LA(C_{ij}^e) = \cup \{c'_{ij} \in c_{ij} | c'_{ij} \leq c_{ij}^e\} \quad (1)$$

The upper approximation set of X_{ij}^e consists of all values within the global set that are greater than or equal to X_{ij}^e .

$$UA(C_{ij}^e) = \cup \{c''_{ij} \in c_{ij} | c''_{ij} \geq c_{ij}^e\} \quad (2)$$

Definition 2. The value C_{ij}^e is represented by a Rough Number (RN), with the lower approximation set denoted as $\underline{Lim}$ and the upper approximation set denoted as $\overline{Lim}$.

The lower approximation set of C_{ij}^e is represented as

$$\underline{LIM} = \left(\sum_e c'_{ij} / n_L | c'_{ij} \in LA(c_{ij}^e) \right) \quad (3)$$

The upper approximation set of C_{ij}^e is represented as

$$\overline{LIM} = \left(\sum_e c''_{ij} / n_U | c''_{ij} \in UA(c_{ij}^e) \right) \quad (4)$$

Definition 3. The aggregation value of RN is

$$RNDWGA\{RN_{(\varphi_1)}, RN_{(\varphi_2)}, \dots, RN_{(\varphi_n)}\} = \left[\frac{\sum_{j=1}^n \underline{Lim}_{(\varphi_j)}}{1 + \left\{ \sum_{j=1}^n w_j \left(\frac{1 - f(\underline{Lim}_{(\varphi_j)})}{f(\underline{Lim}_{(\varphi_j)})} \right)^\rho \right\}^{\frac{1}{\rho}}}, \frac{\sum_{j=1}^n \overline{Lim}_{(\varphi_j)}}{1 + \left\{ \sum_{j=1}^n w_j \left(\frac{1 - f(\overline{Lim}_{(\varphi_j)})}{f(\overline{Lim}_{(\varphi_j)})} \right)^\rho \right\}^{\frac{1}{\rho}}} \right] \quad (5)$$

$$f(RN_{(\varphi_i)}) = \begin{cases} f(\underline{Lim}_{(\varphi_i)}) = \frac{\underline{Lim}_{(\varphi_i)}}{\sum_{j=1}^n \underline{Lim}_{(\varphi_j)}} \\ f(\overline{Lim}_{(\varphi_i)}) = \frac{\overline{Lim}_{(\varphi_i)}}{\sum_{j=1}^n \overline{Lim}_{(\varphi_j)}} \end{cases} \quad (6)$$

where $\rho > 0$ [19].

To interpret the operational mechanism of RDWGA more intuitively, it can be conceptualized as a “data filter with flexible fault-tolerance capabilities.” In traditional expert opinion aggregation, extreme or conflicting scores are often simply averaged out, which inevitably eradicates valuable underlying information. In contrast, RDWGA first utilizes “rough sets” to establish upper and lower approximations around the data, acting like an airbag to absorb the cognitive ambiguity stemming from experts’ diverse professional backgrounds. Subsequently, the “Dombi operator,” through its flexible operational parameters, smoothly aggregates scattered opinions into a highly consensual value while preserving the potential risks highlighted by extreme judgments. This dual mechanism ensures that in

highly uncertain, real-world risk assessments, the model neither neglects critical warnings from minority experts nor suffers from decision distortion caused by fragmented opinions.

3.4. FUCOM

Full Consistency Method (FUCOM) can accurately obtain the weight coefficients of all criteria by comparing them with the previous level, while ensuring the consistency of the comparisons. In real-life situations, pairwise comparison values are not based on precise measurements, but rather on subjective estimates. For instance, if it is determined that A is much more important than B, B is more important than C, and C is more important than A, inconsistencies arise when solving the problem, and the reliability of the results decreases. This issue is particularly evident when there are many criteria involved in pairwise comparisons. FUCOM minimizes the possibility of errors in pairwise comparisons by requiring fewer comparisons and defining the method based on mathematical transitivity conditions. The following outlines the steps involved in FUCOM.

Step 1. Define the evaluation criteria and rank them according to their importance, from the most important to the least important, as shown in Equation (7).

$$C_{j(1)} > C_{j(2)} > \dots > C_{j(k)} \quad (7)$$

Here, k represents the level of the observed criterion. If there are two or more criteria that are judged to be equally significant, an equality sign rather than a ">" sign is placed between these criteria in Equation (7).

Step 2. Criteria sorted from largest to smallest. $(\Phi) = (\varphi_{k/(k+1)}, k=1, 2, \dots, n)$, $C_{j(k)}$ is compared with the comparison priority value of $C_{j(k+1)}$ as shown in Equation (8).

$$\Phi = (\varphi_{1/2}, \varphi_{2/3}, \dots, \varphi_{k/(k+1)}) \quad (8)$$

Step 3. Calculate the weight coefficients of the evaluation criteria. The weight coefficients must satisfy two conditions as shown in Equations (9) and (10).

(1) The ratio of weight coefficients $\frac{w_k}{w_{k+1}}$ is equal to the comparison priority value in the standard $(\varphi_{k/(k+1)})$.

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)} \quad (9)$$

(2) The weight coefficients must satisfy the mathematical transitivity condition.

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \quad (10)$$

Once Equations (9) and (10) are satisfied, complete consistency can be achieved. Based on the formula, the final weight values for the evaluation criteria can be determined using the model shown in Equation (11).

$$\begin{aligned} & \min \chi \\ & \text{s. t.} \\ & \left| \frac{w_k}{w_{k+1}} - \varphi_{\frac{k}{k+1}} \right| \leq \chi, \forall_j \\ & \frac{w_k}{w_{k+2}} = \varphi_{\frac{k}{k+1}} \otimes \varphi_{\frac{k+1}{k+2}} \leq \chi, \forall_j \\ & \sum_{j=1}^n w_j = 1, \forall_j \\ & w_j \geq 0, \forall_j \end{aligned} \quad (11)$$

W_j = Expert Weight.

3.5. DEMATEL

The Decision Making and Trial Evaluation Laboratory (DEMATEL) originated from a research institution in Geneva, and was developed between 1972 and 1976 as part of a scientific and humanitarian project. The method was initially used to solve complex, entangled problems such as race, environmental issues, and energy. DEMATEL is a comprehensive method used to construct and analyze structural models of causal relationships involving complex factors, visualizing the intricate cause-and-effect structures [15]. Below are the steps of the DEMATEL method.

Step 1. Identify the initial direct influence relationship matrix A . Experts use their knowledge and experience to determine the direct influence degree a_{ij} between factor i and factor j using a 5-point scale. The evaluation range is from 0 to 4, where “0, no influence,” “1, very small influence,” “2, small influence,” “3, large influence,” and “4, very large influence.” The opinions of the experts are integrated into the average direct relationship matrix A by calculating the arithmetic mean of individual questionnaires, as shown in Equation (12).

$$A = \begin{bmatrix} 0 & a_{12} & \dots & a_{1n} \\ a_{21} & 0 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & 0 \end{bmatrix}, i, j = 1, 2, \dots, n \quad (12)$$

Step 2. Compute the normalized initial direct relationship matrix X as shown in Equations (13) and (14).

$$X = k \times A \quad (13)$$

$$k = \text{Min} \left[\frac{1}{\max \sum_{j=1}^n |a_{ij}|}, \frac{1}{\max \sum_{i=1}^n |a_{ij}|} \right] \quad (14)$$

Step 3. Calculate the total influence relationship matrix T as shown in Equation (15).

$$T = [t_{ij}]_{n \times n}, i, j = 1, 2, \dots, n \quad (15)$$

$$T^h = X + X^2 + \dots + X^h = X(I - X)^{-1}$$

where I is the identity matrix, as shown in Equation (16).

$$(I - X)(I - X)^{-1} = I \quad (16)$$

Step 4. Compute the row and column sums of matrix T as shown in Equations (17) and (18).

$$R = (r_1, r_2, \dots, r_n)^T = (r_i)_{n \times 1} = \left[\sum_{j=1}^n t_{ij} \right]_{n \times 1}, j = 1, 2, \dots, n \quad (17)$$

$$C = (c_1, c_2, \dots, c_n)^T = (c_j)_{1 \times n} = \left[\sum_{i=1}^n t_{ij} \right]_{1 \times n}, i = 1, 2, \dots, n \quad (18)$$

where $R_i + C_i$ represents the total degree of influence and being influenced by this factor, which reflects the strength of the association of this factor within the problem group. $R_i - C_i$ indicates the intensity of this factor's influence or being influenced. If $R_i - C_i$ is positive, factor i influences other factors (thus called a causal factor). If $R_i - C_i$ is negative, other factors influence factor i (thus called an influenced factor). After obtaining the influence strength of the failure modes, the correlation degree ($R_i + C_i$) is integrated into the total

RPN value through multiplication and addition, as shown in Equations (19) and (20), to obtain the risk value after considering the influence of failure mode relationships.

3.6. Four Weighting Methods

Using four different weighted aggregation methods: WARP, WERP, WURP, and WLRP, the integrated RPN value is then calculated. Finally, the critical failure modes are identified by ranking the final function values from highest to lowest, with the detailed formulas given in Equations (19)–(27). Subsequently, the correlation coefficients from DEMATEL are incorporated to find the critical failure modes that include the DEMATEL values, as shown in Equations (28) and (29).

$$WARP_i = \sum_{j=1}^n w_j^r \times r_{ij}, i = 1, 2, \dots, m \quad (19)$$

$$WERP_i = \sum_{j=1}^n x^{w_j^r \times r_{ij}}, i = 1, 2, \dots, m \quad (20)$$

$$WLRP_i = \sum_{j=1}^n w_j^r \log_{10}(r_{ij}), i = 1, 2, \dots, m \quad (21)$$

$$WURP_i = \sum_{j=1}^n w_j^r \times z^{r_{ij}}, i = 1, 2, \dots, m \quad (22)$$

$$r_k = \frac{WARP_{ij}}{\sum_{i=1}^n WARP_{ij}} \quad (23)$$

$$r_k = \frac{WERP_{ij}}{\sum_{i=1}^n WERP_{ij}} \quad (24)$$

$$r_k = \frac{WLRP_{ij}}{\sum_{i=1}^n WLRP_{ij}} \quad (25)$$

$$r_k = \frac{WURP_{ij}}{\sum_{i=1}^n WURP_{ij}} \quad (26)$$

$$IRPN = \sum_{i=1}^n r_k \quad (27)$$

$$DIRPN_1 = (R_i + C_i) \times IRPN \quad (28)$$

$$DIRPN_2 = (R_i + C_i) \times 0.5 + IRPN \times 0.5 \quad (29)$$

4. Empirical Analysis

An empirical analysis is conducted through the actual vehicle powertrain system development to demonstrate how the proposed FMEA model can be used to evaluate the critical failure modes of the system and prove its effectiveness and robustness.

4.1. Data Collection

4.1.1. System Description

Based on the system Bill of Materials (BOM), this study first identified all potential failure modes using system structural analysis, maintenance history, and relevant literature.

The initial screening process focused on determining the system's key components and routine maintenance items, resulting in nine primary targets, as illustrated in Figure 2.

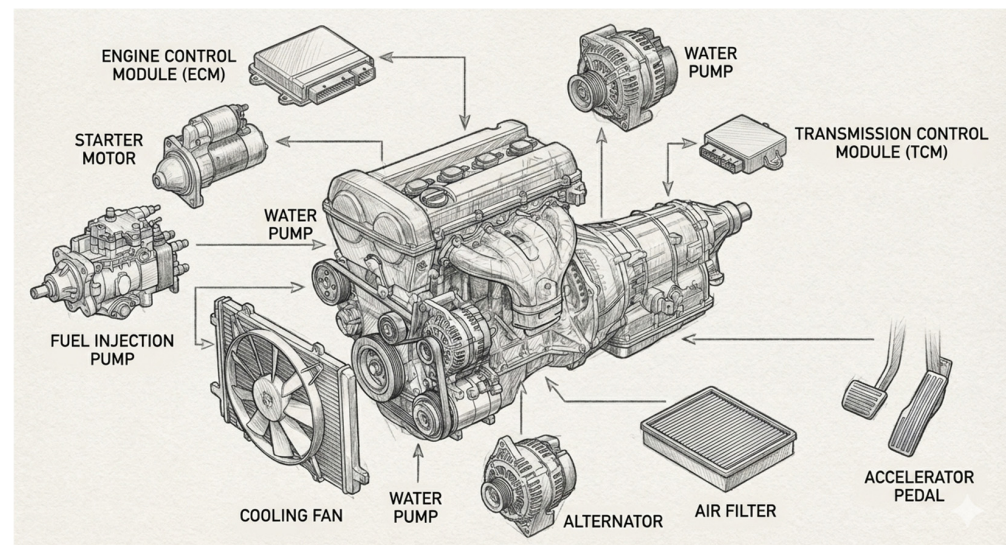


Figure 2. Critical Assembly of the Powertrain System.

A review meeting was subsequently conducted with experts experienced in vehicle design and maintenance, who evaluated the full list using engineering knowledge, risk awareness, and practical service considerations. Through this expert consensus process, the nine failure modes most likely to impact system operation and safety were retained, as summarized in Table 2, and used as the basis for the subsequent risk assessment.

Table 2. Failure modes and definitions of power systems.

FM	Failure Mode	Definition
FM ₁	Engine control module circuit burnt	The transmission control signal cannot be transmitted and cannot operate normally.
FM ₂	Starter motor coil burned out due to short circuit	The motor cannot run and the vehicle cannot start.
FM ₃	Injection pump ruptured	The normal fuel injection function is lost and the engine cannot operate.
FM ₄	Water pump deformed or broken	The cooling water circulation power cannot be provided, causing the cooling system to be unable to operate, and the engine's heat dissipation capacity to decrease, which may result in the vehicle being unable to drive.
FM ₅	Transmission control module circuit burnt	The transmission control signal cannot be transmitted and cannot operate normally.
FM ₆	The cooling fan body is deformed or cracked	The cooling water circulation power cannot be provided, causing the cooling system to be unable to operate, and the engine's heat dissipation capacity to decrease, which may result in the vehicle being unable to drive.
FM ₇	Generator coil burned out due to short circuit	Unable to generate electricity and unable to charge the battery.
FM ₈	Air filter clogged	The air flow that can pass through is reduced, and the engine horsepower is reduced.
FM ₉	Broken accelerator pedal	The engine throttle opening cannot be adjusted, causing engine fuel supply errors.

Although this study demonstrates only nine failure modes, the proposed method can easily be extended to systems with dozens or even hundreds of failure modes. The dependency matrix can be established through expert comparisons or data-driven analysis, and the subsequent prioritization relies on efficient matrix operations. For highly complex systems, hierarchical modeling or subsystem clustering can further simplify computation. Therefore, the framework remains practical for large-scale FMEA applications.

4.1.2. Expert Support System

The expert panel consists of five engineers from the vehicle design team, including senior design engineers and systems engineers. Their expertise spans vehicle powertrain design, transmission systems, structural analysis, safety, and overall system integration. Each expert possesses 6 to 12 years of practical experience in their respective fields. Throughout the FMEA process, the experts contributed to identifying potential failure modes, evaluating S, O, D, and EC, analyzing system BOMs, screening and prioritizing failure modes, and validating the dependency matrices. Their combined knowledge ensures that the assessment reflects both theoretical rigor and practical engineering considerations. Expert background information is shown in Appendix A Table A2.

4.2. Determine the Risk Factor Weights Using FUCOM

This study uses the FUCOM to calculate the weights of failure modes. Due to potential differences in the knowledge or experience of the research team regarding various evaluation items, this study combines the Rough Dombi Aggregator to address the uncertainty and inconsistency of the information. The detailed calculation steps are as follows:

Step 1. Establish the evaluation matrix. Under each criterion, the engineers rank the risk factors and compare the ranked risk factors, using Equations (7) and (8), to obtain the comparison levels and priorities, as shown in Table 3.

Table 3. FMEA Evaluation matrix.

DM			1				
Risk factors	S	=	EC	>	D	>	O
Compare levels	1		1		2		3
Compare priority value			$\varphi_{S/E} = 1/1 = 1.00$		$\varphi_{E/D} = 2/1 = 2.00$		$\varphi_{D/O} = 3/2 = 1.50$
DM			2				
Risk factors	D	=	S	>	O	>	EC
Compare levels	1		1		2		4
Compare priority value			$\varphi_{D/S} = 1/1 = 1.00$		$\varphi_{S/O} = 2/1 = 2.00$		$\varphi_{O/E} = 4/2 = 2.00$
DM			3				
Risk factors	S	=	D	>	EC	>	O
Compare levels	1		1		4		5
Compare priority value			$\varphi_{S/D} = 1/1 = 1.00$		$\varphi_{D/E} = 4/1 = 4.00$		$\varphi_{E/O} = 5/4 = 1.25$
DM			4				
Risk factors	EC	=	D	>	O	>	S
Compare levels	1		1		3		4
Compare priority value			$\varphi_{E/D} = 1/1 = 1.00$		$\varphi_{D/O} = 3/1 = 3.00$		$\varphi_{O/S} = 4/3 = 1.33$
DM			5				
Risk factors	O	=	EC	>	S	>	D
Compare levels	1		1		4		5
Compare priority value			$\varphi_{O/E} = 1/1 = 1.00$		$\varphi_{E/S} = 4/1 = 1.00$		$\varphi_{S/D} = 5/4 = 1.25$

Step 2. Calculate the weight coefficients of the evaluation criteria ($w_1, w_2, \dots, w_n$) through Equations (9) and (10).

$$\begin{aligned} & \text{DM}_1 \\ & \min \chi \\ & \text{s. t.} \left\{ \begin{array}{l} |\frac{w_S}{w_E} - 1| = \chi, |\frac{w_E}{w_O} - 2| = \chi, |\frac{w_O}{w_D} - 1.5| = \chi \\ |\frac{w_S}{w_D} - 2| = \chi, |\frac{w_E}{w_O} - 3| = \chi \\ \sum_{j=1}^4 w_j = 1, w_j \geq 0, \forall_j \end{array} \right. \end{aligned}$$

$$\begin{aligned} & \text{DM}_2 \\ & \min \chi \\ & \text{s. t.} \left\{ \begin{array}{l} |\frac{w_D}{w_S} - 1| = \chi, |\frac{w_S}{w_O} - 2| = \chi, |\frac{w_O}{w_E} - 2| = \chi \\ |\frac{w_D}{w_O} - 2| = \chi, |\frac{w_S}{w_E} - 4| = \chi \\ \sum_{j=1}^4 w_j = 1, w_j \geq 0, \forall_j \end{array} \right. \end{aligned}$$

$$\begin{aligned} & \text{DM}_3 \\ & \min \chi \\ & \text{s. t.} \left\{ \begin{array}{l} |\frac{w_S}{w_D} - 1| = \chi, |\frac{w_D}{w_E} - 4| = \chi, |\frac{w_E}{w_O} - 1.25| = \chi \\ |\frac{w_S}{w_E} - 4| = \chi, |\frac{w_D}{w_O} - 5| = \chi \\ \sum_{j=1}^4 w_j = 1, w_j \geq 0, \forall_j \end{array} \right. \end{aligned}$$

$$\begin{aligned} & \text{DM}_4 \\ & \min \chi \\ & \text{s. t.} \left\{ \begin{array}{l} |\frac{w_E}{w_D} - 1| = \chi, |\frac{w_D}{w_O} - 3| = \chi, |\frac{w_O}{w_S} - 1.33| = \chi \\ |\frac{w_E}{w_O} - 3| = \chi, |\frac{w_D}{w_S} - 4| = \chi \\ \sum_{j=1}^4 w_j = 1, w_j \geq 0, \forall_j \end{array} \right. \end{aligned}$$

$$\begin{aligned} & \text{DM}_5 \\ & \min \chi \\ & \text{s. t.} \left\{ \begin{array}{l} |\frac{w_O}{w_E} - 1| = \chi, |\frac{w_E}{w_S} - 4| = \chi, |\frac{w_S}{w_D} - 1.25| = \chi \\ |\frac{w_O}{w_S} - 4| = \chi, |\frac{w_E}{w_D} - 5| = \chi \\ \sum_{j=1}^4 w_j = 1, w_j \geq 0, \forall_j \end{array} \right. \end{aligned}$$

The weights of S, O, D, and EC for each expert were obtained by solving the proposed model. Specifically, the data in Table 3 were used in Step 2 with the applied constraints to compute the individual weights of S, O, D, and EC for each expert. The final weights were then aggregated using the Rough Dombi aggregator, as shown in Table 4.

Table 4. Weight value.

	DM ₁	DM ₂	DM ₃	DM ₄	DM ₅	Final Weight
S	0.353	0.364	0.408	0.097	0.102	0.264
O	0.118	0.182	0.082	0.129	0.408	0.195
D	0.177	0.364	0.408	0.387	0.082	0.277
EC	0.353	0.091	0.102	0.387	0.408	0.265

Note: The final weights are obtained by normalizing the RDWGA aggregated values [0.243, 0.179, 0.255, 0.244] so that their sum equals 1.000.

4.3. Determine the Dependencies of Failure Modes Using DEMATEL

DEMATEL is a method used to explore the mutual influences between failure modes. This method identifies the relationships and strengths of the influences between modes, and then helps decision-makers identify key causes in complex evaluation systems, while visualizing the complex causal relationships. The following steps outline the DEMATEL process.

Step 1: By consulting experts, evaluate the mutual influence between pairs of failure modes. The scale ranges from 0 to 4, where “0” means no impact, “1”, very small impact, “2”, small impact, “3”, large impact, and “4”, very large impact. This results in an initial direct impact relation matrix. An example from Expert 1 is shown in Table 5.

Table 5. Initial direct influence relationship matrix of DM₁.

	FM ₁	FM ₂	FM ₃	FM ₄	FM ₅	FM ₆	FM ₇	FM ₈	FM ₉
FM ₁	0	1	2	0	0	0	1	0	1
FM ₂	1	0	2	0	1	1	1	1	1
FM ₃	1	0	0	0	0	0	0	4	0
FM ₄	2	0	0	0	0	0	2	0	0
FM ₅	1	1	0	0	0	1	1	1	1
FM ₆	2	1	1	2	1	0	0	0	0
FM ₇	0	1	0	0	1	0	0	0	0
FM ₈	1	0	2	0	0	0	1	0	0
FM ₉	0	0	0	2	1	0	0	0	0

Step 2: The total influence matrix is calculated using Equations (14)–(17), with Expert 1 as an example. This is shown in Table 6.

Table 6. Total influence matrix of DM₁.

	FM ₁	FM ₂	FM ₃	FM ₄	FM ₅	FM ₆	FM ₇	FM ₈	FM ₉
FM ₁	0.002	0.024	0.025	0.001	0.002	0.001	0.024	0.002	0.024
FM ₂	0.027	0.002	0.049	0.002	0.025	0.024	0.025	0.026	0.025
FM ₃	0.001	0.000	0.002	0.000	0.000	0.000	0.001	0.047	0.000
FM ₄	0.050	0.002	0.001	0.000	0.001	0.000	0.048	0.000	0.001
FM ₅	0.027	0.025	0.003	0.002	0.002	0.024	0.025	0.024	0.025
FM ₆	0.050	0.025	0.026	0.047	0.024	0.001	0.005	0.002	0.002
FM ₇	0.071	0.026	0.003	0.000	0.024	0.001	0.003	0.001	0.003
FM ₈	0.025	0.001	0.047	0.000	0.001	0.000	0.024	0.002	0.001
FM ₉	0.003	0.001	0.000	0.047	0.023	0.001	0.003	0.001	0.001

Step 3: The total impact matrix from five experts is shown in Table 7. The experts’ opinions are then integrated using Rough Dombi Aggregator as shown in Equations (1)–(6), resulting in the expert-integrated total impact relation matrix, shown in Table 8. Due to page limitations, the complete raw dataset is accessible in the supplementary file.

Table 7. Total influence relationship matrix of five DM.

	DM ₁	DM ₂	DM ₃	DM ₄	DM ₅
FM ₁ -FM ₁	0.002	0.022	0.020	0.010	0.010
FM ₁ -FM ₂	0.024	0.024	0.020	0.009	0.019
FM ₁ -FM ₃	0.025	0.000	0.020	0.001	0.010
FM ₁ -FM ₄	0.001	0.000	0.019	0.001	0.001
FM ₁ -FM ₅	0.002	0.001	0.000	0.001	0.001
...					

Table 7. Cont.

	DM ₁	DM ₂	DM ₃	DM ₄	DM ₅
FM ₉ -FM ₅	0.023	0.024	0.040	0.019	0.011
FM ₉ -FM ₆	0.001	0.001	0.020	0.020	0.020
FM ₉ -FM ₇	0.003	0.004	0.039	0.028	0.010
FM ₉ -FM ₈	0.001	0.000	0.002	0.000	0.001
FM ₉ -FM ₉	0.001	0.021	0.023	0.010	0.010

Table 8. Total impact relationship matrix after integration in terms of rough numbers.

	FM ₁		FM ₂		FM ₃		FM ₄		FM ₅		FM ₆		FM ₇		FM ₈		FM ₉	
FM ₁	0.006	0.017	0.014	0.022	0.000	0.016	0.000	0.007	0.000	0.001	0.000	0.007	0.000	0.022	0.000	0.004	0.000	0.021
FM ₂	0.001	0.020	0.005	0.017	0.000	0.025	0.000	0.001	0.000	0.022	0.000	0.013	0.000	0.026	0.000	0.009	0.000	0.011
FM ₃	0.000	0.014	0.000	0.007	0.006	0.019	0.000	0.001	0.000	0.010	0.000	0.001	0.002	0.007	0.037	0.064	0.000	0.026
FM ₄	0.001	0.042	0.000	0.005	0.000	0.004	0.000	0.017	0.001	0.016	0.000	0.035	0.000	0.037	0.000	0.000	0.000	0.001
FM ₅	0.000	0.015	0.000	0.015	0.000	0.007	0.000	0.001	0.005	0.017	0.000	0.008	0.000	0.009	0.000	0.008	0.000	0.024
FM ₆	0.005	0.036	0.000	0.016	0.000	0.018	0.000	0.023	0.023	0.039	0.004	0.014	0.000	0.004	0.000	0.001	0.000	0.020
FM ₇	0.000	0.027	0.000	0.017	0.000	0.021	0.000	0.003	0.000	0.011	0.000	0.004	0.006	0.017	0.000	0.011	0.000	0.012
FM ₈	0.001	0.025	0.000	0.001	0.030	0.043	0.000	0.000	0.000	0.001	0.000	0.012	0.000	0.014	0.006	0.019	0.000	0.000
FM ₉	0.001	0.015	0.000	0.007	0.000	0.019	0.026	0.039	0.016	0.029	0.001	0.017	0.005	0.024	0.000	0.001	0.002	0.014

Step 4: The sum of the rows and columns of the total impact relation matrix and the total correlation degree are calculated using Equations (18) and (19). This is shown in Table 9.

Table 9. Total impact relationship matrix.

	R	C	R + C	AV (+)	R − C	AV (−)
FM ₁	0.020	0.118	0.015	0.211	0.035	0.329
FM ₂	0.007	0.145	0.021	0.106	0.027	0.251
FM ₃	0.045	0.150	0.035	0.173	0.081	0.323
FM ₄	0.002	0.156	0.026	0.092	0.029	0.248
FM ₅	0.006	0.105	0.046	0.147	0.052	0.252
FM ₆	0.033	0.171	0.005	0.110	0.038	0.281
FM ₇	0.006	0.123	0.015	0.161	0.021	0.283
FM ₈	0.036	0.115	0.043	0.118	0.079	0.233
FM ₉	0.052	0.165	0.002	0.129	0.055	0.294

Based on the analysis results in Table 9, projecting R + C and R − C onto the coordinate axes allows the construction of the Influential Failure Mode Network. As shown in Figure 3, it can be observed that FM₆ and FM₉ serve as the root causes within the entire set of failure modes.

4.4. Ranking Failure Modes Using Four Weighting Methods

Under each criterion, the engineering team evaluates the 9 failure modes of the vehicle power system using the semantic variable tables in Appendix A Tables A3–A6. These evaluations result in the performance matrix. Experts assign a rating from 1 to 10 to each failure mode under each risk factor. The evaluation scale, defined by the semantic tables, explains the level of each failure mode under the corresponding risk factor. The higher the number, the higher the hazard level; conversely, the lower the number, the lower the hazard level. After consolidating the expert opinions using the Rough Dombi integration method, we converted the resulting values to crisp numbers, producing the final performance matrix presented in Table 10.

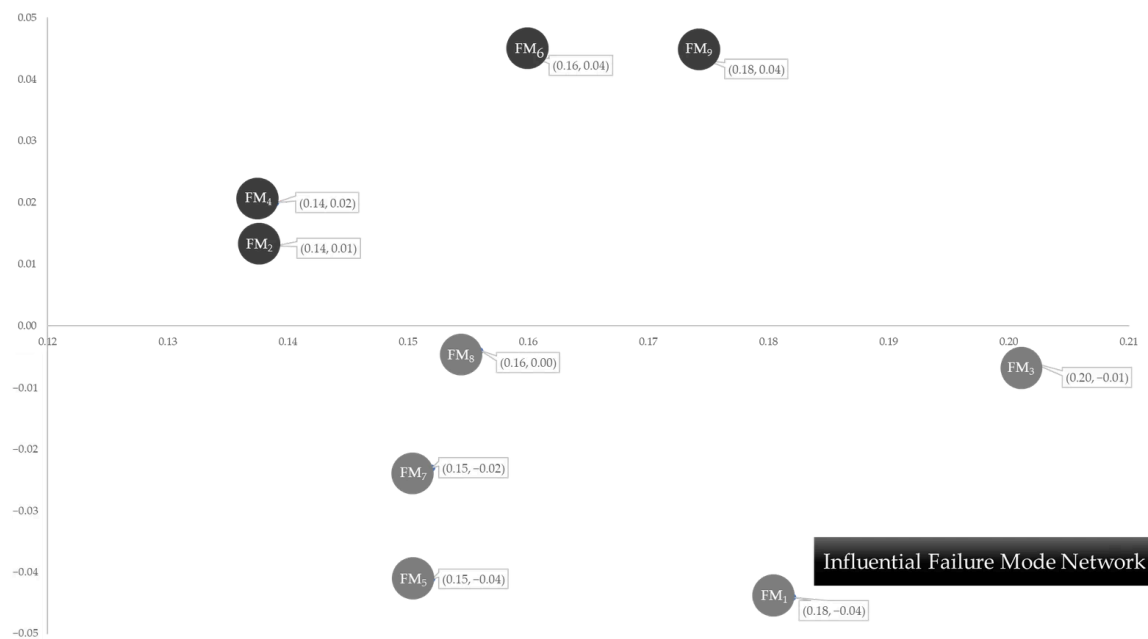


Figure 3. Influential Failure Mode Network.

Table 10. Performance matrix after DM integration.

FM	S	O	D	EC
FM ₁	6.192	2.180	1.739	5.980
FM ₂	7.640	3.568	3.115	6.128
FM ₃	6.192	3.582	2.770	6.371
FM ₄	7.792	3.186	1.125	7.148
FM ₅	7.377	2.291	1.375	6.330
FM ₆	7.792	5.191	2.381	6.896
FM ₇	10.000	3.970	8.359	7.985
FM ₈	8.593	4.322	7.721	2.448
FM ₉	7.171	2.248	1.729	3.508

Step 1. Calculation of the Weighted Matrix for Failure Modes.

In this study, the first step involves calculating the weighted matrix for failure modes to serve as the basis for subsequent RPN evaluation. Based on the four weighting methods proposed in Section 3, namely WARP, WERP, WURP, and WLRP, Equations (19)–(22) are used to compute the weights for each failure mode. The results, presented in Table 11, show the relative importance of each failure mode under different aggregation methods. The sums of WARP, WERP, WURP, and WLRP are [46.451, 98.868, 5.806, 13,909.200], respectively.

Table 11. Weighted matrix.

FM	WARP	WERP	WLRP	WURP
FM ₁	4.123	8.838	0.547	237.030
FM ₂	5.195	10.560	0.686	683.437
FM ₃	4.785	9.646	0.652	295.213
FM ₄	4.880	10.649	0.574	981.210
FM ₅	4.449	9.714	0.550	573.383
FM ₆	5.551	11.297	0.701	938.743
FM ₇	7.839	17.233	0.875	7780.497
FM ₈	5.893	12.568	0.719	2064.211
FM ₉	3.737	8.363	0.504	355.476
SUM	46.451	98.868	5.806	13,909.200

Step 2. Calculation of the Integrated RPN Value and Ranking of Failure Modes.

First, we normalize the four weighted matrices as shown in Equations (23)–(26), and then sum the normalized values as shown in Equation (27) to derive the final function.

$$r_{11} = 4.123/46.451 = 0.089$$

$$r_{12} = 8.838/98.868 = 0.089$$

$$r_{13} = 0.547/5.806 = 0.094$$

$$r_{14} = 237.030/13909.200 = 0.017$$

$$\text{IRPN}_1 = 0.089 + 0.089 + 0.094 + 0.017 = 0.289$$

The remaining results are shown in Table 12.

Table 12. Normalized weighted matrix.

FM	WARPN	WERPN	WLRPN	WURPN	IRPN	RANK
FM ₁	0.089	0.089	0.094	0.017	0.289	8
FM ₂	0.112	0.107	0.118	0.049	0.386	4
FM ₃	0.103	0.098	0.112	0.021	0.334	6
FM ₄	0.105	0.108	0.099	0.071	0.382	5
FM ₅	0.096	0.098	0.095	0.041	0.330	7
FM ₆	0.120	0.114	0.121	0.068	0.422	3
FM ₇	0.169	0.174	0.151	0.559	1.053	1
FM ₈	0.127	0.127	0.124	0.148	0.526	2
FM ₉	0.080	0.085	0.087	0.026	0.278	9

Step 3. Calculation of the RPN Value and Ranking of Failure Modes Considering the Influence of Failure Mode Relationships

The DEMATEL values are incorporated using both multiplication and addition, as shown in Equations (28) and (29). The results are presented in Table 13. Based on the final values, the failure modes are ranked from highest to lowest to identify the critical failure modes. According to the ranking, among the nine failure modes, FM₇ “Generator” ranks the highest, with the IRPN-M presenting the subsequent priority ranking as follows: FM₇ > FM₈ > FM₆ > FM₃ > FM₂ > FM₄ > FM₁ > FM₅ > FM₉, and the IRPN-A exhibiting the subsequent priority ranking as follows: FM₇ > FM₈ > FM₆ > FM₃ > FM₂ > FM₄ > FM₅ > FM₁ > FM₉.

Table 13. Final RPN.

FM	IRPN-M	RANK	IRPN-A	RANK
FM ₁	0.053	7	0.236	8
FM ₂	0.054	5	0.263	5
FM ₃	0.067	4	0.268	4
FM ₄	0.053	6	0.260	6
FM ₅	0.050	8	0.241	7
FM ₆	0.067	3	0.291	3
FM ₇	0.160	1	0.603	1
FM ₈	0.082	2	0.341	2
FM ₉	0.048	9	0.226	9

Note: IRPN-M = IRPN-Multiplication; IRPN-A = IRPN-Addition.

5. Discussion of Results

Following the empirical analysis in Section 4, we proceed to examine and interpret the calculation results. First, the results are compared with traditional FMEA and other MCDM ranking methods, taking into account the risk values after incorporating the interrelationships among failure modes to verify the reliability and robustness of the proposed model. Subsequently, the findings are discussed in greater detail.

5.1. Model Comparison and Sensitivity Analysis

5.1.1. Model Comparison

This study uses an improved FMEA to evaluate the critical failure modes of the vehicle power system. To ensure the validity of the model, the ranking results are compared with those of the traditional FMEA model, the FMEA model with an added risk factor (EC), and the traditional VIKOR method. Owing to space constraints, the detailed procedure for computing VIKOR values is omitted here and can be found in study [50]. Spearman's rank correlation coefficient is used to analyze the priority rankings of the proposed model and other methods. The value of this coefficient ranges between -1 and 1 , where 1 indicates a perfect positive correlation, 0 indicates a weak correlation, and -1 indicates a perfect negative correlation. In other words, the greater the absolute value of the correlation coefficient, the higher the degree of correlation between the two methods. Specifically, the Spearman coefficient measures the degree of agreement between the priority rankings obtained from the proposed FMEA model (with S, O, D, and EC) and those from alternative methods such as VIKOR and IRPN. The coefficients range from 0.867 to 1.000 , indicating a strong positive correlation among the methods. The failure mode ranking results of the aforementioned methods and their Spearman correlation coefficients will be listed in Table 14.

Table 14. Model ranking comparison.

FM	FMEA (S, O, D)	FMEA (S, O, D, EC)	VIKOR	IRPN	IRPN (Multiplication)	IRPN (Addition)
FM ₁	7	8	7	8	7	8
FM ₂	6	6	6	4	5	4
FM ₃	4	4	4	6	4	6
FM ₄	5	5	5	5	6	5
FM ₅	8	9	8	7	8	7
FM ₆	3	3	3	3	3	3
FM ₇	1	1	1	1	1	1
FM ₈	2	2	2	2	2	2
FM ₉	9	7	9	9	9	9
Spearman	0.917	0.867	0.917	1.000	0.933	1.000

In conclusion, the ranking results of IRPN and IRPN (addition) show minimal differences compared to other methods, thus validating the reliability of the improved FMEA model for evaluating the critical failure modes in the system. However, after confirming the model's credibility, although the calculation of RPN in the improved model is more complex than traditional FMEA, it can resolve disputes regarding the scale of mathematical operations among experts, making the results more persuasive.

5.1.2. Sensitivity Analysis

To validate the robustness and reliability of the proposed evaluation framework, a sensitivity analysis was conducted. Based on the weight configurations of S, O, D, and EC outlined in Appendix A Table A7 (represented as scenarios RUN₁ to RUN₉), the rankings and variation trends of the nine failure modes (FM₁ to FM₉) were observed across different scenarios. The analysis results are illustrated in Figure 4.

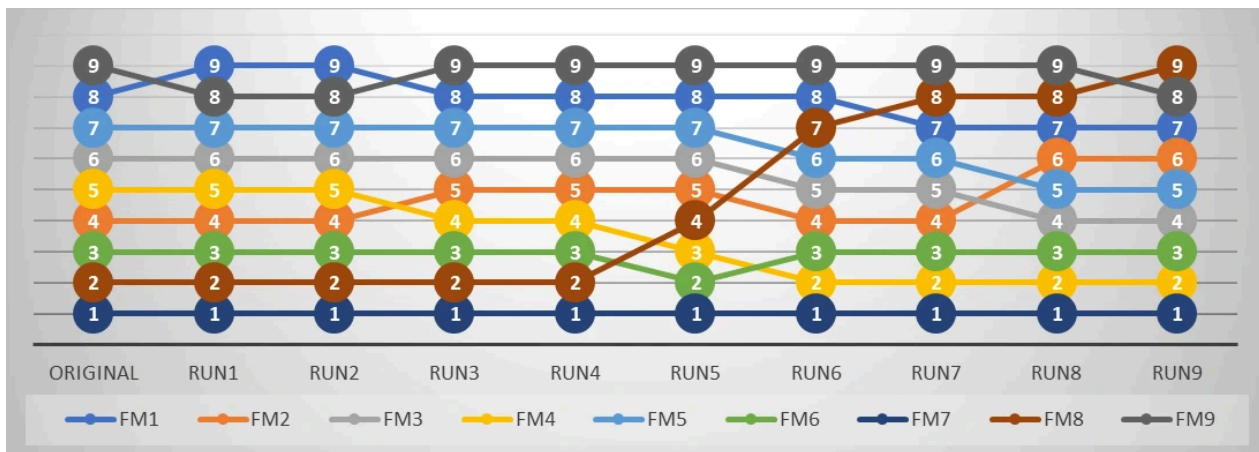


Figure 4. Rankings of failure modes under different scenarios.

The trend in the figure reveals an exceptionally high overall stability: under most weight fluctuation scenarios, the rankings of the majority of failure modes demonstrate strong consistency. Notably, FM₇ (dark blue) consistently holds the 1st rank (highest risk) across all scenarios, while FM₁ (blue) and FM₉ (gray) reliably remain at the 8th and 9th positions (lowest risk group). This indicates that the baseline evaluation results are not easily shaken by minor adjustments in weights, thereby confirming the robustness of the proposed decision-making model. In terms of the sensitivity variations in specific failure modes, despite the general stability of the framework, certain failure modes still exhibit a degree of sensitivity to weight alterations. The most prominent variation occurs in FM₈ (brown), which originally occupies a lower-risk position at the 2nd rank from the ORIGINAL scenario through RUN₄. However, with the weight adjustments from RUN₅ to RUN₇, its risk ranking rises sharply to the 7th rank, eventually reaching the 9th rank in RUN₉. Regarding rank reversals among medium-risk items, FM₄ (yellow), FM₂ (orange), FM₆ (green), and FM₃ (light gray) display frequent crossover phenomena within the mid-tier rankings (2nd to 5th ranks). For instance, the ranking of FM₄ (yellow) drops significantly after RUN₄, whereas FM₆ (green) briefly dips to the 2nd rank in RUN₅ before recovering in RUN₆.

In conclusion, although specific weight scenarios induce rank shifting among certain mid-to-low-risk failure modes (such as FM₈ and FM₄), the core risk items (such as FM₇, FM₁, and FM₉) maintain an extremely high degree of sorting consistency under various extreme weight changes. These results fully demonstrate that the priority ranking of critical failure modes obtained in this study possesses sufficient decision-making credibility.

5.2. Management Implications

Based on the analysis of the improved FMEA model, the top three critical failure modes among the nine identified are: the seventh failure mode, “Generator Coil Short Circuit and Burnout”; the eighth, “Air Filter Blockage”; and the sixth, “Cooling Fan Deformation or Rupture.” Among these, the seventh failure mode, “Generator Coil Short Circuit and Burnout,” is identified as the most critical and should be prioritized for improvement. The generator converts mechanical energy into electrical energy, primarily producing driving torque and serving as the main power source for various machines. Its failure could compromise the overall functionality of the system. These analytical results explicitly demonstrate that the generator coil and the air filter represent the most critical components within the vehicle powertrain system, directly justifying the focus of subsequent risk mitigation.

To fully understand these priorities, the engineering implications of the causal relationships derived from DEMATEL must be examined. In terms of system physics, these top failure modes do not operate in isolation but form a tight causal chain. The “Air Filter Blockage” (an engineering cause/dispatcher) restricts intake airflow and alters the air-fuel ratio, forcing the engine to run inefficiently and generate excessive thermal loads. This prolonged thermal strain directly accelerates the thermal degradation of insulation materials within the “Generator Coil”, ultimately precipitating the “Short Circuit and Burnout” (a critical engineering effect/receiver). Simultaneously, the severe thermal accumulation escalates the operating temperature of the surrounding environment, causing thermal fatigue that induces “Cooling Fan Deformation or Rupture.” Therefore, from a system engineering perspective, risk mitigation must target the root cause rather than merely treating the symptoms; by implementing design modifications—such as enhancing the thermal resilience of the coil insulation or introducing differential pressure sensors for early block detection—engineers can break this cascading fault propagation path at its source.

From a management perspective, these findings suggest several important implications. First, organizations should prioritize maintenance resources toward the most critical failure modes, particularly for core components such as generators, by establishing stringent monitoring, maintenance, and inspection routines to reduce the risk of major failures. Second, for secondary but influential failure modes like air filter blockage and cooling fan deformation, managers should implement regular inspection and replacement schedules to maintain system efficiency and prevent cascading failures. Finally, adopting a systematic, risk-based approach provides decision-makers with actionable insights for risk management and equipment reliability enhancement, enabling more effective allocation of resources under constraints.

6. Conclusions and Future Recommendations

This study utilizes the proactive risk assessment characteristics of FMEA and proposes an improved version of FMEA to evaluate the failure modes of systems. Using the vehicle system design as a case study, the study demonstrates the effectiveness and practicality of the proposed model. The following presents the conclusions of this study and suggestions for future research directions.

6.1. Conclusions

Through an in-depth understanding of the advantages and disadvantages of traditional FMEA methods, as well as the issues raised by various scholars, the research objectives and motivations were established. After reviewing the literature to identify research gaps, an improved FMEA model was proposed. Considering the premise of vehicle sustainability, the powertrain system is identified as a primary area of concern. This study used this as a practical case for analysis. After actively participating in the vehicle system design process, key failure modes were identified through discussions with the engineering team. DEMATEL and FUCOM were used to calculate the degree of influence and the weights of risk factors. Additionally, discussions with the engineering team and recording of failure modes under various risk factors were used to improve the analysis of traditional FMEA. Moreover, the traditional RPN calculation formula was controversial due to its multiplication of values, so four different weighted RPN calculation methods were used. Finally, the final function values were integrated and ranked to prioritize critical failure modes. This allows the engineering design team to have a more systematic and accurate way to predict and improve critical failure modes within limited time and resources, maximizing benefits. The contributions of this study can be summarized as follows:

1. Addressing the issues of traditional FMEA by incorporating cost factors into failure factors, allowing the analysis to more closely reflect real-world situations.
2. Better integration of expert information and uncertainty through Rough Set Theory.
3. Considering the interrelationships between failure modes by using DEMATEL to calculate the influence between failure modes and incorporating this into the RPN calculation.
4. Providing an improved FMEA model to evaluate the key failure modes of the powertrain system, offering a more systematic reference for design engineers and decision-makers during design discussions and accelerating the decision-making process.
5. Using FUCOM to obtain the weights of risk factors that are more aligned with real-world conditions.
6. Through a series of analyses and validation detailed in Section 5, it was confirmed that the generator coil short-circuit burn and air filter blockage are the more critical components in the vehicle powertrain system. Corresponding preventive measures have been proposed based on these findings, providing experts with references during the design process.

6.2. Limitations and Future Recommendations

This study integrates a modified FMEA framework with advanced aggregation mechanisms to handle uncertainty and prioritize critical failure modes in the design stage. While the approach is effective, several limitations should be acknowledged:

1. The current empirical validation is restricted to the powertrain subsystem. Future studies should expand the analysis to the complete vehicle system to capture cross-subsystem interactions and better reflect real-world engineering complexity.
2. Expert-based inputs were used for scoring and dependency relationships. Broader participation—such as cross-departmental teams or multiple organizations—may improve generalizability and reduce potential bias.
3. Although this study applies the enhanced FMEA approach to vehicle design, the methodology can be extended to broader domains that require proactive risk assessment, such as healthcare system planning, electronic product development, transportation infrastructure monitoring, emergency response systems, and sustainable energy management.
4. The proposed framework primarily focuses on a static risk assessment during the design phase. However, real-world engineering environments are inherently dynamic, where failure profiles shift over time due to component degradation, operational variations, and environmental changes.

Future research may further explore automated data-driven learning mechanisms, enabling large-scale systems to derive failure dependencies and probability estimates from operating data rather than relying solely on expert judgment.

7. Glossary

While Appendix A provides S, O, and D tables tailored for vehicle power systems, we note that these tables are illustrative. For other industries, the numerical scales should be adjusted to reflect domain-specific severity, likelihood, and detectability. The methodological framework presented in this paper, including the handling of dependencies among failure modes, is generalizable and can be applied to a wide range of FMEA applications, provided the S, O, and D values are appropriately adapted. Furthermore, the relevant terms and definitions adopted in this study are summarized in Table 15 for reference.

Table 15. Term definition.

Term	Definition
Failure Mode and Effects Analysis (FMEA)	A systematic risk management tool used to identify potential failure modes, evaluate their impacts, and prioritize them to prevent issues.
Risk Priority Number (RPN)	A key indicator in FMEA, calculated as the product of three evaluation criteria—Severity, Occurrence, and Detection—to assess the risk level of a failure mode.
Severity (S)	Represents the extent of impact a failure mode has on a system or customer; higher scores indicate more severe consequences.
Occurrence (O)	Measures the likelihood that a failure mode will occur; higher scores signify a higher probability of failure.
Detection (D)	Assesses the ability of current control measures to detect a failure mode; higher scores indicate lower detectability.
Multi-Criteria Decision-Making (MCDM)	A set of decision-making methodologies used to evaluate and prioritize alternatives when multiple, often conflicting, criteria are involved.
Decision Making and Trial Evaluation Laboratory (DEMATEL)	An MCDM method used to analyze causal relationships and the degree of influence among factors, suitable for modeling complex problem structures.
Fuzzy Analytical Hierarchy Process (FAHP)	A method that integrates fuzzy logic with AHP to address the limitations of traditional AHP in handling uncertainty and ambiguity.
Rough Set Theory (RST)	A mathematical approach for handling uncertainty and vagueness, analyzing the relationships between attributes and decisions through lower and upper approximations.
Fuzzy VIKOR (FVIKOR)	A fuzzy MCDM method emphasizing compromise solutions by simultaneously considering closeness to the ideal solution and the maximum regret.
Rough Number	A numerical representation used in RST to express uncertainty or vagueness in expert judgments.
Rough Dombi Weighted Geometric Averaging (RDWGA)	An aggregation algorithm for rough numbers that incorporates Dombi operations and geometric means to integrate expert evaluations with assigned weights.

Supplementary Materials: The complete raw dataset can be downloaded at: <https://reurl.cc/nlj781>.

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Appendix A

Appendix A.1

Table A1. Symbol definition.

Abbreviation	Definition	Abbreviation	Definition
FM	Failure Mode	R	Influencing/Cause
DM	expert	C	Influenced/Effect
LIM	Approximate Boundary	R + C	Reflects the strength
RN	Rough Number	R – C	Causal Relationship
W	Weights	rk	k refers to the weighted method
i	Row index	j	Column index
n	Row count	m	Column count

Appendix A.2

Table A2. Expert Background Table.

Expert ID	Position/Role	Expertise Area	Experience
DM ₁	Senior Design Engineer	Vehicle Powertrain Design	10
DM ₂	Systems Engineer	Transmission Systems & Structural Analysis	8
DM ₃	Design Engineer	Powertrain & Transmission Integration	6
DM ₄	Senior Design Engineer	Vehicle Structure & Safety	12
DM ₅	Systems Engineer	Vehicle System Analysis & Integration	7

Appendix A.3

Table A3. S assessment scale.

Assessment	Influence	Severity Impact
10	Danger—No Warning	System damage without prior warning results in failure related to system operational safety or non-compliance with government regulations.
9	Danger—Warning	The system has advance warning, resulting in damage resulting in failure related to system operational safety or non-compliance with government regulations.
8	Extremely Serious	The system loses important performance and is completely inoperable but does not cause safety-related failures in system operation or violate government regulations.
7	Highly Serious	The system's performance is reduced, requiring auxiliary means to complete important tasks, and causing users to have a very bad experience.
6	Moderate to High Severity	The system's performance is reduced, some tasks cannot be completed, and the user has a bad experience.
5	Moderately Severe	The system's critical performance is reduced, requiring auxiliary means to complete some tasks, and causing users to have a somewhat bad experience.
4	Low to Medium Impact	Items such as appearance, flexibility, accuracy, and collision noise do not meet user needs or secondary functions are lost, and most users may be aware of it.
3	Low Severity	Items such as appearance, flexibility, accuracy, and collision noise do not meet user needs or have reduced secondary functions, and may be noticed by ordinary users.
2	Very Low Impact	Items such as appearance, flexibility, accuracy, and collision noise do not meet user needs or secondary functions are reduced, and only users with strong observation skills may notice it.
1	No Impact	Those who have no impact on system operations and tasks.

Appendix A.4

Table A4. O assessment scale.

Assessment	Failure Probability	Failure Rate per 1000 Units
10	Extremely High	≥ 100
9	Very High	50
8	Repeated Failure	20
7	High	10
6	Medium to High	5
5	Middle	2
4	Medium to Low	1
3	Low	0.5
2	Very Low	0.1
1	Close to 0	≤ 0.01

Appendix A.5

Table A5. D assessment scale.

Assessment	Detection Ability	Severity Impact
10	Almost Impossible to Detect	Current design methods cannot discover this potential cause/mechanism and its resulting failure mode, or there is no detection method at all.
9	Very Small Chance	The current design method has a very small chance of discovering this potential cause/mechanism and the resulting failure mode, and it can only be discovered when used under special operating conditions.
8	Small Chance	The current design method has a small chance of discovering this potential cause/mechanism and the resulting failure mode, which can only be discovered during operation.
7	Very Low	The ability of current design methods to discover this potential cause/mechanism and the resulting failure mode is very low, and it can only be discovered through assembly testing at the system level.
6	Low	The current design method has a low probability of discovering this potential cause/mechanism and the resulting failure mode, which can only be discovered through assembly testing at a higher hardware level.
5	Moderate	Current design methods have a moderate probability of discovering this potential cause/mechanism and the resulting failure mode, which requires the use of special equipment and techniques.
4	Middle to High	Current design methods have a medium to high probability of discovering this potential cause/mechanism and the resulting failure mode, which can only be discovered using existing specialized equipment and professionally trained and qualified personnel.
3	High	Current design methods have a high probability of discovering this potential cause/mechanism and the resulting failure mode using ordinary equipment, but it requires professionally trained and qualified personnel to discover it.
2	Very High	Current design methods have a very high probability of discovering this potential cause/mechanism and the resulting failure mode, which can be discovered using ordinary equipment and techniques.
1	Almost Certainly	Current design methods can almost certainly detect this potential cause/mechanism and the resulting failure mode, using simple equipment and techniques.

Appendix A.6

Table A6. EC assessment scale.

Assessment	Cost Amount	Expected Cost Description
10	Very Expensive	The cost of returning the system to the factory for repair is very expensive
9	Expensive	Returning the system to the factory for repair is expensive
8	Very High	The cost of returning the system to the factory for repair is very high
7	High	The cost of returning the system to the factory for repair is high
6	Middle to High	The cost of system return to the factory for repair is medium to high.
5	Middle	System return to the factory for repair costs
4	Medium Low	The system returns to the factory for low maintenance costs
3	Low	The system returns to the factory for low maintenance costs
2	Very Low	The cost of returning the system to the factory for repair is very low
1	No Cost	Almost no cost

Appendix A.7

Table A7. Weight allocations under different scenarios.

	S	O	D	EC
Original	0.036	0.026	0.038	0.900
Run1	0.323	0.238	0.339	0.100
Run2	0.287	0.212	0.301	0.200
Run3	0.251	0.185	0.263	0.300
Run4	0.215	0.159	0.226	0.400
Run5	0.179	0.132	0.188	0.500
Run6	0.144	0.106	0.151	0.600
Run7	0.108	0.079	0.113	0.700
Run8	0.072	0.053	0.075	0.800
Run9	0.036	0.026	0.038	0.900

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