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Risk Assessment in Sustainable Production: Utilizing a Hybrid Evaluation Model to Identify the Waste Factors in Steel Plate Manufacturing

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Abstract: In the realm of industrial development, steel has consistently played a pivotal role due to its extensive applications. This research aims to refine the process of steel plate manufacturing, focusing on reducing waste as a critical step towards embracing sustainable development and aligning with the Sustainable Development Goals (SDGs). Our approach integrates a hybrid analytical model grounded in Failure Mode and Effects Analysis (FMEA) to thoroughly investigate the waste-producing elements in steel plate production. The methodology of this study is structured in a three-pronged approach, as follows: Initially, it involves meticulous on-site inspections across various factories to pinpoint potential sources of waste. Subsequently, we employ the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to intricately analyze the interconnectedness and impact of various risk factors. The final phase utilizes the Performance Calculation technique within the Integrated Multiple Multi-Attribute Decision-Making (PCIM-MADM) framework for aggregating and evaluating risk scores. This multifaceted approach aids in establishing the priorities for corrective actions aimed at waste reduction. Our findings present innovative solutions for identifying and mitigating critical waste factors, contributing to a more efficient and sustainable steel manufacturing process. These strategies promise scalability and adaptability for broader industrial applications and provide critical insights into resource optimization. This research directly supports the objectives of SDG 9, which focuses on building resilient infrastructure and promoting sustainable industrialization. Furthermore, it resonates with SDG 12, advocating for sustainable consumption and production patterns. By enhancing the efficiency and cost effectiveness of steel plate production, this study significantly contributes to minimizing waste and elevating the sustainability of industrial practices.

Keywords: SDGs; FMEA; MADM; sustainable manufacturing

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1. Introduction

Steel, as an essential metal, plays a pivotal role in the foundation of industries. Historically, its broad application has been instrumental throughout various stages of human industrial evolution. In contemporary economic activities, industries continue to heavily rely on and extensively use steel [1], which is evident in its incorporation into materials for automobiles, construction, medical purposes, and even the electronics sector. This underscores the significance and versatility of steel [2]. From a business perspective, identifying the potential issues or risks in the production process and proactively implementing effective strategies can mitigate these challenges, thereby reducing material waste and subsequently lowering the operational costs [3].

Past research has been predominantly dedicated to understanding the Sustainable Development Goals (SDGs) and analyzing their implementation across various industries and practical scenarios [4,5]. This extensive research has gained recognition and frequent citations in many follow-up studies [6]. This study is anchored in the pursuit of improving production methodologies in order to align with sustainable development principles. The essence of this study centers on the optimization of the steel plate manufacturing process to decrease waste, resonating with two SDGs. Firstly, for SDG 9 (industry, innovation, and infrastructure), by addressing the nuances of waste and risk minimization, the research promotes a more resilient infrastructure, driving forward the aspirations of inclusive and innovative industrial growth [7]. Concurrently, for SDG 12 (sustainable consumption and production), the focus on sustainable consumption patterns underscores the intent to render the production of steel plates more efficient and economically viable, ultimately reducing waste and amplifying sustainability [8].

The selection of SDGs 9 and 12 as focal points for this research is strategically aligned with the core objectives of the study, which seeks to enhance the efficiency and sustainability of steel plate manufacturing processes. SDG 9, which focuses on industry, innovation, and infrastructure, is inherently connected to the aim of this research. The steel industry, a fundamental component of the industrial sector, requires innovative approaches to minimize waste and risk in the production processes [9]. By focusing on SDG 9, this study contributes to building resilient infrastructure by optimizing industrial practices. It addresses the nuances of waste minimization and risk management in steel plate manufacturing, facilitating more inclusive and innovative industrial growth [10].

Similarly, SDG 12, which emphasizes sustainable consumption and production, is directly relevant to the objectives of this research. The study's methodology and findings are designed to make steel plate production more efficient and economically viable. This aligns with SDG 12's emphasis on sustainable production patterns, as the study aims to reduce waste, thus contributing to a more sustainable consumption model in the industry [11]. By implementing the strategies and methodologies developed in this research, the steel plate manufacturing process can become more aligned with sustainability principles, resonating with responsible consumption and production goals [12].

Various risk diagnostic tools and techniques have been developed to address the inherent risks in different products, processes, and projects [13]. In this study, we conduct an in-depth examination of the potential waste factors in steel plate production. Using a hybrid model anchored in Failure Mode and Effects Analysis (FMEA), we discern the risk scores of these latent waste factors, subsequently determining their order of priority for improvement.

The contributions and innovations of this research are summarized as follows:

- The waste factors in the steel-plate-cutting process have been effectively identified.
- The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is utilized to determine the weights of the four risk factors pertaining to the issue.
- PCIM-MADM (Performance Calculation technique of the Integrated Multiple Multi-Attribute Decision Making) is applied to integrate the computational outcomes of SAW (Simple Additive Weight), VIKOR (VlseKriterijuska Optimizacija I Komoromisno Resenje), GRA (Grey Relational Analysis), and COPRAS (COmplex PRoportional ASsessment), thereby yielding a more reliable final risk score for the fault modes.
- Improvement strategies are devised for the fault modes with the highest risk scores in order to diminish waste during the steel-plate-cutting process.
- The research concept and methodology proposed offer replicability, serving as a foundation for waste factor evaluations in other industries.

In light of these considerations, the primary objective of this research is to develop a comprehensive and scalable model for identifying and prioritizing waste factors in steel plate manufacturing, thereby contributing to sustainable industrial practices. Specifically, the study aims to carry out the following:

- Systematically identify the waste factors in the steel-plate-cutting process by using an integrated approach that combines FMEA with advanced Multi-Criteria Decision-Making (MCDM) methods.
- Apply the DEMATEL method to quantitatively assess the interdependencies among the identified risk factors, thereby enhancing the accuracy of risk prioritization.
- Utilize the Performance Calculation technique of Integrated Multiple Multi-Attribute Decision Making (PCIM-MADM) to amalgamate various analytical outcomes, thereby deriving a robust and reliable final risk score for each identified fault mode.
- Develop and propose targeted improvement strategies for the most critical waste factors, aiming to significantly reduce waste and enhance the efficiency of the steel plate manufacturing process.
- Demonstrate the replicability and applicability of the proposed model across different industrial sectors, thereby broadening its utility in addressing similar challenges in waste management and sustainable manufacturing practices.

By achieving these objectives, this study endeavors to make a substantial contribution to the field of sustainable manufacturing, particularly in aligning industrial processes with SDGs 9 and 12, which focus on building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering sustainable consumption and production patterns [14].

The structure of this paper is organized as follows: Following this introduction, Section 2 delves into a detailed literature review, elucidating the current state of research in waste minimization and steel quality enhancement, with a focus on the integration of FMEA/FMECA and MCDM techniques. Section 3 describes the methodology employed in this study. In Section 4, we present the results of our analysis. Section 5 concludes the paper, summarizing the key outcomes of the research.

2. Literature Review

In recent years, the integration of FMEA and Failure Mode, Effects, and Criticality Analysis (FMECA) with various MCDM techniques has garnered significant attention in the realm of system optimization and risk assessment. Pantazopoulos and Tsinopoulos [15] comprehensively examine the metal forming industry's process Failure Modes and Effects Analysis (PFMEA) methodology. The results showcase it as an effective tool for identifying and evaluating the potential failure modes in metal-forming operations. The article emphasizes the importance of PFMEA in systematic risk assessment, highlighting its role in facilitating continuous improvement and reducing operational failures. Ahmed, Carpitella, and Certa [16] present a hybrid methodological approach integrating MCDM with FMEA for optimizing maintenance management in complex engineering systems. This approach is designed to address the main failures in systems undergoing predictive maintenance, considering the strengths and weaknesses of traditional FMEA. It incorporates the ELimination Et Choix Traduisant la REalité TRI method for categorizing the failure modes into risk priority classes and the DEMATEL to identify the most influential failures within each risk class. Applied to a real service system with the critical components monitored with sensors, this method demonstrates its effectiveness in identifying the key elements that influence the occurrence of other failures within specific risk classes. This insight significantly contributes to implementing efficient maintenance strategies, thereby enhancing the system's overall performance and lifecycle management. Papadopoulou et al. [17] have discovered a comprehensive approach to diagnosing and resolving failures in metal forming products and parts. This study emphasizes the use of root cause analysis as a systematic technique to uncover the root causes of failure in the metal forming industry. This approach provides a deeper understanding of failure mechanisms and their influencing factors, allowing for more effective resolution strategies. This study highlights the importance of thorough, methodical analysis for failure prevention and improving metal forming processes continuously.

Gajdzik and Sitko [18] employ the Pareto chart and FMEA to assess the faultiness of these products. The analysis found several problems with the bolts, such as not meeting the required tolerances for size, having the wrong surface roughness, not being pre-machined, the electroplating not working with the bolts, and surface faults. Similar defects were found in ball bushings, with additional issues like sharp edges and material splitting. The importance of quality management in metallurgical enterprises is emphasized, highlighting the role of quality control systems in ensuring superior steel products and minimizing defects. Zhang et al. [19] present an enhanced System Theoretic Process Analysis (STPA) method for assessing the risk at hydrogen refueling stations. This method significantly improves the traditional STPA by integrating the DEMATEL approach to assess unsafe control actions (UCA) quantitatively. The process begins with defining the risk analysis purpose and analyzing system-level losses, hazards, and constraints at the refueling station. It then constructs the control structure of the system, delineates the system boundaries, and develops a control structure diagram. The innovative aspect of this approach lies in identifying UCAs based on control actions and quantitatively analyzing them using DEMATEL to determine their occurrence probability. This analysis facilitates the identification of loss scenarios and causation analysis for UCAs with higher occurrence probabilities, leading to the proposition of improvement measures and risk control recommendations. This refined STPA method enables a comprehensive understanding of each subsystem's safety performance and potential problems in the hydrogen refueling station system, offering actionable insights to mitigate risks and enhance the overall safety. Mzougui et al. [20] address the critical issue of managing supply chain risks (SCRs) in the automotive industry, a sector prone to significant economic losses and reputation damage due to these risks. This method integrates an MCDM approach, utilizing the Analytic Hierarchy Process (AHP) for determining the factor weights and the fuzzy DEMATEL for evaluating the new factor of 'dependence' among the risks. The study also addresses the uncertainties in input data by employing fuzzy numbers. The efficacy of this approach is demonstrated through a case study in the automotive industry, highlighting the importance of prioritizing prevention and mitigation strategies for supply chain disruptions due to natural disasters, human resources policies and processes in manufacturing facilities, and inefficient transport.

Liu, Bi, and Liu [21] introduce an advanced FMEA framework for supercritical water gasification (SCWG) systems, a crucial technology for sewage sludge treatment. This FMEA framework incorporates evidence theory and bounded confidence, addressing the complexities and unique requirements of SCWG systems. The framework is designed to accommodate the diverse professional knowledge and operational skills of a large team of evaluators, reflecting their distinct personality traits and the interdependencies between various factors within the SCWG system. The key elements of the framework include transforming assessments into mass functions using probability linguistic term sets and employing a bounded confidence-based clustering method that respects the team members' willingness to interact. The framework also manages evidence conflicts with a novel discounting method that accounts for the TMs' stubbornness. Furthermore, it utilizes the evidence-theory-based DEMATEL method to analyze cross-correspondences between factors and uses regret theory to prioritize the failure modes. The paper demonstrates the framework's effectiveness through a case study on an SCWG system, showcasing its superiority in managing complex risk evaluations. Ervural and Ayaz [22] introduce a fully data-driven FMEA framework aimed at objectively identifying and prioritizing the potential risks in manufacturing processes. The traditional FMEA methods often face criticism for subjective assessments and inadequate risk prioritization. To overcome these limitations, this approach utilizes data-driven risk factors, such as the frequency and stability of failures, time, and product loss cost due to failure, providing a more accurate depiction of the impact of risk factors on the failure modes. The framework employs the modified criteria ranking importance with the intra-criteria correlation method to assign weights to these risk factors, indicating their importance in the analysis. Additionally, it uses the alternative-by-alternative comparison method to establish the risk priorities of the failure modes. This approach's practical application and effectiveness are showcased through a case study in the food industry, emphasizing the significance of objective risk calculations in FMEA and the value of data-driven models in risk analysis.

The emphasis on steel quality is not just a matter of meeting industry standards, but also a pivotal factor in reducing waste and enhancing sustainability in manufacturing practices. The traditional processes, burdened by high costs and long production cycles, are contrasted with modern needs for speed, low cost, and quality. Carli et al. [23] investigate recent trends in Information and Communications Technology (ICT)-based methodologies for sheet metal forming, aiming to bridge the gap between the existing processes and modern market requirements. The authors categorize metal forming into cold and hot processes, each with unique challenges and requirements. It emphasizes the importance of proper process design to prevent defects like wrinkling, tearing, and buckling, thereby reducing the production costs and time. Also, the paper identifies the gaps in current ICT-based design methodologies, suggesting the need for autonomous, fast, adaptive, and efficient design and control approaches. It proposes integrating Finite Element Method (FEM)-based techniques with optimization tools like MATLAB to enhance process predictions and control. The goal is to create a cyber–physical system that integrates design simulation models and optimization techniques, enabling real-time control and reducing the gap between real processes and simulations. This approach aligns with the Industry 4.0 framework, aiming to revolutionize sheet metal forming processes. Cavone et al. [24] focus on improving the metalworking process known as deep drawing, where a metal sheet is plastically deformed to fit a predefined mold. This process, crucial in the automotive sector, faces challenges like wrinkling, tearing, and springback, affecting the product quality. The authors introduce Model Predictive Control (MPC)-based process control architecture, employing a Hammerstein–Wiener model for better handling the relationship between the blank holder force (BHF) and the draw-in of critical points around the die. This approach aims to enhance the product quality by reducing defects such as abnormal metal sheet sliding during forming. Addressing these issues is vital for advancing towards zero-defect manufacturing in the Industry 4.0 framework, as current methods often lead to considerable waste and inefficiencies. The new methodology is effective in an actual case study, contrasting it with traditional proportional-integral-derivative (PID)-based control systems.

Gajdzik and Sitko [25] underscore the increasing importance of product quality in enhancing the competitive advantage in production enterprises. The quality of metallurgical products, determined by attributes like chemical composition, physical and chemical properties, quality precision, and functionality, must meet both production standards and customer-specific requirements. The precision of quality control, influenced by the accuracy of the measurements taken by staff, varies, and can significantly impact the final product quality. The research identified the primary material factors causing complaints, including cold shuts, surface cracks, material delamination, corrosion pits, and uneven application of the protective layers. These factors significantly affect the steel-sheet-cutting process. Mechanical factors, such as potential damage during transport, and human factors, such as incorrect measurements and improper machine settings, also contribute to complaints. Trzepieciński [26] reviews the advancements in sheet metal forming (SMF) technologies, an essential process in aircraft, automotive, food, and home appliances. The author focuses on the developments from the last decade, especially between 2015 and 2020, highlighting the evolution of conventional and innovative SMF methods. The key areas of progress include enhancing material formability, producing complex-shaped parts with superior surface quality, accelerating production cycles, reducing operational steps, and improving environmental performance.

3. Methods

The implementation of our proposed model unfolds across three distinct phases. The initial phase involves identifying the risk factors and failure modes. Within the FMEA framework, risk factors such as S, O, D, and E are established as criteria. This phase primarily focuses on assessing potential risks for failures or damages that are yet to occur. We rely on expert consultations to ascertain these risks, drawing upon their extensive knowledge and experience for informed opinions. In the second phase, the model prioritizes the failure modes. Here, the DEMATEL method determines the risk factors' weights and examines their interrelationships. Subsequently, we employ four MADM methods—SAW, VIKOR, GRA, and COPRAS—to categorize the failure modes. An integration method, inspired by the TOPSIS concept, is then developed. This method consolidates the assessment scores derived from the four MADM methods to finalize the ranking of the failure modes. The third and final phase of the model is dedicated to formulating strategies for improving and eliminating critical failure modes, thereby enhancing the overall system's efficiency and reliability.

3.1. Theory of FMEA

FMEA is a systematic and proactive reliability management tool, recognized as one of the prevailing methods for identifying critical failure modes [27]. It investigates existing or potential failure modes and eliminates potential risk factors associated with products, designs, processes, services, and systems, thereby enhancing their reliability [28]. The primary objective of FMEA is to prevent potential failure modes, reduce the likelihood of faults, and avert the occurrence of hazardous events or minimize their probability, rather than seeking remedial measures [29]. Chang et al. [30] also underscored the ethos of FMEA as "prevention is better than cure", providing proactive protection against possible future faults, effectively reducing maintenance costs and time. Due to its ease of understanding and operation, it is extensively utilized across various sectors, including the aerospace industry, manufacturing sector [31], automotive industry [32], and marine engineering [33], among others. Particularly in the automotive industry, FMEA is employed as a principal system for reducing errors and risks [34]. Furthermore, a study by Huang et al. [35] indicated that most published papers were from the manufacturing sector, signifying the criticality of FMEA as a process safety or product reliability technique within this sector.

Establishing a priority order for improvements through FMEA effectively prevents failure modes. The successful implementation of FMEA considerably reduces the occurrence of system and product failures, thereby enhancing the operational robustness of both government and enterprise entities [27,33]. Experts perform traditional FMEA assessments by rating failure modes on a scale of 1 to 10 based on risk factors and then multiplying these ratings. The resulting product is the Risk Priority Number (RPN), which ranks critical failure modes. A higher RPN value indicates a higher associated risk, and failure modes with larger RPN values require more substantial attention. The three risk factors are categorized into severity (S), occurrence (O), and detection (D), as illustrated in Table 1.

Table 1. Description of risk factors.

Risk Factor	Description	References
Severity (S)	Severity evaluates the extent of damage and impact caused by a failure mode on the overall system. It assesses the level of influence that a failure mode exerts on the entire system, product, equipment, or process when it occurs.	[27,29,33]
Occurrence (O)	Occurrence measures the likelihood or probability of a failure mode manifesting. The frequency of failure mode occurrences can be estimated by examining past related failure records. A higher value indicates a higher probability of the failure mode occurring. Typically, the frequency of a failure mode over a specific period determines the level.	[28,29,33]
Detectability (D)	Detectability refers to the possibility of or difficulty in identifying a failure mode when it occurs in the system, product, equipment, or process. If a failure mode can be effectively and timely predicted before its occurrence, the generation of the failure mode can be reduced. High detectability implies a lower risk of failure, while low detectability suggests a higher probability of risk emergence.	[27,31,32]

In the formula, S, O, and D are absolute values, and the resulting RPN is a definite value. However, this algorithm has been considered to have several deficiencies in many studies [3,28,29,31,35], which have been described as follows:

i. Different risk factors might yield the same RPN value, but their underlying risks may not be identical. For instance, two failure modes with S, O, and D values of 1, 3, and 6, and 2, 3, and 3, respectively, both yield an RPN value of 18. Therefore, these two failure modes might be perceived as being equally significant by decision makers, although one may pose a higher risk. This failure mode may lead to the malfunction of other components, affecting the safety and reliability of the product and process.
ii. The formula for RPN is contentious, as it only considers three risk factors, overlooking the interrelationship among them and other factors influencing risk. Additionally, the traditional RPN computation often oversimplifies the interrelationship among these risk factors and their influence on overall risk [36]. Risk is a complex and multifaceted concept involving various factors, including technical, operational, and economic considerations. The traditional approach treats these factors in isolation, which can lead to an incomplete understanding of the true risk landscape. Furthermore, using a single numerical value like RPN can create a false sense of precision and may not capture the full spectrum of risks associated with a system or process. This limitation becomes particularly evident when comparing different failure modes with varying economic implications [37].
iii. When calculating the RPN, the relative importance of the three risks is not considered. All three factors bear the same weight, and the ambiguity and subjectivity involved in the process are often overlooked. Practically, each risk holds a different level of importance.
iv. The formula for RPN is overly simplistic, lacking a robust mathematical foundation. It is susceptible to changes in risk factors; moreover, a slight variation could significantly impact the final RPN value, which is not conducive to determining rankings.

3.2. FMEA-Based MADM

To overcome the drawbacks mentioned above, numerous methods have been adopted in the literature to enhance and integrate Multiple Multi-Attribute Decision Making (MADM) with traditional FMEA, such as the Analytic Hierarchy Process (AHP), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, among others, to extend the applicability of traditional FMEA [38]. The primary directions of improvement are categorized into the following three types:

i. Adjustment of risk factor weights.
ii. Calculation of the RPN formula.
iii. Information uncertainty.

Mohsen and Fereshteh [39] enhanced traditional FMEA by incorporating AHP and the entropy method to consider subjective–objective weights, coupling it with Z-Numbers and the VIKOR-designed failure mode assessment framework for evaluating geothermal power plants. According to sensitivity analysis, this method showed improved applicability. Lo and Liou [28] also considered different weights for risk factors, applying the Best–Worst Method (BWM) to determine weights and using Grey Relational Analysis (GRA) to address information uncertainty. The weights of risk factors should be adjusted according to the circumstances to increase stability in practical cases. Chang, Lo, Chen, and Liou [30] introduced a new risk factor—anticipated cost—calculated weights through R-BWM, and employed an enhanced the TOPSIS technique for failure mode ranking, rendering the evaluation more comprehensive. Dhalmahapatra et al. [40] presented a similar argument, adding anticipated maintenance cost as a new risk factor and pointed out that the uncertainty and imprecision related to expert opinions could lead to inaccuracies in failure mode prioritization. Thus, the Double Upper Approximated Rough Number (DUARN), Full Consistency Method (FUCOM), and TOPSIS were considered to improve RPN outcomes.

Başhan, Demirel, and Gul [33] accounted for the risks encountered during ship navigation and determined priorities through FMEA-based TOPSIS, eventually incorporating sensitivity analysis to identify risk rankings. Lastly, Wang et al. [41] refined the concept concerning the interactions among failure modes on RPN. The new approach considered the initial strength of failure modes on risk propagation, ensuring the accuracy of RPN.

Moslem et al. [42] proposed an improved FMEA model that employs the Fuzzy Best–Worst Method (FBWM) for weighting parameters and utilizes the Fuzzy Bayesian Network (FBN) to establish a system based on fuzzy rules to mitigate the drawbacks of RPN. Acknowledging the fuzziness of human judgments, Liu and Li [43] introduced an approach that considers the risk attitudes of experts, based on the consideration of loss to the entire system, which can easily encompass aversion or avoidance sentiments. The study acknowledged that experts from different domains and departments possess varying knowledge structures and professional backgrounds. By integrating risk attitudes into the FMEA model, the study developed the K-means clustering method to categorize experts based on their FMEA evaluations. From a collective consensus perspective, an expert weight calculation model was built based on the proposed similarity formula, which can enhance the efficiency of risk assessment and ensure fairness and reasonability in valuing FMEA experts' opinions. Moreover, considering the emotion of regret avoidance, a combined RT-PROMETHEE II final ranking method was proposed.

Wang, Liu, Chen, and Qin [8] shared a similar perspective, noting that traditional FMEA overlooks the psychological behaviors of experts and the uncertainty of risk factors. In the model developed in their study, generalized trapezoidal fuzzy numbers were used to describe the uncertainty in risk analysis. An improved weighted arithmetic averaging operator of GTrFN (GTrFN-WAA) based on similarity measures was constructed to aggregate expert risk assessment information, effectively obtaining more reasonable risk assessment results. Liu et al. [44] integrated the Hesitant Fuzzy Set theory into the analysis methods (BWM and Weighted Aggregated Sum Product Assessment, WASPAS), considering experts' uncertainty during the evaluation process. Boral et al. [45] indicated that the fuzzy MADM methods most integrated with FMEA are TOPSIS, VIKOR, COPRAS, and MOORA, demonstrating the ongoing pursuit in the literature to address the inherent limitations of traditional FMEA and strive for more precise, nuanced, and comprehensive risk assessment methodologies.

This study, anchored on a steel-plate-cutting factory, identifies a lacuna in the existing literature regarding the analysis and attention towards operational risk factors associated with steel-plate-cutting factories. Hence, this research focuses on minimizing raw material wastage, reducing the operational costs of enterprises, and reviewing the risk analysis literature alongside FMEA to ascertain the research methodology.

A novel method termed PCIM-MADM (Process Capability Index Measurement-Multi-Attribute Decision Making) is employed in this research to identify and rank the risk factors leading to raw material wastage and operational costs. Recommendations are proffered to mitigate the highest risks, contributing to the existing body of knowledge.

The primary distinctions between this study and related research are outlined here, as follows:

- Previous studies need to address or discuss the risks inherent in the cutting process of steel-plate-cutting factories. This research, therefore, centers on this niche, targeting the reduction in raw material wastage and operational costs of enterprises. It delves into the major failure modes in the operations of steel-plate-cutting factories, identifying the modes requiring priority consideration and improvement, making the findings applicable in practice.
- The PCIM-MADM method is utilized for ranking, diverging from traditional FMEA risk assessment studies. Following the suggestions of Lo et al. [46], the incorporation of anticipated cost (E) significantly enhances the reliability of risk assessment. By amalgamating various MADM techniques, failure modes are ranked, thus offering

a fresh perspective on prioritizing and addressing operational risks in steel-plate-cutting factories.

3.3. Determining the Influential Weights Using DEMATEL

The DEMATEL method originated from the Battelle Memorial Association at the Geneva Research Center, as proposed by [47], to examine the interrelationships among the factors in intricate evaluation systems. The values assigned to these factors determine their significance in the overall evaluation framework. For the DEMATEL implementation procedure, please refer to [47]. For related research on DEMATEL, please refer to Section 2.

3.4. Using the SAW, VIKOR, GRA, and COPRAS Methods to Obtain the Rankings of the Failure Modes

The risk scores and rankings of failure modes are calculated using methods such as SAW, VIKOR, GRA, and COPRAS. These are then integrated through PCIM-MADM. For the calculation procedures of VIKOR, GRA, and COPRAS, please refer to Lo et al. [48].

3.5. PCIM-MADM

In the context of evaluation or selection, different MADM methods might generate different sorting results for the alternatives. If all alternative rankings are the same for the different MADM methods, then the decision-making process is simple; however, such results are rare. Furthermore, as the number of criteria or alternatives in the problem increases, the ranking results obtained with the different MADM methods become increasingly inconsistent [49], because each MADM method applies a different logic to rank the alternatives. As a consequence, risk managers are forced to integrate multiple MADM methods to obtain a comprehensive result.

In this study, four MADM methods—based on the utility function, gap ratio, and concepts of similarity, but using different approaches—are applied to rank the alternatives. However, an appropriate integration method is essential to determine the final utility degree for each alternative. The proposed integrated model can assist risk managers to make more comprehensive decisions in the ranking of failure modes.

The detailed steps of integrated multiple MADM methods are as follows:

Step 1: The failure mode scores are converted to an index between 0 and 1

The ranking indexes of SAW, VIKOR, GRA, and COPRAS are denoted by SAW_h, Q_h, GRA_h, and C_h, respectively. Because VIKOR's ranking index is better when smaller, we convert it to a benefit index $(1 - Q_h)$.

Step 2: Obtain the z^+ and z^- (maximum and minimum scores for each column)

Obtain the maximum and minimum scores (z^+ and z^-) for all failure modes from each method, as follows:

$$z^+ = \max_h\{SAW_h, Q_h, GRA_h, C_h\} = \{z_1^+, z_2^+, z_3^+, z_4^+\} \tag{1}$$

$$z^- = \min_h\{SAW_h, Q_h, GRA_h, C_h\} = \{z_1^-, z_2^-, z_3^-, z_4^-\} \tag{2}$$

Step 3: Calculate the distance between each failure mode and z^+ and z^-

The distance of each failure mode from the positive (z^+) and negative (z^-) ideal solutions (denoted as PIS and NIS, respectively) can be calculated as follows:

$$\alpha_h^+ = \sqrt{(SAW_h - z_1^+)^2 + (Q_h - z_2^+)^2 + (GRA_h - z_3^+)^2 + (C_h - z_4^+)^2},\ h = 1,\ 2, \ldots,\ m; \tag{3}$$

$$\alpha_h^- = \sqrt{(SAW_h - z_1^-)^2 + (Q_h - z_2^-)^2 + (GRA_h - z_3^-)^2 + (C_h - z_4^-)^2},\ h = 1,\ 2, \ldots,\ m. \tag{4}$$

Step 4: Generate the final ranking index

The FRI_i is a reliable ranking index that defines the standard for the final ranking. For the ranking index in the proposed model, we consider the separation distance from the positive ideal solution and negative ideal solution for four MADM methods, formulated as follows:

$$FRI_h = \left(\alpha_h^- / \sum_{h=1}^{m} \alpha_h^-\right) - \left(\alpha_h^+ / \sum_{h=1}^{m} \alpha_h^+\right), -1 \le FRI_h \le 1. \quad (5)$$

4. Results

This study utilizes a sample case of a specific company, employing the PCIM-MADM model introduced in Section 3 to examine the critical risk factors found in the steel-cutting process within the steel-cutting factory under investigation. Through meticulous analysis for identification and ranking, the study aims to devise apt preventative measures and strategies. The anticipated outcome is to effectively reduce the operational costs, achieve proactive prevention, minimize the occurrence of issues, and enhance the long-term financial viability and market competitiveness of the enterprise.

4.1. Algorithm Execution and Analysis

In this study, the research process is bifurcated into two steps. The initial step involves engaging experts from the cutting department with over a decade of operational experience to identify the failure modes. These experts provide practical observations and insights, sharing their experiences of issues encountered during the cutting process or instances that could lead to product inaccuracies. Following a comprehensive discussion among the experts, 16 failure modes were identified, as delineated in Table 2. These encompass the following: steel plate deformation (FM1), excessive internal holes in steel plate (FM2), incorrect exterior processing dimensions (FM3), flatness/perpendicularity exceeding tolerances (FM4), automatic feeding equipment malfunction (FM5), mismatch in production control handover and business information (FM6), client/order-taking window oversight (FM7), cutting equipment failure (FM8), saw blade breakage (FM9), cutter breakage anomaly (FM10), inadequate packaging and delivery (FM11), excessive residual material production (FM12), tool clamping (FM13), tool arm malfunction (FM14), saw blade wheel/wheel shaft eccentricity (FM15), and tungsten steel seat clamp too loose/tight (FM16). The fault diagrams are shown in Figures 1–15.

Figure 1. Steel Plate Surface Deformation (Arrows indicating the deformation area).

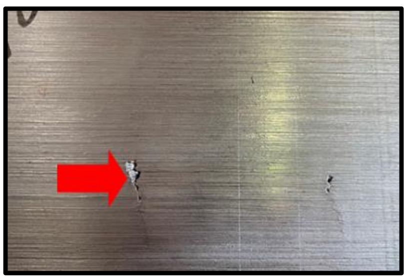


Figure 2. Schematic of Holes in Steel Plate.

Table 2. Average influence matrix.

Failure Mode	Description	Possible Causes	Figure Reference
FM1	Surface Deformation of Steel Plate	Excessive clamp pressure, leading to extrusion and uneven steel plate surface	Figure 1
FM2	Excessive Internal Holes in Steel Plate	Upstream material factors and insufficient rolling ratio during raw material production, leading to the formation of air or sand holes internally	Figure 2
FM3	Incorrect Dimensioning in Exterior Processing, Non-conformity in Workpiece Dimensions	Misinterpretation of order dimensions by on-site operators, leading to non-conformity in processing dimensions	Figure 3
FM4	Workpiece Precision Deviation, Flatness/Perpendicularity exceeding tolerances	Machines not calibrated for an extended period, leading to cutting position displacement	Figure 4
FM5	Automatic Feeding Equipment Malfunction, Abnormal Cutting Position, Inaccurate Calibration/Positioning	Linear rail/screw rail failure	Figure 5
FM6	Mismatch in Workpiece Dimensions with Production Control Handover and Business Information	Communication lapse among production control, business, and on-site workers, leading to misinformation during handover	N/A
FM7	Client/Order-taking Window Oversight, Non-conformity in Workpiece Dimensions	Client/order-taking window oversight without re-confirming order details, leading to erroneous order content	N/A
FM8	Hydraulic Oil Pipeline Abnormality, Elevated Cutting Rate	Oil pipe leakage, leading to increased cutting rate, possibly resulting in insufficient workpiece dimensions	Figure 6
FM9	Saw Blade Breakage	Wear and tear or aging of the saw blade or usage of incorrect saw blade	Figure 7
FM10	Saw Blade Teeth Damage	Wear and tear or aging of the saw blade or usage of incorrect saw blade	Figure 8
FM11	Inadequate Packaging and Delivery, leading to Workpiece Wear or Damage	Absence of standard SOP or staff education, resulting in drivers or shipping personnel not packaging the workpieces adequately	Figure 9
FM12	Excessive Residual Material Production	Lack of detailed optimal cutting plan setting	Figure 10
FM13	Steel Plate Clamping onto the Tool during Cutting Process	Machine bed unevenness with height differences	Figures 11 and 12
FM14	Tool Arm Malfunction	1. Long-term operation at machine limits, leading to tool arm offset 2. Unaddressed human-induced collisions	Figure 13
FM15	Saw Blade Wheel/Wheel Shaft Eccentricity	Improper operation and long-term usage without wheel replacement, leading to wheel eccentricity or even wheel shaft displacement	Figure 14
FM16	Tungsten Steel Seat Clamp too Loose/Tight	1. Consumables not replaced in time 2. Hydraulic inaccuracy 3. On-site operator procedural errors	Figure 15

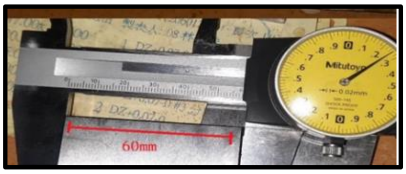


Figure 3. Schematic of Dimensional Error Due to Misreading Order (Order dimension is 58 mm, but actual measurement is 60 mm).

Figure 4. Schematic of Planarity/Perpendicularity Exceeding Tolerance.

Figure 5. Schematic of Linear Slide Rail/Screw Rail Failure (Box highlights the slide rail).

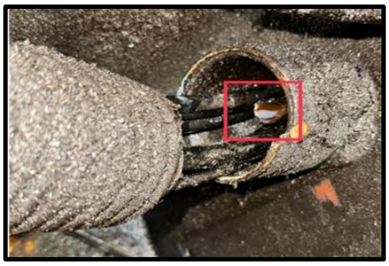


Figure 6. Schematic of Hydraulic Oil Pipeline Anomaly (Box highlights the rupture area in the pipeline).

Figure 7. Schematic of Saw Blade Breakage (Arrow indicates the breakage area).

Figure 8. Schematic of Saw Blade Tooth Damage.

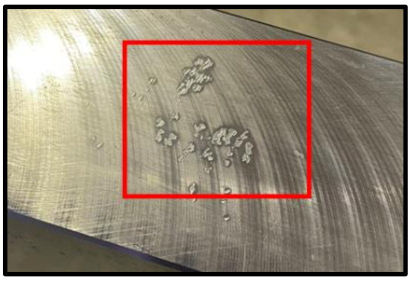


Figure 9. Schematic of Workpiece Damage Due to Inadequate Packaging (Box highlights the damage area).

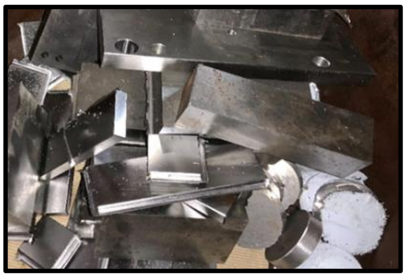


Figure 10. Schematic of Excess Material.

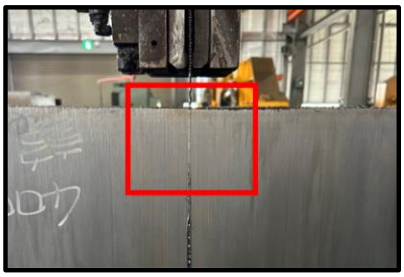


Figure 11. Schematic of Tool Clamping (Box highlights the clamping area).

Figure 12. Schematic of Uneven Bed.

Figure 13. Schematic of Tool Arm.

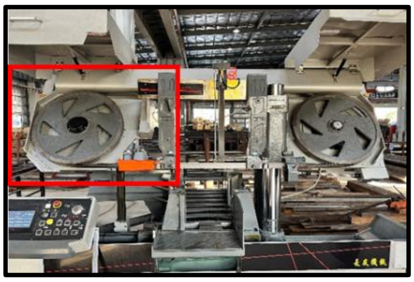


Figure 14. Schematic of Saw Blade Wheel (Box highlights the saw blade wheel).

Figure 15. Schematic of Tungsten Carbide Seat.

The second phase entails applying the PCIM-MADM methodology that Lo and Liou et al. (2021) [48] proposed to rank the failure modes. Ten experts were enlisted to assess the levels of severity (S), occurrence (O), detection (D), and anticipated cost (E) when such failure modes occur. Posing the following questions to the experts facilitated the assessment:

- What is the severity level post-occurrence of the failure mode?
- What is the probability of occurrence for this failure mode?
- How feasible is it to detect this failure mode prior to its occurrence?
- What are the costs associated with repair or loss when this failure mode occurs?

This study involves a case analysis of Company H, which specializes in steel plate cutting. For this research, we selected 10 experts from the company, each with over a decade of experience in the steel industry. Table 3 presents the background of the experts in this study, detailing their respective positions and years of experience in the steel industry. Table 4 provides a detailed breakdown of the individual risk assessment scores for various failure modes (FM_1 to FM_{16}), as evaluated by a panel of ten experts. These scores are categorized under four key risk criteria. Each expert's assessment is represented numerically, with their scores arranged sequentially from the first to the tenth expert, moving from left to right. This arrangement allows for a comprehensive comparison of the perspectives across the different experts regarding the risk associated with each failure mode. The table is a critical tool for analyzing the variance in risk perception among the experts. Such variance highlights the subjective nature of risk assessment and underscores the importance of incorporating a diverse range of expert opinions. Aggregating these individual assessments will form the basis for calculating a consolidated RPN for each failure mode, guiding strategic decisions to mitigate risks effectively in the manufacturing process. The insights gathered from Table 4 are instrumental in identifying the most critical failure modes that require immediate attention, thereby contributing to the development of targeted risk mitigation strategies. This detailed expert evaluation is crucial for enhancing the reliability and safety of the manufacturing process under study. The initial data were generated by averaging the sum of the responses from the ten experts, as illustrated in Table 5.

Table 3. Experts' background.

Expert No.	Department	Position	Years of Experience
1	Management	Chairman	30
2	Management	Manager	22
3	Management	Plant Manager	25
4	Management	Assistant Plant Manager	17
5	Sales	Sales Manager	23
6	Sales	Senior Sales	13
7	Sales	Senior Sales	15
8	Cutting	Team Leader	11
9	Cutting	Team Leader	19
10	Cutting	Senior Technician	24

Table 4. Individual risk assessment scores by the experts.

Failure Mode	S	O	D	E
FM_1	(5, 3, 6, 7, 6, 6, 6, 4, 5, 5)	(6, 2, 6, 2, 3, 2, 4, 4, 3, 4)	(6, 2, 3, 2, 3, 2, 4, 3, 4, 4)	(4, 3, 4, 6, 4, 4, 3, 3, 4, 3)
FM_2	(7, 5, 9, 9, 9, 8, 5, 8, 9, 7)	(3, 1, 2, 1, 1, 2, 2, 2, 3, 3)	(5, 9, 7, 9, 8, 5, 8, 8, 9, 7)	(5, 9, 6, 6, 6, 8, 6, 8, 7, 7)
FM_3	(6, 7, 9, 10, 10, 6, 8, 6, 7, 6)	(6, 3, 3, 3, 6, 4, 6, 6, 6, 5)	(5, 6, 3, 7, 5, 3, 4, 4, 4, 3)	(4, 6, 7, 5, 5, 5, 4, 3, 5, 5)
FM_4	(7, 7, 7, 4, 7, 7, 7, 5, 7, 4)	(6, 3, 3, 5, 5, 4, 3, 6, 4, 5)	(4, 6, 3, 3, 2, 4, 5, 4, 3, 3)	(4, 7, 4, 5, 4, 7, 3, 3, 5, 4)
FM_5	(5, 3, 4, 5, 2, 6, 2, 3, 5, 3)	(3, 2, 1, 3, 2, 2, 2, 4, 3, 2)	(7, 3, 3, 3, 7, 3, 7, 7, 3, 4)	(4, 3, 6, 2, 2, 3, 3, 4, 2, 4)
FM_6	(4, 5, 8, 8, 8, 5, 6, 4, 6, 6)	(6, 3, 4, 2, 2, 4, 4, 4, 6, 3)	(7, 3, 3, 3, 3, 3, 7, 7, 5, 4)	(4, 7, 4, 4, 7, 7, 5, 7, 6, 5)
FM_7	(4, 4, 9, 9, 9, 5, 6, 4, 6, 6)	(6, 5, 4, 4, 2, 4, 4, 3, 6, 3)	(7, 3, 3, 3, 3, 4, 6, 7, 5, 4)	(4, 4, 6, 4, 8, 7, 5, 8, 4, 5)
FM_8	(4, 2, 5, 5, 2, 2, 4, 2, 3, 4)	(4, 2, 2, 1, 2, 2, 3, 4, 2, 2)	(7, 9, 9, 3, 8, 3, 7, 9, 4, 6)	(4, 3, 7, 4, 3, 3, 6, 5, 5, 4)
FM_9	(3, 2, 5, 4, 2, 2, 6, 2, 3, 2)	(2, 2, 1, 3, 4, 1, 2, 4, 3, 2)	(7, 3, 8, 3, 8, 3, 8, 8, 3, 4)	(3, 4, 4, 5, 4, 3, 5, 2, 5, 4)
FM_{10}	(3, 2, 3, 4, 3, 1, 5, 2, 3, 2)	(6, 2, 3, 3, 5, 2, 2, 4, 3, 3)	(5, 3, 7, 3, 7, 2, 5, 3, 3, 3)	(3, 2, 5, 5, 3, 2, 4, 2, 4, 3)
FM_{11}	(6, 2, 6, 5, 6, 2, 3, 5, 2, 4)	(5, 3, 3, 3, 6, 3, 4, 4, 4, 3)	(6, 3, 2, 2, 6, 2, 6, 3, 2, 2)	(3, 3, 7, 5, 4, 6, 5, 3, 6, 5)
FM_{12}	(6, 4, 7, 7, 3, 4, 3, 6, 5, 4)	(8, 4, 6, 4, 8, 4, 8, 5, 7, 5)	(3, 3, 2, 2, 2, 3, 6, 5, 2, 2)	(6, 2, 6, 5, 4, 5, 2, 3, 3, 3)
FM_{13}	(4, 2, 6, 4, 2, 3, 6, 2, 4, 3)	(5, 2, 2, 4, 3, 2, 6, 3, 4, 3)	(6, 3, 6, 3, 8, 3, 4, 8, 3, 5)	(4, 2, 6, 5, 2, 3, 3, 2, 2, 3)
FM_{14}	(4, 2, 6, 4, 2, 2, 6, 2, 4, 4)	(6, 2, 2, 4, 2, 2, 6, 3, 4, 3)	(7, 3, 7, 3, 8, 3, 3, 8, 3, 5)	(3, 2, 6, 5, 2, 2, 4, 3, 3, 4)
FM_{15}	(3, 3, 6, 4, 2, 2, 6, 2, 6, 4)	(5, 2, 2, 3, 1, 1, 5, 3, 2, 2)	(6, 3, 7, 3, 8, 3, 4, 8, 4, 5)	(3, 3, 7, 5, 4, 2, 3, 3, 5, 3)
FM_{16}	(4, 2, 6, 4, 5, 2, 6, 2, 6, 2)	(5, 2, 2, 3, 3, 1, 5, 2, 2, 3)	(6, 3, 7, 3, 3, 3, 4, 7, 4, 4)	(4, 3, 7, 5, 3, 3, 4, 3, 3, 3)

Four MADM methods (SAW, VIKOR, GRA, and COPRAS) were employed to analyze the failure modes after confirmation of the initial data. However, the diverging computational logic used by these methods led to discrepancies in the numerical values. To avoid significant differences in numbers that might change the final PCIM-MADM results, a normalization process was used with a set formula to ensure that each method's results were on the same scale, which went from 0 to 1. The normalization process is instrumental in eliminating numerical disparities among different methods, ensuring a uniform scale for comparison and integration. In this way, the study can look at all of the results from all of the different methods and add them to PCIM-MADM to make more accurate and reliable decisions.

Table 5. Initial data.

Failure Mode	S	O	D	E
Wi	0.213	0.215	0.258	0.313
FM_1	5.300	3.600	3.300	3.800
FM_2	7.700	3.500	7.500	6.800
FM_3	7.500	4.800	4.400	4.900
FM_4	6.200	4.400	3.700	4.600
FM_5	3.800	2.400	4.700	3.300
FM_6	6.000	3.800	4.500	5.600
FM_7	6.200	4.100	4.500	5.500
FM_8	3.300	2.400	6.500	4.400
FM_9	3.100	2.400	5.500	3.900
FM_{10}	2.800	3.300	4.100	3.300
FM_{11}	4.100	3.800	3.400	4.700
FM_{12}	4.900	5.900	3.000	3.900
FM_{13}	3.600	3.400	4.900	3.200
FM_{14}	3.600	3.400	5.000	3.400
FM_{15}	3.800	2.600	5.100	3.800
FM_{16}	3.900	2.800	4.400	3.800

4.2. SAW

In the SAW method, this study necessitates an initial normalization process to ensure that the scores of the different risk factors are comparable. The risk factors in this study are all benefit criteria. Therefore, in the first step, the initial data are divided by the maximum value, Max (Xij), in the initial data to obtain the normalized evaluation matrix. The maximum value in this data is 7.70, and the data post-normalization can be seen in Table 6. This step allows for the scores of each risk factor to range between 0 and 1.

Table 6. SAW weighted normalized evaluation matrix.

Failure Mode	S	O	D	E	SAW_h
FM_1	0.149	0.102	0.112	0.157	0.519
FM_2	0.213	0.057	0.255	0.280	0.805
FM_3	0.210	0.136	0.149	0.202	0.698
FM_4	0.174	0.125	0.126	0.190	0.614
FM_5	0.107	0.068	0.160	0.136	0.470
FM_6	0.168	0.108	0.153	0.231	0.660
FM_7	0.174	0.116	0.153	0.227	0.670
FM_8	0.093	0.068	0.221	0.181	0.563
FM_9	0.087	0.068	0.187	0.161	0.503
FM_{10}	0.079	0.094	0.139	0.136	0.447
FM_{11}	0.115	0.108	0.115	0.194	0.532
FM_{12}	0.138	0.167	0.102	0.161	0.567
FM_{13}	0.101	0.096	0.166	0.132	0.496
FM_{14}	0.101	0.096	0.170	0.140	0.507
FM_{15}	0.107	0.074	0.173	0.157	0.510
FM_{16}	0.109	0.079	0.149	0.157	0.495

4.3. VIKOR

Similar to SAW, VIKOR also necessitates the normalization of the initial data. However, there is a variation in the method. VIKOR normalizes by dividing the initial data by the maximum and minimum values found within the initial data. This differs slightly from the normalization technique employed in SAW, but the ultimate objective is still to ensure comparability among the different risk factors. In the initial data, the maximum value is 7.70, while the minimum is 2.40. The values post-normalization via the VIKOR method are presented in Table 7.

Table 7. VIKOR weighted normalized evaluation matrix.

Failure Mode	S	O	D	E	S_j	R_j
FM_1	0.088	0.154	0.198	0.212	0.652	0.212
FM_2	0.000	0.215	0.005	0.045	0.265	0.215
FM_3	0.004	0.108	0.147	0.151	0.410	0.151
FM_4	0.053	0.123	0.180	0.168	0.524	0.180
FM_5	0.145	0.200	0.134	0.240	0.719	0.240
FM_6	0.061	0.146	0.143	0.112	0.462	0.146
FM_7	0.053	0.135	0.143	0.117	0.448	0.143
FM_8	0.164	0.200	0.051	0.179	0.593	0.200
FM_9	0.171	0.200	0.097	0.207	0.675	0.207
FM_{10}	0.183	0.165	0.161	0.240	0.750	0.240
FM_{11}	0.133	0.146	0.194	0.162	0.635	0.194
FM_{12}	0.103	0.065	0.212	0.207	0.587	0.212
FM_{13}	0.152	0.162	0.124	0.246	0.684	0.246
FM_{14}	0.152	0.162	0.120	0.235	0.669	0.235
FM_{15}	0.145	0.192	0.115	0.212	0.665	0.212
FM_{16}	0.141	0.185	0.147	0.212	0.686	0.212

The second step is multiplying the normalized decision matrix by the corresponding weights. Then, the weighted scores for all of the failure modes are combined to obtain the aggregate benefit Sj and individual regret Rj values. The aggregate benefit refers to the overall effect of considering all of the risk factors, evaluating each failure mode's performance across multiple risk factors, essentially representing the disparity of the failure mode from the worst-case scenario under each risk factor. A more considerable aggregate benefit indicates that the failure mode requires less immediate consideration. On the other hand, individual regret reflects the level of performance adequacy of each failure mode under the risk factors.

It is understood that the Sj value is the sum of the weighted scores, while the Rj value is the maximum value among the four risk factors for each failure mode. For instance, in the case of FM1, the Sj value is 0.088 + 0.154 + 0.198 + 0.212 = 0.652, and the Rj value is 0.212. Ultimately, the final comprehensive indicator Qi value—also denoted as Qh—is calculated. The computation process is detailed in Table 8.

Table 8. VIKOR composite index.

Failure Mode	Si	R	$V \times S$	$(1-V) \times R$	$Qj(Q_h)$
FM_1	0.652	0.212	0.399	0.337	0.737
FM_2	0.265	0.215	0.000	0.352	0.352
FM_3	0.410	0.151	0.150	0.039	0.189
FM_4	0.524	0.180	0.267	0.179	0.446
FM_5	0.719	0.240	0.468	0.473	0.941
FM_6	0.462	0.146	0.203	0.016	0.219
FM_7	0.448	0.143	0.189	0.000	0.189
FM_8	0.593	0.200	0.339	0.277	0.616
FM_9	0.675	0.207	0.423	0.310	0.733
FM_{10}	0.750	0.240	0.500	0.473	0.973
FM_{11}	0.635	0.194	0.382	0.246	0.628
FM_{12}	0.587	0.212	0.332	0.335	0.667
FM_{13}	0.684	0.246	0.432	0.500	0.932
FM_{14}	0.669	0.235	0.416	0.446	0.862
FM_{15}	0.665	0.212	0.412	0.337	0.750
FM_{16}	0.686	0.212	0.434	0.337	0.771

4.4. GRA

The first step in the GRA calculation is to classify the criteria into cost or benefit criteria, after which their normalization occurs. We formalize the benefit criteria to obtain the normalized evaluation matrix. This is because all of the criteria in the study are benefit criteria.

In the second step, we utilize the best solution and the comparison solution to calculate the gray correlation distance. As all of the values have been normalized, they all fall within the range of 0–1, thereby making the maximum value 1. Subsequently, we consider the relationship between gray correlation distance to find the gray correlation coefficient, where ξ is the distinguishing coefficient. In this study, $\xi = 0.5$ is used in the formula to derive the grey relational coefficient, as illustrated in Table 9.

Table 9. GRA grey relational distance.

Failure Mode	S	O	D	E
FM_1	0.411	0.714	0.768	0.679
FM_2	0.000	1.000	0.018	0.143
FM_3	0.018	0.500	0.571	0.482
FM_4	0.250	0.571	0.696	0.536
FM_5	0.679	0.929	0.518	0.768
FM_6	0.286	0.679	0.554	0.357
FM_7	0.250	0.625	0.554	0.375
FM_8	0.768	0.929	0.196	0.571
FM_9	0.804	0.929	0.375	0.661
FM_{10}	0.857	0.768	0.625	0.768
FM_{11}	0.625	0.679	0.750	0.518
FM_{12}	0.482	0.304	0.821	0.661
FM_{13}	0.714	0.750	0.482	0.786
FM_{14}	0.714	0.750	0.464	0.750
FM_{15}	0.679	0.893	0.446	0.679
FM_{16}	0.661	0.857	0.571	0.679

We utilize it to compute the grey relational grade upon obtaining the grey relational coefficient. For instance, for FM1, the value of GRAh is computed as follows: $(0.549 \times 0.213) + (0.412 \times 0.215) + (0.394 \times 0.258) + (0.424 \times 0.313) = 0.440$ $(0.549 \times 0.213) + (0.412 \times 0.215) + (0.394 \times 0.258) + (0.424 \times 0.313) = 0.440$. The values of the grey relational grade are displayed in Table 10.

Table 10. GRA grey relational degree.

Failure Mode	S	O	D	E	GRA_h
FM_1	0.117	0.089	0.102	0.133	0.440
FM_2	0.213	0.072	0.249	0.244	0.778
FM_3	0.206	0.108	0.120	0.159	0.594
FM_4	0.142	0.101	0.108	0.151	0.502
FM_5	0.090	0.075	0.127	0.123	0.416
FM_6	0.136	0.091	0.122	0.183	0.532
FM_7	0.142	0.096	0.122	0.179	0.539
FM_8	0.084	0.075	0.185	0.146	0.491
FM_9	0.082	0.075	0.147	0.135	0.440
FM_{10}	0.079	0.085	0.115	0.123	0.402
FM_{11}	0.095	0.091	0.103	0.154	0.443
FM_{12}	0.109	0.134	0.098	0.135	0.475

4.5. COPRAS

The underlying principle of COPRAS closely aligns with that of SAW. However, COPRAS refines the SAW methodology by obviating the prerequisite of unifying the attributes of the criteria into either benefit or cost criteria before normalization. Contrarily, COPRAS ameliorates this facet, permitting the criteria to undergo normalization based on their respective attributes and executing multiplicative operations with the corresponding criterion weights. This process culminates in aggregating the results of identical attributes to yield S+ and S− values for each failure mode. The normalization procedure used in COPRAS entails the summation of each risk factor individually, followed by division with the original data. This study categorizes all four of the risk factors (S, O, D, and E) as benefit criteria. Illustratively, for failure mode FM1, the normalized S is derived as 5.3/(5.3 + 7.6 + 7.5. . .3.8 + 3.9) = 0.07, and the S+ for FM1 is computed as 0.015 + 0.014 + 0.011 + 0.017 = 0.058, while S- remains invariably at 0. The computations for the subsequent failure modes adhere to this delineated pattern (Table 11).

Table 11. COPRAS weighted normalized evaluation matrix.

Failure Mode	S	O	D	E	S^+	S^-	C_h
FM_1	0.015	0.014	0.011	0.017	0.058	0	0.058
FM_2	0.021	0.008	0.026	0.031	0.086	0	0.086
FM_3	0.021	0.019	0.015	0.022	0.077	0	0.077
FM_4	0.017	0.017	0.013	0.021	0.068	0	0.068
FM_5	0.011	0.009	0.016	0.015	0.051	0	0.051
FM_6	0.017	0.015	0.016	0.025	0.073	0	0.073
FM_7	0.017	0.016	0.016	0.025	0.074	0	0.074
FM_8	0.009	0.009	0.023	0.020	0.061	0	0.061
FM_9	0.009	0.009	0.019	0.018	0.055	0	0.055
FM_{10}	0.008	0.013	0.014	0.015	0.050	0	0.050
FM_{11}	0.012	0.015	0.012	0.021	0.060	0	0.060
FM_{12}	0.014	0.023	0.010	0.018	0.065	0	0.065
FM_{13}	0.010	0.013	0.017	0.015	0.055	0	0.055
FM_{14}	0.010	0.013	0.017	0.015	0.056	0	0.056
FM_{15}	0.011	0.010	0.018	0.017	0.056	0	0.056
FM_{16}	0.011	0.011	0.015	0.017	0.054	0	0.054

In the calculations within COPRAS, this study aims to compute the C_h index in order to evaluate the priority order of failure modes. The C_h index is the result of subtracting S^- from S^+. Based on the C_h index, this study can assess the priority order of the failure modes. A higher index indicates that, under the calculations of COPRAS, the respective failure mode requires earlier attention and handling.

4.6. PCIM

Table 12 consolidates the normalized results and rankings obtained from the four MADM methods, with a noteworthy modification in the VIKOR method, where the characteristic of "the smaller, the better" is converted to "the larger, the better" (1 − Qh). It is observable from the table that each MADM method yields a different order of failure modes. This study employs PCIM-MADM, which integrates the four MADM methods to garner a more comprehensive assessment result. Utilizing Equations (1) to (5), the distances of the four methods to the positive and negative ideal solutions are calculated, providing the final rankings, as seen in Table 13. The analysis results elucidate a descending order of evaluation results as follows: FM2 > FM3 > FM7 > FM6 > FM4 > FM12 > FM8 > FM11 > FM1 > FM15 > FM9 > FM16 > FM14 > FM13 > FM5 > FM10. The delineation of failure modes facilitates the identification of priority order and resource allocation, enabling decision makers to focus on addressing the most critical failure modes. The ranking results also clearly indicate which failure modes may impact the cutting process or product stability, thus offering a robust basis for targeted management strategies.

Table 12. Consolidation table of four MADM methods.

Method	**SAW**		**VIKOR**		**GRA**		**COPRAS**	
Failure Mode	SAW_h	**Rank**	$1 - Q_h$	**Rank**	GRA_h	**Rank**	C_h	**Rank**
FM_1	0.202	9	0.301	10	0.103	9	0.214	9
FM_2	1.000	1	0.792	4	1.000	1	1.000	1
FM_3	0.701	2	1.000	1	0.510	2	0.759	2
FM_4	0.466	5	0.672	5	0.266	5	0.509	5
FM_5	0.064	15	0.041	15	0.038	15	0.038	15
FM_6	0.594	4	0.961	3	0.347	4	0.631	4
FM_7	0.622	3	1.000	2	0.366	3	0.667	3
FM_8	0.323	7	0.455	6	0.237	6	0.310	7
FM_9	0.154	12	0.306	9	0.101	10	0.136	13
FM_{10}	0.000	16	0.000	16	0.000	16	0.000	16
FM_{11}	0.237	8	0.440	7	0.110	8	0.265	8
FM_{12}	0.336	6	0.390	8	0.195	7	0.415	6
FM_{13}	0.135	13	0.052	14	0.068	13	0.137	12
FM_{14}	0.168	11	0.142	13	0.083	12	0.172	10
FM_{15}	0.176	10	0.285	11	0.094	11	0.161	11
FM_{16}	0.133	14	0.258	12	0.061	14	0.123	14

Table 13. PCIM-MADM results.

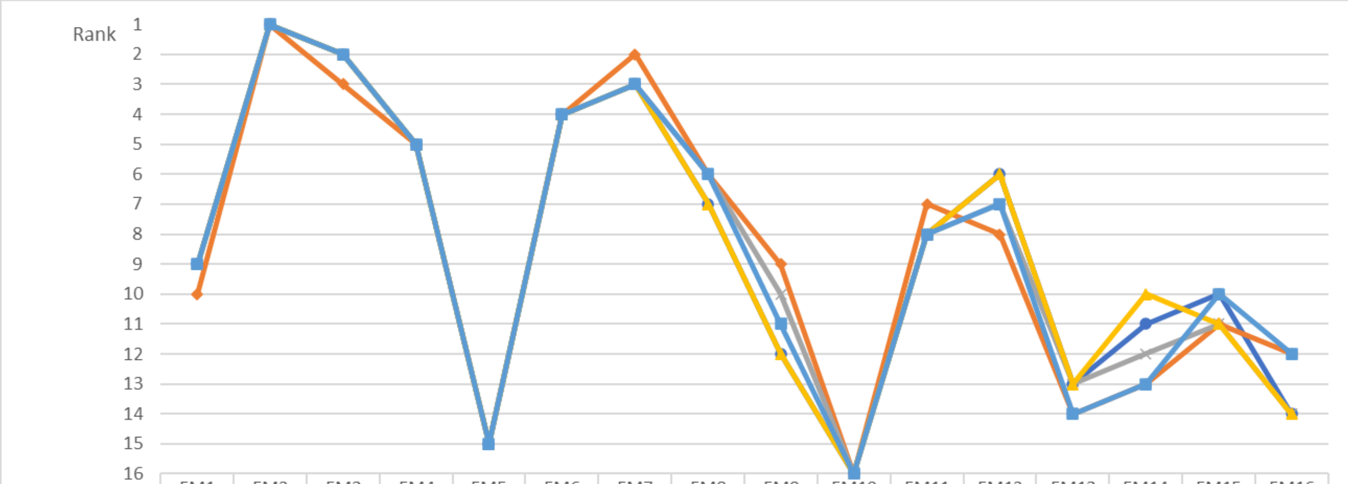
Failure Mode	**Normalized** $\alpha_h{}^+$	**Normalized** $\alpha_h{}^-$	FRI_h	**Rank**
FM_1	0.073	0.039	−0.035	9
FM_2	0.010	0.170	0.160	1
FM_3	0.029	0.136	0.107	2
FM_4	0.050	0.089	0.039	5
FM_5	0.088	0.008	−0.079	15
FM_6	0.039	0.119	0.080	4
FM_7	0.037	0.125	0.088	3
FM_8	0.062	0.061	−0.001	7
FM_9	0.076	0.034	−0.042	11
FM_{10}	0.092	0.000	−0.092	16
FM_{11}	0.068	0.051	−0.017	8
FM_{12}	0.062	0.061	0.000	6
FM_{13}	0.083	0.019	−0.064	14
FM_{14}	0.079	0.026	−0.053	13
FM_{15}	0.076	0.034	−0.041	10
FM_{16}	0.079	0.029	−0.050	12

Further research will analyze the top five failure modes in order to reduce risks while cutting through the recommended improvement measures. The top five failure modes are identified as excessive hole occurrences in plates (FM2), incorrect external processing dimensions (FM3), lapses in customer-side/order window (FM7), discrepancies between production control handover work order content and business information (FM6), and deviations in flatness/verticality beyond the specified tolerances (FM4). The research aims to enhance operational efficiency and product quality through detailed analysis and implementation of corrective strategies for these predominant failure modes, thereby fostering a more resilient and competitive manufacturing operation.

4.7. Comparison of Research Method

Figure 16 presents a comparative graph among the five methods. The graph illustrates that the top five failure modes identified by four different MADM methods are as follows: excessive hole punctures (FM2), incorrect dimension processing (FM3), customer/order window negligence (FM7), mismatch between production control handover work order and business information (FM6), and flatness/perpendicularity exceeding tolerance (FM4). The ranking results are as follows:

- SAW Ranking: FM2 > FM3 > FM7 > FM6 > FM4.
- VIKOR Ranking: FM2 > FM7 > FM3 > FM6 > FM4.
- GRA Ranking: FM2 > FM3 > FM7 > FM6 > FM4.
- COPRAS Ranking: FM2 > FM3 > FM7 > FM6 > FM4.



	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9	FM10	FM11	FM12	FM13	FM14	FM15	FM16
SAW	9	1	2	5	15	4	3	7	12	16	8	6	13	11	10	14
VIKOR	10	1	3	5	15	4	2	6	9	16	7	8	14	13	11	12
GRA	9	1	2	5	15	4	3	6	10	16	8	7	13	12	11	14
COPRAS	9	1	2	5	15	4	3	7	12	16	8	6	13	10	11	14
PCIM	9	1	2	5	15	4	3	6	11	16	8	7	14	13	10	12

Figure 16. Ranking Comparison Chart of Five MADM Methods.

These rankings provide a structured outlook on the failure modes based on different analytical methodologies, assisting in understanding the relative significance and the need for prioritization among them for further analysis or remedial actions.

There is not much variation in the ranking order derived from the four methods. This study employs PCIM-MADM, which aggregates four MADM methods based on utility functions, gap ratio, and similarity concepts. By validating this approach, the final outcomes exhibit consistency and reliability, affirming the top five failure modes as the primary risks to address. This methodology facilitates a balanced consideration amidst different factors, garnering a more comprehensive and rational result. In other practical scenarios, relying on a single method for data analysis might not thoroughly consider the actual issues, possibly leading to a biased or insufficiently holistic outcome. Since each method operates on different logic, dependence on a single method might not yield a comprehensive solution. Hence, amalgamating multiple methods could perhaps harness the strengths of each, effectively reducing decision risks and aiding in averting biases while addressing real-world problems, thereby obtaining more feasible solutions. The contribution of the PCIM-MADM method lies in offering a framework that integrates multiple MADM methods. Given that each distinct MADM method operates on different logic, the strengths of each are synthesized by combining various methods, effectively diminishing decision risks.

4.8. Sensitivity Analysis

Sensitivity analysis is principally conducted to understand whether adjusting the most crucial risk factors would change the ranking of the failure modes. By modifying the weight ratios, the relative importance of each risk factor in the calculation process can also be discerned. In this study, the most significant risk factor is the anticipated cost (E), with a weight of 0.313, which considerably impacts the overall assessment outcome. To comprehend the degree of E's influence on the results, this study will incrementally adjust the weight of E from 0.1 to 0.9, while proportionally modifying the weights of the other risk factors, as shown in Table 14.

Table 14. Sensitivity analysis.

	S	O	D	E
Initial results	0.213	0.215	0.258	0.313
RUN1	0.279	0.282	0.338	0.1
RUN2	0.248	0.251	0.301	0.2
RUN3	0.217	0.22	0.263	0.3
RUN4	0.186	0.188	0.225	0.4
RUN5	0.155	0.157	0.188	0.5
RUN6	0.124	0.125	0.15	0.6
RUN7	0.093	0.094	0.113	0.7
RUN8	0.062	0.063	0.075	0.8
RUN9	0.031	0.031	0.038	0.9

From the outcomes of the sensitivity analysis, it can be observed that, even with the adjustment of weights for the risk factors severity (S), occurrence rate (O), probability of failure detection (D), and anticipated cost (E), the impact on the ranking of the top five failure modes is not significant. The failure modes that require priority attention remain to be excessive hole piercing (FM2), erroneous outer processing dimensions (FM3), customer-end/ordering window negligence (FM7), misalignment of information between production control and business during work order handover (FM6), and exceeding flatness/verticality tolerance (FM4). On the other hand, it is also evident that, regardless of how the weight of E is adjusted, the final ranking outcome remains relatively stable.

5. Conclusions

This research chiefly delves into the risks encountered during the process of steel plate cutting. Through discussions with experts, 16 failure modes were identified, and questionnaires were distributed among the experts. The data collected were analyzed using the PCIM-MADM method, which amalgamates four MADM methods (SAW, GRA, VIKOR, and COPRAS) in order to consolidate the ranking of failure modes, providing an in-depth and comprehensive assessment of each failure mode along with substantial commercial recommendations. The PCIM-MADM method, which combines different evaluation points of view, makes it possible to look at the risk levels of failure modes more thoroughly than when only one method is used. This makes the research more reliable. Moreover, it aids in identifying which failure modes are more critical in causing potential losses during the steel-plate-cutting process and proposes improvement plans and suggestions for the failure modes that need priority consideration.

By implementing the expert-recommended measures for these failure modes, the occurrence of failure modes can be effectively reduced, thereby minimizing resource waste and operational costs. The expert questionnaire method is used in this study to look into the failure modes found in steel-plate-cutting operations. The results provide a well-structured reference for improving the process workflows involved. Nevertheless, the study embodies certain limitations that provide fertile ground for further scholarly exploration. Firstly, despite its merit, the expert questionnaire method is bound by the limited number of experts surveyed, coupled with the inherent subjectivity and biases of the responses garnered. It is envisaged that future studies could burgeon the sample size and incorporate fuzzy theory in order to yield more comprehensive insights, thereby diluting the biases intrinsic to the expert questionnaire method. Secondly, the current inquiry, conducted through astute dialogues with experts, only unveils 16 failure modes. However, a realm of opportunity exists to probe further by unearthing additional failure modes and engaging diverse MADM methods for a comparative dissection, hence bolstering the reliability and validity of the research outcomes. Lastly, the PCIM-MADM framework, a novel theoretical construct, finds its application across myriad industries that are relatively nascent. It is propounded that ensuing research could broaden the application spectrum of PCIM-MADM across various industries to harvest more reliable and eclectic research outcomes. This expanded application could serve as a crucible for validating the efficacy and versatility of the PCIM-MADM method, nurturing a profound understanding of its potency in tackling operational quandaries across an expansive array of industrial milieus.

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