Fault Interaction Analysis with Extended FMEA Model using Cloud Model Theory and DEMATEL: A Novel Approach to Risk Assessment

By

Osama Ahmed Awan

(Registration No: 00000400154)

Thesis Supervisor: Dr. Afshan Naseem

Department of Engineering Management

College of Electrical and Mechanical Engineering (CEME)

National University of Sciences and Technology (NUST)

Islamabad, Pakistan

(2024)

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS/MPhil thesis written by Osama Ahmed Awan Registration No. 00000400154 of MS (Engineering Management) has been vetted by undersigned, found complete in all respects as per NUST Statutes/ Regulations, is free of plagiarism, errors and mistakes and is accepted as partial fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature: Afshan Naseem

Name of Supervisor: Dr. Afshan Naseem

Dated: 02 Jul 2024

Signature: Yasir

Name of HOD: Dr. Yasir Ahmad

Dated: 02 Jul 2024

Signature (Dean/Principal): Rashid

Dated: 02 JUL 2024

Dedication

Dedicated to my parents and siblings, whose unwavering love and support have been the canvas on which I painted this remarkable achievement.

ACKNOWLEDGEMENTS

I begin with a profound expression of gratitude to Allah Almighty, whose countless blessings and guidance have been the cornerstone of my journey towards this thesis. It is with utmost humility and thankfulness that I embark on this endeavor.

My parents have been a wellspring of love, affection, and unwavering support throughout my academic pursuit. Their sacrifices and encouragement have been my driving force. I owe them a debt of gratitude that words alone cannot repay.

I am also indebted to my siblings for their unconditional love and support. Their belief in my abilities has propelled me forward, and their constant encouragement has been a source of strength.

I extend heartfelt thanks to my thesis supervisor, Dr. Afshan Naseen. Her guidance, wisdom, and unwavering support have been invaluable. Her mentorship has not only enriched my academic journey but also broadened my horizons.

I would like to express my appreciation to the members of my GEC committee, Dr. Shujaat Ali and A/P Ali Salman, for their meticulous feedback and corrections. Their insights and expertise have been instrumental in shaping the quality of this thesis.

I extend special thanks to my class, whose dedication to the well-being of our collective academic journey has been truly commendable. Moreover, my friends have consistently provided inspiration serving as a constant source of support, and I am sincerely grateful for their meaningful presence in my life.

I also extend my thanks to the management of my department. Their efforts in providing a conducive academic environment and resources have been vital in facilitating my research.

In a nutshell, I acknowledge the combined efforts of these individuals and entities in shaping my academic path. Their support, encouragement, and faith in me have been essential to the accomplishment of this thesis. As I progress, I bring with me the lessons, guidance, and blessings they have shared, and I am committed to applying them to make a meaningful contribution to my field.

Engr. Osama Ahmed Awan

ABSTRACT

The failure mode and effect analysis (FMEA) is a method to identify and mitigate different problems in many manufacturing processes, its effectiveness is questionable unless it is more closely linked to solve difficult problems. In addition, the disruptions experienced in the production process are interrelated and cannot be considered independently of each other. Instead, they are intertwined, and without adequate attention to this relationship, research will reflect the accuracy of its conclusions. It is therefore important to determine not only the significance of the faults, but also the nature of the faults. This course includes the use of cloud modeling theory and the evaluation of decision-making experiments and test models to meet the needs of the business and overcome the limitations of traditional practices. Three contributions of this approach are: First, using Cloud Model Theory to solve the problem of random and uncertain decisions. Second, decision-making and trial evaluation laboratory (DEMATEL) has been extended to consider cloud model configuration to detect critical errors. Third, a case study is presented to demonstrate the advantages and effectiveness of the approach. The integration of Cloud Model Theory and DEMATEL reveals the novelty of this work by extending the failure model and related analysis, realizing its applicability in the system production process. This approach ensures that managers are aware of the biggest risk areas and take precautions in advance. As a result, losses resulting from negative effects are minimized and production processes become efficient and effective.

Keywords: Failure Mode and Effect Analysis (FMEA), Decision Making and Trial Evaluation Laboratory (DEMATEL), Cloud model theory

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

FMEA	Failure Mode and Effect Analysis
RPN	Risk Priority Number
DEMATEL	Decision Making Trial and Evaluation Laboratory
CMT	Cloud Model Theory
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
FMECA	Failure Mode, Effect and Criticality Analysis
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
TODIM	An Acronym in Portuguese for Interactive Multi-Criteria Decision Making
ANP	Analytical Network Process
AHP	Analytical Hierarchy Process
SWARA	Stepwise Weight Assessment Ratio Analysis
DST	Dempster Shafer Theory
MCDM	Multicriteria Decision-Making

CHAPTER 1. INTRODUCTION

The following topics are covered in this chapter: research background and purpose of this study, industry setting, research rationale and objective of the research. It also encompasses research problems and problem statements. Thesis structure has also been provided at the end of this section.

1.1 BACKGROUND

Due to the rapid expansion of manufacturing industries, ensuring quality and defect-free output has become increasingly critical. With intense market competition, attracting new customers and retaining existing ones demands substantial effort. In this context, the production of competitive, high-quality, and defect-free products takes precedence. Businesses must identify faults in production lines that compromise product quality, allowing them to rectify these issues, address challenges, and improve overall production processes. An effective method for achieving this is through the early detection of defects (Ostadi & Masouleh, 2019). As competition intensifies, manufacturing companies are compelled to adopt a range of quality control tools and strategies to maintain their competitive edge (Vinodh & Santhosh, 2012).

Reliability assessment methods can be categorized into three main types: qualitative, quantitative, or hybrid. Ultimately, employing quantitative methods provides a more thorough comprehension of the system in contrast to qualitative methods based on analytical approximation. This is because quantitative methods demand additional resources and expertise. Hybrid approaches, which either integrate qualitative and quantitative research methods or incorporate other indicators, hold significant appeal as they combine the strengths of both research methodologies. (Tazi et al., 2017).

Integrating a criticality analysis into a qualitative Failure Mode and Effects Analysis (FMEA) facilitates the evolution of FMEA into a quantitative Failure Mode, Effects, and Criticality Analysis (FMECA), offering a more thorough examination. Failure Mode Effects Analysis (FMEA) and Fault Tree Analysis (FTA) are frequently employed methods for evaluating failures. FMEA, employing a bottom-up approach, demands more detailed user information compared to Fault Tree Analysis. The Food and Drug Administration (FDA) developed the FTA method (Peeters et al., 2018).

During the design and manufacturing phases of a system, the Failure Mode and Effect Criticality Analysis approach is frequently used to analyze probable failure modes in the system's components and overall system reliability. This approach aims to identify weak links and propose effective solutions to enhance overall dependability (Y. Chen et al., 2012).

The FMEA methodology is grounded in reliability theory. It uses a bottom-up methodology for failure risk assessment, starting with the smallest parts of the system and working its way up to analyze how a failure might affect the system as a whole. The subsequent stage of the component's failure analysis starts with each degree of failure. Furthermore, there is potential for collaboration between Failure Mode and Effects Analysis (FMEA) and Failure Trend Analysis (FTA) to uncover additional failure scenarios and root causes (Sulaman et al., 2019). FMEA, as a preventative methodology for problem identification and resolution, involves a systematic progression through five key stages. Firstly, it entails the critical decision of which process to subject to analysis. Subsequently, an interdisciplinary group of experts is formed in the second stage, ensuring a diverse range of perspectives. The third stage involves the meticulous gathering of data pertaining to the selected process. Following this, in the fourth stage, a comprehensive risk assessment is conducted, evaluating potential vulnerabilities and failure modes. Finally, the fifth stage revolves around the implementation of plans derived from the assessment, with a parallel focus on monitoring and evaluating the effectiveness of these implemented strategies. This structured approach empowers organizations to proactively manage and enhance the reliability of their processes (Chiozza & Ponzetti, 2009).

During the FMEA process, Risk Priority Numbers (RPNs) are calculated by multiplying the scores assigned to incidence, severity, and detection, each ranked on a scale from 1 to 10. As the RPN values increase for each identified failure mode, so does the perceived risk to the system. Corrective actions are then implemented to safeguard the system based on the determined RPN values. However, the RPN technique has limitations in its applicability. Firstly, the evaluation of failure modes using three risk variables may not fully represent the intricacies of the actual process or system in use. Secondly, accurately rating the three risk factors—occurrence, severity, and detection—can be challenging. Moreover, the RPN analysis does not account for the relative weights of occurrence, severity, and detection. Additionally, there is ongoing debate about the computation formula for RPN, as different combinations of values for occurrence, severity, and detection can yield the same RPN value, introducing ambiguity into the analysis. Despite these limitations, FMEA remains a crucial preemptive activity in risk management (Liu et al., 2019)

The RPN technique is challenged by three notable drawbacks. Firstly, there is a high likelihood of duplicating RPN values, introducing ambiguity into the assessment. Secondly, the method lacks the capability to take into account the severity, incidence, and detection weights in order, which could result in an oversimplified depiction of risk variables. Thirdly, the RPN technique proves inefficient in accurately calculating the reciprocal interaction between faults, limiting its ability to provide a nuanced understanding of how different failure modes may interact. These limitations underscore the need for caution and supplementary analyses when relying on RPN values for a comprehensive risk assessment (Chang et al., 2014). Furthermore, the inherent fuzziness and ambiguity within the assessment process can contribute to imprecision in the precise values used to express Risk Priority Numbers (RPNs) in a standard FMEA. This introduces the potential for errors or inadequacies in the representation of risk, emphasizing the importance of considering uncertainties and the limitations of the assessment methodology (Zhang & Chu, 2011). Likewise, in its more traditional form, FMEA concentrates solely on examining how a system responds to the consequences of individual failures. Analyzing numerous failure modes with all possible combinations and permutations in a complex system becomes unrealistic due to the multitude of potential failure scenarios. The complexity of such systems introduces challenges in comprehensively addressing every conceivable failure mode, underscoring the need for a focused and practical approach within the constraints of the analysis (Xiao et al., 2011).

FMEA techniques that are based on Multi-Criteria Decision Making (MCDM) have proven useful in achieving a comprehensive analysis of potential failures and hazards. For the industrial sector to ensure continual development, it is imperative to efficiently identify severe failures related to components or processes. However, it's worth noting that rankings of failure modes can vary depending on the specific MCDM method employed in their generation. The emphasis on MCDM in FMEA reflects a commitment to enhancing the precision and effectiveness of failure analysis within the industrial context (Lo et al., 2020). According to a different explanation, selecting a

Multiple Attribute Decision Making (MADM) method for an issue that calls for strong decision-making is a difficult and time-consuming process. The challenge is compounded when dealing with MADM situations that involve a variety of suitable MADM algorithms, making the decision-making process even more intricate. The selection of the most appropriate MADM approach becomes a critical aspect of navigating the complexities inherent in decision-making under these circumstances (Chakraborty, 2022). Conversely, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach shows promise as a practical and innovative replacement for traditional multi-criteria decision-making (MCDM) methods. Its emphasis on identifying causal relationships between variables is its unique strength. Moreover, DEMATEL utilizes pre-existing information to scrutinize relationships among various failure types, delving into the relative significance of each component. The method employs cause-and-effect diagrams to visually represent deduced relationships derived from the available evidence, enhancing the interpretability and depth of the analysis (Y.-T. Chen, 2016a).

1.2 INDUSTRY SETTING

It is evident that the textile industry contributes significantly to the economies of countries globally, despite the certain environmental concerns associated with textile production, such as waste generation, the industry remains a vital contributor to economic growth. Beyond economic contributions, the industry also generates employment opportunities, serving as a potential income source for many individuals and contributing to the gross national product of governments worldwide. Moreover, the manufacturing processes within the textile industry bear similarities to production lines in other sectors. Consequently, like any other industry, the textile sector may address challenges within its production line, including issues like intermingling defects, through the implementation of efficient approaches that offer preventive measures.

1.3 RESEARCH RATIONALE

This study aims to discover the interactions among the faults which are identified in the production processes of the manufacturing industry. to classify these errors into the appropriate cause-and-effect categories and determine the degree of their mutual influence. The main goal of this study is to improve understanding of the complex interactions between known defects in the manufacturing industry. By delving into the relationships and impact levels of these faults, the study aims to furnish the industry with valuable insights. Specifically, it aims to offer a set of preventative measures that can be employed to avert issues in the manufacturing process. The ultimate goal is to enhance the industry's competence and efficiency by proactively addressing potential challenges in its production processes.

1.4 RESEARCH OBJECTIVES

Following are the research objectives of this study.

- To systematically identify and list faults occurring in the production line of the manufacturing process.
- To explore and establish the inter-relationships among the identified faults, understanding how they may be interconnected.
- To categorize the identified faults into distinct cause-and-effect groups, providing clarity on their relationships within the production process.
- To quantify and determine the level of influence each identified fault has on others, gauging the impact within the manufacturing system.
- To formulate a comprehensive set of preventive measures aimed at proactively mitigating potential disruptions in the manufacturing process.

1.5 RESEARCH PROBLEM

Companies often incur substantial losses when they overlook the implications of numerous risk variables in manufacturing processes, where a multitude of errors is prevalent. These losses encompass reductions in manufacturing volume, as well as inefficiencies in time and energy utilization. Moreover, they adversely impact the overall productivity of organizations, tarnish their reputations, and undermine efforts to retain customers. The challenge for companies lies in accurately assessing the severity of each issue and understanding the intricate interconnections between these faults. It's observed that these flaws are often interconnected, making it difficult to discern the causes from the consequences. Complicating matters further, a specific defect may trigger a cascade of effects, activating multiple other faults and serving as the root cause for additional issues. Faults tend to set off a chain reaction, making it impractical to solely consider individual characteristics and rank them by severity. Consequently, this research aims to delve into the interrelationship among these faults, identifying areas most prone to failure. The goal is to assist industries in eliminating these faults through preventive measures, thereby reducing susceptibility to the complex repercussions arising from the interconnected nature of these issues.

1.5.1 Problem Statement

The problem statement for this study is to clearly identify the types of the faults, to understand the nature of the faults and their mutual dependency on each other, and to categorize those faults into cause-and-effect groups.

1.6 THESIS STRUCTURE

The first chapter of the study serves as an introduction to the research topic, outlining key aspects such as the background of the study, its objectives, and the rationale behind the research goals. It also underscores the significance of the research problem. Additionally, the first chapter places a deliberate emphasis on providing context to the industry under investigation and highlights the anticipated contribution that the study aims to make within this specific industry context.

The second chapter of the study will centre on a comprehensive review of relevant previous work. This will encompass the theoretical framework, existing studies conducted by researchers on the same topic, and an assessment of the applicability and relevance of this research to the industry. The scope of this chapter aims to build a foundation of understanding by drawing upon the existing body of knowledge related to the research topic.

The third chapter of the study will delve into the methodology and mathematical models employed. This discussion will primarily cover the research paradigm, research setting, and research design, providing a detailed insight into the chosen methodology. The chapter will articulate the rationale behind the selection of this particular methodology and shed light on any constraints imposed on the research design. This section aims to offer transparency and clarity regarding the approach taken in the study and the underlying mathematical models.

In the fourth chapter of this study, thorough coverage will be provided for the results obtained from the study. This section will encompass a detailed analysis of the results, along with interpretations and arguments derived from these findings. The chapter aims to present a comprehensive and insightful exploration of the data, shedding light on the implications and significance of the results in the context of the research objectives and overarching study goals.

The fifth and final chapter of this study encompasses the conclusion, offering a succinct summary of the inquiry undertaken throughout the study. It will articulate the theoretical underpinnings and practical contributions of the research, providing insight into the broader implications of the findings. Additionally, the conclusion will address the limitations of the research, acknowledging any constraints or potential areas for improvement. Moreover, it will illuminate the future direction that subsequent researchers could explore, offering guidance on potential avenues for further investigation within the scope of the study.

The concluding section of this study will focus on presenting the references used in the study, along with any appendices and collected questionnaires. This section serves as a comprehensive reference point for readers, allowing them to explore the sources and supplementary materials that contributed to the research and its findings.

CHAPTER 2. LITERATURE REVIEW

2.1 GENERAL

This chapter deals with the critical evaluation of the existing body of knowledge related to the study's topic. It involves a thorough examination of the literature and aims to identify any gaps that exist in current research. Additionally, the chapter discusses the theoretical framework that the study draws upon for guidance. It outlines the specific questions that this study aims to address, highlighting the research objectives and providing a clear roadmap for the subsequent investigation. This section sets the stage for the study by framing it within the context of existing scholarship and outlining the unique contributions it seeks to make.

2.2 EVOLUTION OF EXITSTING KNOWLEDGE

2.2.1 Applications and Evolution of FMEA

The FMEA tool is used in manufacturing processes to find any flaws in the final product, the workflow, and the system as a whole. Its application is instrumental in minimizing the risk of failure throughout the design and production phases of innovative products. By systematically pinpointing and evaluating probable failure modes, FMEA enables a proactive strategy for risk reduction, contributing to the creation of more reliable and successful products (Moreira et al., 2021). FMEA generally comprises five stages: preparation, identification, ranking, risk reduction, and reassessment. The calculation of the Risk Priority Number (RPN) involves multiplying Severity, Occurrence, and Detection scores, offering a quantitative measure to evaluate the risks associated with different failure modes. In the context of FMEA, a higher RPN value indicates an increased risk level, signalling a greater probability of failure for a particular failure mode (Kumar & Parameshwaran, 2020). In the traditional Risk Priority Number (RPN) approach, severity, occurrence, and detection are assigned equal importance. This equal weighting of risk factors can be a limitation, leading to scenarios where different risk combinations result in the same RPN values. This limitation can lead to overly optimistic outcomes in practical settings. Additionally, the subjective nature of FMEA analysis, influenced by potential gaps in knowledge and experience, as well as language barriers, can introduce subjectivity into the assessment. To address these shortcomings, various risk assessment approaches, such as RPN modification tools, can be employed. These tools aim to enhance the robustness of FMEA by providing mechanisms to better capture and evaluate the nuanced aspects of risk, offering a more comprehensive and accurate analysis (Fabis-Domagala et al., 2021).

Indeed, there has been a suggestion to replace the Risk Priority Number (RPN) approach with alternative models to increase the effectiveness of FMEA. The idea is to explore and adopt alternative models that may offer advantages over the traditional RPN method. These alternative models could provide a more nuanced and accurate representation of risk by addressing the limitations associated with equal weighting of severity, occurrence, and detection in the RPN approach. Such a shift aims to improve the overall risk assessment process in FMEA, leading to more robust and reliable outcomes (Liu et al., 2013). Challenges in FMEA, such as ordering of failure mode severity and variable risk ratings by FMEA teams, have prompted the development of solutions. To address these issues, a resilient and flexible decision-making framework has been proposed. This framework integrates a cloud model to handle fuzziness and incorporates the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) technique. By leveraging these methodologies, the aim is to enhance the precision and adaptability of the decision-making process in FMEA, providing a more comprehensive and effective approach to addressing challenges related to failure mode severity and variable risk ratings (Liu et al., 2017). A considerable number of aircraft disasters stem from malfunctioning parts. While the FMEA proves to be a valuable method to evaluate possible results and create strategies for minimizing risks., the use of crisp Risk Priority Number (RPN) values can introduce complications. To address this limitation, research has delved into fuzzy group decision-making, aiming to boost the efficiency of FMEA. The fuzzy FMEA allows for a more nuanced and flexible assessment, acknowledging and addressing uncertainties inherent in the evaluation of potential failure modes in complex systems like aircraft (Yazdi et al., 2017).

Despite its inherent limitations, FMEA is subject to continual revision to accommodate emerging developments in the industries where it is applied. Since its inception, FMEA has undergone multiple iterations, reflecting a commitment to refinement and modification. Investigating the initial creation of FMEA and its subsequent evolutionary phases is essential for comprehending the trajectory of this methodology. The ongoing improvements aim to achieve several key objectives; Firstly, FMEA seeks to find solutions to challenging problems encountered in various industrial processes. This reflects the methodology's dynamic nature and its responsiveness to the evolving landscape of challenges within industries. Secondly, there is a persistent effort to enhance the applicability of FMEA. By adapting to changing contexts and industry requirements, FMEA aims to remain a versatile and valuable tool for risk management and process improvement. Thirdly, FMEA aims to effectively represent causes and effects within complex systems. This involves refining the methodology to capture the intricacies of relationships between different elements and variables. Lastly, the continuous development of FMEA is driven by the goal of analysing risks comprehensively. By incorporating new insights and addressing limitations, The goal of FMEA is to offer a strong framework for locating, evaluating, and reducing risks in various industrial environments. These objectives underscore the proactive and adaptive nature of FMEA, positioning it as a valuable methodology in the ongoing pursuit of excellence and risk mitigation within industries (Spreafico et al., 2017).

In addition to its standalone application, Failure Mode, Effects, and Criticality Analysis (FMECA) is frequently integrated with various multi-criteria decision-making (MCDM) approaches. This integration serves to enhance the utility and broaden the application scope of FMECA in tackling the multifaceted aspects of engineering challenges. The purpose is to augment FMECA's effectiveness in responding to these challenges and make it more versatile and applicable across diverse contexts. By combining FMECA with MCDM methodologies, a synergistic approach is employed, leveraging the strengths of both techniques to provide more comprehensive and nuanced solutions to complex engineering difficulties. This integration reflects a strategic effort to maximize the analytical capabilities and relevance of FMECA in a variety of applications (Abu Dabous et al., 2021).

To effectively prioritize hazards within the context of Health, Safety, and Environment Management, an innovative approach combines FMEA and Robust Data Envelopment Analysis (RDEA). This strategy considers inputs such as severity, occurrence, and detection, while evaluating outputs including cost and treatment time. Additionally, the approach takes into account both the attractiveness of the parameter and its associated uncertainty. When applied by an auto parts maker, the results were compared with those obtained from traditional DEA models and Risk Priority Number (RPN) assessments. This extended methodology enhances the credibility and persuasiveness of risk prioritization in comparison to basic FMEA, providing a more robust foundation for decision-making in health, safety, and environmental management (Yousefi et al., 2018). MCDM, when coupled with the grey theory of FMEA, introduces a supplementary method for determining the sequence of risk priority in product development. This fusion facilitates the retention of ranked failure modes via probability-based interval analysis. By harnessing Multi-Criteria Decision Making (MCDM) alongside grey theory within the FMEA framework, this methodology enriches the accuracy and dependability of risk prioritization throughout the product development phase. The utilization of probability-based interval analysis further contributes to a nuanced understanding of potential failure modes, providing a comprehensive and probabilistic assessment to inform decision-making in product development (Lo & Liou, 2018).

In traditional FMEA, the failure modes are often not distinctly differentiated. To address this limitation, it is suggested to employ a fuzzy hybrid FMEA model for evaluating enhanced failure modes. By introducing fuzziness and a hybrid approach, this model aims to provide a more nuanced and accurate assessment of failure modes, incorporating a fuzzy logic framework for risk prioritization in a manner that accounts for uncertainties and complexities inherent in real-world scenarios (Fattahi & Khalilzadeh, 2018). An enhancement to the conventional FMEA method is achieved through an extended FMEA framework. In this approach, FMEA is utilized to identify potential failure modes and attribute corresponding values to Risk Priority Numbers (RPNs). Simultaneously, the Fuzzy Best-Worst Method (FBWM) is employed to ascertain factor weights, contributing a fuzzy logic element to the process. Furthermore, the Z-MOORA method is utilized to rank the failures. This extended framework combines traditional FMEA with fuzzy and multi-criteria decision-making techniques, aiming to refine the assessment of failure modes and their prioritization, thereby contributing to a more comprehensive and nuanced risk analysis (Ghoushchi et al., 2019). The hybrid framework of FMEA facilitates a comprehensive understanding of the complexities involved in risk assessment. It employs the TODIM methodology for decision-making, particularly in situations involving uncertainty and multiple criteria. Furthermore, the Choquet integral method is utilized to capture the mutually beneficial relationships between various elements. The representation of uncertainty in risk assessment is handled through generalized trapezoidal fuzzy numbers, contributing to a more nuanced and realistic modelling of the psychological and uncertain dimensions inherent in FMEA processes (W. Wang et al., 2019).

Identification of faults in a warehouse setting can be effectively carried out through the integration of Design FMEA and Fuzzy Analytic Hierarchy Process (fuzzy-AHP) analysis. Design FMEA specifically targets failure modes that contribute to inefficiencies in the warehouse design, providing a systematic approach to recognizing potential issues. On the other hand, fuzzy-AHP comes into play to mitigate subjectivity in weighting criteria. This methodology introduces a fuzzy logic-based approach to the Analytic Hierarchy Process, enhancing the precision and reliability of the criteria weighting process. By combining the strengths of both Design FMEA and fuzzy-AHP, this approach offers a comprehensive strategy for identifying and addressing faults in the warehouse, ensuring a more robust and objective analysis (A. Hassan et al., 2019). Addressing the limitations in the Risk Priority Number (RPN) calculation within FMEA, prospect theory emerges as a potential solution. By integrating prospect theory into the methodology, this enables the improvement of precision and efficiency in risk assessment. Simultaneously, the utilization of Fuzzy Analytic Hierarchy Process (Fuzzy AHP) is deployed to ascertain weights for occurrence and detection. Additionally, Fuzzy TODIM is utilized to organize failure modes based on their RPN scores. This integrated approach leverages prospect theory and fuzzy logic to overcome shortcomings in traditional RPN calculations, providing a more nuanced and comprehensive evaluation of failure modes within the FMEA framework (Sagnak et al., 2020). To enhance the accuracy of FMEA risk estimates, an integrated MCDM approach is proposed. This approach combines the Fuzzy Analytical Hierarchy Process (FAHP) with a modified version of Fuzzy Multi-Attribute Ideal Real Comparative Analysis (FMAIRCA). By integrating these methodologies, the approach provides a framework to effectively handle fuzziness and improve risk ranking within the FMEA process. The integration of FAHP and modified FMAIRCA is designed to yield more realistic and nuanced results, contributing to a more comprehensive understanding and assessment of risks associated with failure modes (Boral et al., 2020). To evaluate flaws in the plastic manufacturing process, a combination of the Fuzzy Bayesian Network (FBN) and the Fuzzy Best-Worst Method (FBWM) is employed. This integrated approach aims to refine the computations involved in the traditional FMEA risk priority number (RPN). By incorporating FBN and FBWM, this methodology introduces a fuzzy logic framework to improve the precision and reliability of the risk assessment procedure. This comprehensive approach allows for a more nuanced evaluation of potential flaws in the plastic manufacturing process, ensuring that the identified risks are prioritized in a manner that better reflects the complexities and uncertainties involved (Gul et al., 2020).

The improved FMARCOS (Fuzzy Measurement of Alternatives and Ranking according to Compromise Solution) approach incorporates the risk factors' relative relevance ascertained through the use of the Analytic Hierarchy Process (AHP). This combined methodology is employed to rank failure modes, aiming to overcome a limitation inherent in the conventional FMEA approach. By incorporating AHP for factor significance determination and integrating it into the modified FMARCOS method, this approach seeks to provide a more comprehensive and nuanced ranking of failure modes, addressing shortcomings associated with traditional FMEA methodologies (Boral et al., 2020). The traditional Risk Priority Number (RPN) technique employed in standard FMEA tends to overlook the intricate interdependencies among failure modes within complex systems, such as construction projects. Additionally, it lacks consideration for the inherent fuzziness associated with certain aspects of risk assessment. Contrastingly, a hybrid framework incorporating fuzzy FMEA, fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATHEL), and the Analytical Network Process (ANP) offers a more comprehensive solution. This integrated approach not only determines RPN values but also identifies interrelationships among failure modes and prioritizes them. By embracing fuzziness and leveraging advanced methodologies, this hybrid framework enhances the accuracy and applicability of risk assessment in complex systems like construction projects (Karamoozian & Wu, 2020). The combination of the Evidential Reasoning (ER) method and Interval Type-2 Fuzzy Sets (IT2FSs) offers a promising solution to address some of the limitations present in the conventional FMEA approach. This integrated approach is particularly effective in handling uncertainty associated with risk assessment. By incorporating the ER method and IT2FSs, the methodology gains the ability to capture and manage uncertainties in a more robust manner. This advancement allows for a more nuanced and realistic evaluation of failure modes, addressing certain inherent limitations of conventional FMEA and thereby fostering enhanced decision-making in complex and uncertain environments (Qin et al., 2020).

Coal-to-methanol plants, facing inherent uncertainty, necessitate thorough risk analysis. The FMEA-CM technique plays a crucial role in this evaluation by mitigating various types of uncertainty, including unpredictability and fuzziness. By employing the FMEA-CM (FMEA for Coal-to-Methanol) technique, the risk analysis process becomes more robust and effective, addressing uncertainties associated with the complex nature of coal-to-methanol production. This method aids in systematically identifying potential failure modes, assessing their impacts, and implementing strategies to enhance the overall reliability and safety of coal-to-methanol plants (L. Wang et al., 2021). The risks linked to the landfill in Tehran are assessed through a combination of FMEA and Analytic Hierarchy Process (AHP). In this approach, AHP utilizes pairwise comparison as the method to rate risks based on the severity of their consequences. This integrated methodology allows for a comprehensive evaluation of potential failure modes and their respective impacts on the landfill in Tehran. By leveraging both FMEA and AHP, this approach provides a structured and systematic way to pinpoint, prioritize, and tackle risks linked to the landfill., contributing to enhanced risk management and decision-making processes (Sadeghi et al., 2021). In the context of building projects, several methods are proposed for risk identification and assessment in a fuzzy environment, addressing limitations associated with traditional FMEA. These methods include FMEA itself, Stepwise Weight Assessment Ratio Analysis (SWARA), and Weighted Aggregated Sum Product Assessment (WASPAS). By introducing a fuzzy environment, these methodologies aim to enhance the precision and flexibility of risk assessment. SWARA and WASPAS, in particular, provide alternative approaches to rectify the deficiencies of traditional FMEA. in handling uncertainties and complexities associated with building projects. The integration of these fuzzy techniques contributes to a more comprehensive and nuanced risk management process in construction projects (Alvand et al., 2023).

An AHP-FMEA analysis is used to get around the FMEA's restrictions while looking into floating offshore wind turbine failures. With this method, the Analytic Hierarchy Process (AHP) methodology and a recommended normalization procedure are used to calculate a Failure Risk Index (RPN). The RPN is calculated using two sets of data: the relative significance of severity, occurrence, and detection (determined through the proposed normalization algorithm), and their respective weights (established through the AHP methodology). By integrating AHP with FMEA, this analysis provides a more comprehensive and refined evaluation of failure modes in floating offshore wind turbines, contributing to a more effective risk assessment process (H. Li et al., 2021). A multidimensional approach to risk assessment is introduced by the FMEA framework's integration of Grey Relations Theory (GRT) and Fuzzy Rule Base (FRB). By leveraging FRB and the GRT, the modified FMEA framework becomes more comprehensive, allowing for a more nuanced and adaptable evaluation of failure modes. This integrated methodology facilitates a holistic understanding of risks, taking into account the uncertainties and complexities inherent in various assessment factors (S. Hassan et al., 2022).

2.2.2 Applications of Cloud Model Theory

In the process of when assessing the environmental performance of alternative suppliers, decision-makers may often employ linguistic descriptors, leading to potential ambiguity in their conclusions. This ambiguity arises from a lack of knowledge and the inherently vague nature of the expertise provided by specialists. A framework appropriate for an MCDM model is produced by combining cloud model theory (CMT) with Qualitative Flexible Multiple Criteria (QUALIFLEX). This innovative method enables the assessment of the capabilities of different suppliers, providing a more structured and nuanced evaluation that addresses the challenges associated with linguistic descriptors and helps make better-informed decisions when choosing suppliers based on their environmental performance (K.-Q. Wang et al., 2017).

A novel integrated FMEA model has been developed by incorporating cloud model theory (CMT) and the hierarchical Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This model serves the purpose of analysing and ranking various failure possibilities. Leveraging the advantages offered by cloud model theory, this approach addresses the challenge of inherent unpredictability in language evaluations. The use of cloud computing contributes to a more robust and structured analysis of failure modes, enhancing the reliability of the FMEA model. This integrated strategy provides a solution to the uncertainties associated with language-based evaluations, offering a more informed and effective approach to ranking potential failures (Liu et al., 2019a).

(Gong et al., 2021) utilized CMT to describe asset liquidity and profitability trends in a multi-objective portfolio selection model. This approach was chosen due to its effectiveness in handling uncertainty. (Xie et al., 2021) created a novel quantitative risk assessment technique to determine the risk of fire and explosion incidents in oil depots using the Bow-tie (BT) model and CMT. This method was chosen because it can deal with uncertainty and information lacking.

2.2.3 Applications of DEMATEL

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is used to identify the relationship between processes and control the interaction between certain processes. This is particularly useful for quality analysis and details in urban waste management. Due to the uncertainty of this measurement, experts often have difficulty expressing their preferences using numerical values (Tseng & Lin, 2009). DEMATEL is a detailed method for investigating causal linkages. It requires only a small number of samples and enables the assessment of the degree of correlation between elements (Zhou & Chen, 2018).

The DEMATEL method is utilized to identify interdependencies among criteria. However, Multi-Criteria Decision Making (MCDM) analysis becomes complex due to the inherent fuzziness in human life and subjectivity. To quantify this fuzziness in subjective notions, a theory is needed. Hence, fuzzy logic is employed to address bias in evaluation criteria (Büyüközkan & Çifçi, 2012).(Si et al., 2018) The DEMATEL method is highly regarded for its ability to dissect complex systems and identify their causes and effects. There have been numerous publications discussing the practical applications and different versions of DEMATEL. In a study spanning from 2006 to 2016, which analyzed 346 international journal papers, DEMATEL was classified into five domains based on the methodologies used: Classical DEMATEL, fuzzy DEMATEL, grey DEMATEL, Analytical Network Process-based (ANP-based) DEMATEL, and other variations (Si et al., 2018).

(Han & Deng, 2018) expanded the fuzzy DEMATEL method to identify Critical Success Factors (CSFs) by incorporating the Dempster-Shafer evidence theory. They applied the Dempster-Shafer theory in combination with DEMATEL. Intuitionistic Fuzzy Numbers (IFNs) were used by experts to examine direct factor relationships. Use the Dempster Combination Rule to combine the IFNs after converting them to Basic

Probability Assignments (BPA). The DEMATEL process can now categorize modifications according to relationships. (Dinçer & Yüksel, 2018) proposed a hybrid decision-making process combining DEMATEL and TOPSIS methods to evaluate G20 economies using inputs from financial markets. In this approach, TOPSIS is used to evaluate G20 economies according to their performance, while DEMATEL is used to give weight to the basic model and thus improve the evaluation process as a whole.

Despite the advances in DEMATEL technology, they still maintain their status. To solve this limitation, a method was developed using the Dempster-Shafer theory of evidence to improve DEMATEL by integrating information and objectives, thereby increasing the overall reliability and validity of the analysis (Du & Zhou, 2019). DEMATEL is widely used in many areas. For example, it is used for understanding of the complex interrelationships in library services, provides good insights and offers suggestions for improvement in the field (Y.-T. Chen, 2016b). (Pandey et al., 2019) categorized key mobility issues (CMI) according to relationships by using the Fuzzy-DEMATEL approach. According to their research, the most effective technique for analyzing different issues that arise when developing mobile applications is Fuzzy-DEMATEL as compared to other techniques such as E-DEMATEL and G-DEMATEL. DEMATEL combined with TOPSIS is used to assess risks associated with hydrogen production units. TOPSIS is used to identify defects and provide risk values, while in case of doubt, DEMATEL determines the severity and investigates the interaction of various factors that contribute to the overall chance of risk assessment process (J. Li et al., 2020).

(Yazdi et al., 2020) developed a decision-making framework for effective security management using a combination of the DEMATEL method, worst-case method (BWM) and Bayesian network (BN). This integration involves the integration of risk factors and information and increases the efficiency and reliability of safety management decisions. (J. Li et al., 2020) emphasized the importance of analyzing the interaction between key performance factors to identify key drivers and improve business growth quality and competitive strategy. In their research, they used the fuzzy DEMATEL method to identify the most important features of traffic lights after the strategies were developed. This approach helps businesses prioritize actions and make informed decisions to develop competitive advantage and achieve sustainable growth.

The integration of AHP, TOPSIS and DEMATEL methods provides a good way to improve the quality assessment of e-services in the banking sector. AHP helps to identify and monitor the importance of key quality factors. TOPSIS helps compare banks based on these factors, and DEMATEL provides a better understanding of strategies that improve quality by creating relationships between factors (Agrawal et al., 2022). (J. Li et al., 2020) showed that the use of non-standard techniques DEMATEL and TOPSIS to assess hazards in hydrogen power plants can detect interactions and cause risks. Good luck with your decision. While the TOPSIS model calculates risk values by prioritizing threats, DEMATEL evaluates social risks and determines their importance within the scope of the established hydrogen risk assessment.

The AHP-DEMATEL method is used to select delivery locations and provides a cost-effective analysis for potential local logistics service providers and logistics subcontractors. This approach helps to improve the services by allowing decision-makers to consider the important patterns and understand the relationship between various factors affecting logistics operations (Ly et al., 2021). (Garg, 2021) used a method combining DEMATEL and Gray's theory to examine the relationship between different e-material processes. The Gray-DEMATEL method was used to identify the best interventions in e-waste management and evaluate their relative importance. This collaboration provides insight into the importance of effective strategies to manage e-waste.

Skeleton diagrams are used in warehouse operations with the DEMATEL method. While the fishbone diagram separates the causes and effects of a problem, DEMATEL examines the relationship between these factors. This comprehensive guide will help understand the principles of problems and their complex interactions, supporting better problem solving and decision making in product management (Po-Heng Tsou & Hsin-Yao Hsu, 2022). The use of fuzzy DEMATEL is useful to improve the supplier selection process by analyzing the correlation between various parameters. This approach helps evaluate how these processes interact and influence each other, providing a better understanding of supplier evaluation and decision making (Mirmousa & Dehnavi, 2016).

In a nutshell, DEMATEL is perfect for analyzing multicausal systems. It helps identify key elements and their relationships, providing insight for risk assessment and prioritization when making decisions. It uses a visual model to evaluate the connections between identified processes and identify the most important patterns for decision-making purposes (Nguyen & Chu, 2023).

2.3 RESEARCH GAP

In the light of the traditional FMEA method, In order to evaluate and rank failure modes in goods, a novel integrated FMEA model has surfaced that combines cloud model theory with the hierarchical TOPSIS technique. (Liu et al., 2019b). The cloud model functions as an uncertainty model that makes it easier to comprehend the shift from qualitative to quantitative elements, especially when it comes to natural language expressions. This transition involves shifting between conceptual and quantitative representations, facilitated by uncertainty and randomness within the cloud model framework (Shi et al., 2008). The cloud model serves as a cognitive paradigm that facilitates bidirectional transmission between qualitative notions and quantitative data by utilizing fuzzy set theory and probability statistics. The cloud model framework's Expectation (Ex), Entropy (En), and Hyper Entropy (He) components help to communicate the essence of thoughts (G. Wang et al., 2014).

The integration of Cloud Model Theory (CMT) with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) has proven to be a promising approach for addressing uncertainty, particularly in the context of risk and failure determination in the cigarette manufacturing industry (Ahsan et al., 2023). This method demonstrates superiority in classifying failures throughout the manufacturing process. TOPSIS is a type of Multi-Criteria Decision Making (MCDM) that is used to choose the best options from a small number of available options. Traditionally, TOPSIS is recognized as a rational and effective instrument; however, it has been critiqued for its inability to account for interdependencies between criteria (Xu et al., 2015).

Faults within a production process not only disrupt the process itself but also impact the produced items. It's crucial to acknowledge and prioritize these faults to enhance process efficiency. However, isolating faults is inadequate since they often intertwine, causing overlapping effects. Furthermore, not all mistakes are equal; some may be causes while others are impacts. Hence, understanding the mutual relationship and nature of interactions among errors is essential for comprehensive analysis and mitigating their effects.

Hence, there's a recognized research gap emphasizing the importance of studying the interrelationship among faults within a production process and categorizing them based on their types, rather than solely focusing on ranking them. However, if studies fail to establish how these flaws interact and their underlying causes, there's a risk of rendering the entire procedure insufficient and ineffectual.

2.4 THEORETICAL FRAMEWORK

The traditional FMEA method is limited in its ability to rank the importance of individual influence factors, making it inefficient for systems with multiple concurrent or interacting failure modes. This limitation renders conventional FMEA unsuitable for such systems, as it fails to accurately identify mutual influences between system components. In such cases, DEMATEL proves valuable by identifying the chain of events leading to problems and assigning priority to these events, enabling prompt and effective resolution of critical issues, thus enhancing system performance (Tsai et al., 2017). Moreover, a novel FMEA evaluation approach, integrating fuzzy logic and DEMATEL theory, has been developed to enhance system resilience by establishing inter-relationships between failures. This strategy aims to improve the system's ability to recover from failures. After defuzzification of Risk Priority Numbers (RPNs), they serve as inputs for DEMATEL analysis to explore causal levels of failure and associated factors (Liu et al., 2019b).

The United States Army pioneered the conceptualization of FMEA as a risk reduction tool in 1949. Subsequently, it was adopted for the same purpose in the Apollo space mission, which initially developed it. Businesses widely employ FMEA for various purposes, including engineering design encompasses various manufacturing processes, product development, and product maintenance throughout its lifecycle (S. Parsana & T. Patel, 2014). DEMATEL originated in the 1970s at the Battelle Research Centre with the aim of understanding causality issues prevalent in industry applications at the time. It operates on the premise that not only these criteria have connections, but they also interact with each other to achieve its established goals (Dinçer & Yüksel, 2018).

Therefore, this study utilizes the following framework: first, the Cloud Model Theory (CMT) is employed to convert qualitative linguistic terms into quantitative data; second, the DEMATEL method is utilized to determine the interrelationships between identified faults and rank them accordingly.

2.6 RESEARCH QUESTIONS

This study aim to uncover the answers to the following questions,

- What specific types of faults are commonly occurred in the textile manufacturing industry, affecting the overall quality of produced textiles?
- How are the critical faults ranked in the textile manufacturing industry, and what criteria or metrics are commonly used for this ranking process?
- How do different types of faults in textile manufacturing interact with each other that lead to more severe defects in the final textile products?

CHAPTER 3. METHODOLOGY AND MATHEMATICAL MODELS

3.1 GENERAL

Methodology, mathematical models, sampling technique, techniques used in the investigation, and the overall research design of the study are all covered in this chapter.

3.2 RESEARCH PARADIGM

Specialists provided evaluations in the form of linguistic variables, which were then transformed into cloud form as part of a mixed hybrid strategy for data manipulation. The study utilized both primary and secondary sources of information. Primary data were collected from industry professionals using an Excel-based opinion form, while secondary data were sourced from the organization's production database and manufacturing process manuals. Experts rated the influence of failure modes on each other using a 9-point linguistic scale, chosen for its ability to capture nuanced judgments from knowledgeable specialists. This scale allowed for diverse viewpoints, enhanced data analysis, improved reliability, and reduced measurement errors. The opinion form was developed through expert consultation and literature review. Participants included supervisors, technicians, and servicing coordinators, totaling six individuals selected for their specialized expertise in textile production. The choice of six participants was based on FMEA’s requirement for specialized knowledge and the scope of the problem being studied. The figure below provides an overview of the research procedures.

3.3 RESEARCH SETTING

This study focuses on the textile manufacturing industry in Pakistan as its target population. Professionals from the textile sector were approached to provide feedback using linguistic terms via an opinion form. Participants were purposefully selected based on their level of expertise and information, employing purposive sampling. Additionally, weights were assigned to participants to demonstrate the credibility of their evaluations, rendering the study non-probabilistic. When determining the weight of each respondent's opinion, factors such as professional titles and years of experience were taken into consideration.

3.4 RESEARCH METHOD

Using the secondary data, a total of twenty faults were found, all of which contributed to different failures in the production process. In order to give primary data that is based on these flaws, an opinion form that is built using Excel and seeks assistance from the available literature has been designed. Data manipulation is accomplished with the help of Microsoft Excel. In addition to this, the bidirectional cognitive transfer between qualitative linguistic judgment and quantitative data is altered by the application of the cloud model theory. The DEMATEL approach is utilized in order to rate the defects and establish an understanding of the interrelationships between the problems.

3.5 MATHEMATICAL MODELS

3.5.1 Conversion of Linguistic Values into Cloud Setting

Linguistic concepts are converted into cloud representations using the Golden Segmentation approach. (Liu et al., 2019). This method states that a universal set with a domain$U = [X_{max}, X_{min}]$ and L to be a linguistic set represented by $G = \{g_0, g_1, \ldots, g_i\}$, it is possible to obtain $i + 1$ clouds using the following procedure:

$$\tilde{y}_0 = (Ex_0, En_0, He_0), \tilde{y}_1 = (Ex_1, En_1, He_1), \ldots., \tilde{y}_i = (Ex_i, En_i, He_i) \quad (1)$$

For a 9-point linguistic scale, the representation of G_k for $k = 9$ is as follows,

$G = \{g_0 = No\ Influence\ (NI), g_1 = Very\ Low\ (VL), g_2 = Low\ (L), g_3 = Medium\ Low\ (ML), g_4 = Medium\ (M), g_5 = Medium\ High\ (MH), g_6 = High(H), g_7 = Extremely\ High(EH), g_8 = Profound\ Influence\ (PI)\}$

Numeric Values of Clouds are calculated as follows;

$$\tilde{y}_0 = (Ex_0, En_0, He_0) = \left(X_{min} + 3En_0, \frac{En_1}{0.618}, \frac{He_1}{0.618}\right) \quad (2)$$

$$\tilde{y}_1 = (Ex_1, En_1, He_1) = \left(Ex_2 - 0.382 * (Ex_2 - Ex_0), \frac{En_2}{0.618}, \frac{He_2}{0.618}\right) \quad (3)$$

$$\tilde{y}_2 = (Ex_2, En_2, He_2) = \left(Ex_3 - 0.382 * (Ex_3 - Ex_0), \quad \frac{En_3}{0.618}, \quad \frac{He_3}{0.618}\right) \quad (4)$$

$$\tilde{y}_3 = (Ex_3, En_3, He_3) = \left(Ex_4 - 0.382 * (Ex_4 - Ex_0), \quad \frac{En_4}{0.618}, \quad \frac{He_4}{0.618}\right) \quad (5)$$

$$\tilde{y}_4 = (Ex_4, En_4, He_4) = \left(\frac{(X_{min} + X_{mzx})}{2}, 0.382 * \left(\frac{X_{max} + X_{min}}{3(g+2)}\right), He_4\right) \quad (6)$$

$$\tilde{y}_5 = (Ex_5, En_5, He_5) = \left(Ex_4 + 0.382 * (Ex_8 - Ex_4), \quad \frac{En_5}{0.618}, \quad \frac{He_5}{0.618}\right) \quad (7)$$

$$\tilde{y}_6 = (Ex_6, En_6, He_6) = \left(Ex_5 + 0.382 * (Ex_8 - Ex_5), \quad \frac{En_5}{0.618}, \quad \frac{He_5}{0.618}\right) \quad (8)$$

$$\tilde{y}_7 = (Ex_7, En_7, He_7) = \left(Ex_6 + 0.382 * (Ex_8 - Ex_6), \quad \frac{En_6}{0.618}, \quad \frac{He_6}{0.618}\right) \quad (9)$$

$$\tilde{y}_8 = (Ex_8, En_8, He_8) = \left(X_{max} - 3En_8,\ \frac{En_7}{0.618},\ \frac{He_7}{0.618}\right) \quad (10)$$

The domain $U = [X_{min}, X_{max}]$ and H_{e_4} are set prior to the clouds' numerical quantities being calculated. H_{e_4} has value lower than $1/3$.

3.5.2 Assigning Weights to the Decision Makers

Decision makers are weighted according to their knowledge, skills and seniority. These weights are determined according to subjective or objective criteria. This study uses a weighted distribution strategy to consider various factors that impact decision makers. Out of these factors, the difference in the knowledge and skills of decision makers plays an important role. Furthermore, this methodology enhances the dependability of data and addresses the issue of insufficient objective data. The productivity matrix, which is based on two crucial variables—seniority level and industry experience—forms the weight distribution table. While experience-based scoring is based on the number of years of industry experience of decision makers, seniority-based scoring is based on their professional titles. Next, using the given equation, the decision makers' overall score is determined.

$$\omega_k = \frac{H_k}{\sum_{k=1}^{n} H_k}, k = 1,2,3, \dots, n \quad (33)$$

In above equation, $\omega_{\boldsymbol{k}}$ represents the decision-makers' weights, where k stands for each individual decision-maker and n for the overall number of decision-makers, which is six in this instance (n=6). These team members are the most knowledgeable subject matter experts in the procedure under investigation. Hence, the weights can be denoted as $w_k = w_1, w_2, w_3, \dots w_n$. The cumulative score of all decision makers, denoted as H_k, is determined by assigning scores according to seniority and experience levels. The scores from the competency matrix, which is based on professional titles and years of industry experience, are added to provide this total score. Table 4-1 can be used to determine the weights for each decision maker based on this score.

Following step are involved in the application of DEMATEL (Si et al., 2018)

3.5.3 Determine the Collective Direct Relation Matrix

The following equation is used to convert the cloud matrices—which are used to calculate the decision-makers' weight allocation—into a collective direct-relation matrix, or $\tilde{Z} = [\tilde{z}]_{n\times n}$,

$$\tilde{z}_{ij} = \sum_{k=1}^{m} w_k \tilde{z}_{ij}^{k} = \sum_{k=1}^{m} w_k \left(Ex_{ij}^{k}, En_{ij}^{k}, He_{ij}^{k}\right) = \left(\sum_{k=1}^{m} w_k Ex_{ij}^{k} , \sqrt{\sum_{k=1}^{m} w_k \left(En_{ij}^{k}\right)^2} , \sqrt{\sum_{k=1}^{m} w_k \left(He_{ij}^{k}\right)^2}\right) (1$$

Here numbers, i and j stand for the rows and columns of the opinion forms that are used to get the experts' data. The opinion forms that are used to gather data are based on a 20×20 square matrix. $\tilde{Z} = [\tilde{z}]_{20\times 20}$ is the result. In this case, $k = 1, 2,3, \dots, 6$ represents the number of decision-makers. Furthermore, m=n=6.

The opinion forms that were initially based on language phrases are next converted into numerical values of (E_x), entropy (E_n) and hyper-entropy (H_e) following the conversion of linguistic terms into numerical values of clouds in the preceding stage. Here, ij shows where a specific value is located in the matrix, ranging from $ij = 1 \times 1, 1 \times 2, 1 \times 3, \dots, 20 \times 20$. Following the conversion, the decision-makers' weights are now multiplied by each expectation, entropy, and hyper-entropy value in accordance with the equation. The weighted values of expectation, entropy, and hyper-entropy are then added from the six opinion forms to produce a single collective direct-relation matrix.

The following is the depiction of the collective direct-relation matrix that was produced:

$$\tilde{Z} = \sum_{k=1}^{m} \left(w_k \tilde{Z}^k\right) = \begin{bmatrix} Ex_{11}, En_{11}, He_{11} & \cdots & Ex_{1n}, En_{1n}, He_{1n} \\ \vdots & \ddots & \vdots \\ Ex_{n1}, En_{n1}, He_{n1} & \cdots & Ex_{nn}, En_{nn}, He_{nn} \end{bmatrix}$$

3.5.4 Determine the Normalized Collective Direct Relation Matrix

After obtaining the collective direct-relation matrix $\tilde{Z} = [\tilde{z}]_{n\times n}$, the subsequent step involves calculating the normalized collective direct-relation matrix $X = \left[x_{ij}\right]_{n\times n}$ through the following procedure:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{bmatrix}$$

Using

$$x_{ij} = \left(Ex_{ij}^N, En_{ij}^N, He_{ij}^N\right) = \left(\frac{Ex_{ij}}{\alpha}, \frac{En_{ij}}{\beta}, \frac{He_{ij}}{\gamma}\right) \tag{12}$$

$$\alpha = \left(max\left\{max_{1\le i\le n}\sum_{j=1}^{n} Ex_{ij}\, , max_{1\le j\le n}\sum_{i=1}^{n} Ex_{ij}\right\}\right) \tag{13}$$

$$\beta = \left(max\left\{max_{1\le i\le n}\sum_{j=1}^{n} En_{ij}\, , max_{1\le j\le n}\sum_{i=1}^{n} En_{ij}\right\}\right) \tag{14}$$

$$\gamma = \left(max\left\{max_{1\le i\le n}\sum_{j=1}^{n} He_{ij}\, , max_{1\le j\le n}\sum_{i=1}^{n} He_{ij}\right\}\right) \tag{15}$$

Here $0 \le Ex_{ij}^N, En_{ij}^N, He_{ij}^N \le 1$

The variables α, β and γ reflect the highest values found in the matrices' rows and columns of E_x, E_n and H_e respectively.

3.5.5 Determine the Over Relation Matrix

Compute the overall-relation matrix $T = \left[t_{ij}\right]_{n\times n}$ following the computation of the normalized collective direct-relation matrix $X = \left[x_{ij}\right]_{n\times n}$. In order to obtain crisp numbers, the normalized collective direct-relation matrix is partitioned into three matrices. The reason for this divide is that the normalized collective direct-relation matrix has the shape of clouds, and it is not possible to compute its inverse directly. The three new matrices obtained are displayed as,

$$A = \left[Ex_{ij}^N\right]_{n\times n} \tag{16}$$

$$B = \left[En_{ij}^N\right]_{n\times n} \tag{17}$$

$$C = \left[He_{ij}^N\right]_{n\times n} \tag{18}$$

Consequently, the following is how the overall-relation matrix can be obtained:

$$T_A = A + A^2 + A^3 + \cdots = \sum_{i=1}^{\infty} A^i = A(I - A)^{-1} = \left[Ex_{ij}^T\right]_{n\times n} \tag{19}$$

$$T_B = B + B^2 + B^3 + \cdots = \sum_{i=1}^{\infty} B^i = B(I - B)^{-1} = \left[En_{ij}^T\right]_{n\times n} \tag{20}$$

$$T_C = C + C^2 + C^3 + \cdots = \sum_{i=1}^{\infty} C^i = C(I - C)^{-1} = \left[He_{ij}^T\right]_{n\times n} \tag{21}$$

Here I symbolizes a matrix of identities. Consequently, the resulting overall-relation matrix is displayed as,

$$T = \left[t_{ij}\right]_{n\times n} = \begin{bmatrix} t_{11} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots \\ t_{n1} & \cdots & t_{nn} \end{bmatrix}$$

3.5.6 Calculate the influence degree and degree of being influenced

The next step is to use the following equations to calculate the influence degree P_i and the degree of being influenced R_j after the overall-relation matrix has been calculated,

$$P_i = \sum_{j=1}^{n} t_{ij} = \sum_{j=1}^{n} \left(Ex_{ij}^T, En_{ij}^T, He_{ij}^T\right) = \left(\sum_{j=1}^{n} Ex_{ij}^T, \sqrt{\sum_{j=1}^{n} \left(En_{ij}^T\right)^2}, \sqrt{\sum_{j=1}^{n} \left(He_{ij}^T\right)^2}\right), i = 1,2,3,\dots,n \tag{22}$$

$$R_j = \sum_{i=1}^{n} t_{ij} = \sum_{i=1}^{n} \left(Ex_{ij}^T, En_{ij}^T, He_{ij}^T\right) = \left(\sum_{i=1}^{n} Ex_{ij}^T, \sqrt{\sum_{i=1}^{n} \left(En_{ij}^T\right)^2}, \sqrt{\sum_{i=1}^{n} \left(He_{ij}^T\right)^2}\right), j = 1,2,3,\dots,n \tag{23}$$

3.5.7 Calculate the Prominence and Relation

Following the computation of the degree of influence and the degree of being influenced, the subsequent stage involves calculating the prominence p_i and relation r_i by using the equations below,

$$p_i = P_i + R_j \tag{24}$$

$$p_i = \left(\sum_{j=1}^{n} Ex_{ij}^{T} + \sum_{i=1}^{n} Ex_{ij}^{T}, \sqrt{\sum_{j=1}^{n} \left(En_{ij}^{T}\right)^2 + \sum_{i=1}^{n} \left(En_{ij}^{T}\right)^2}, \sqrt{\sum_{j=1}^{n} \left(He_{ij}^{T}\right)^2 + \sum_{i=1}^{n} \left(He_{ij}^{T}\right)^2}, i = 1,2, \dots, n, \right)$$

And

$$r_i = P_i - R_j \tag{26}$$

$$r_i = \left(\sum_{j=1}^{n} Ex_{ij}^{T} - \sum_{i=1}^{n} Ex_{ij}^{T}, \sqrt{\sum_{j=1}^{n} \left(En_{ij}^{T}\right)^2 + \sum_{i=1}^{n} \left(En_{ij}^{T}\right)^2}, \sqrt{\sum_{j=1}^{n} \left(He_{ij}^{T}\right)^2 + \sum_{i=1}^{n} \left(He_{ij}^{T}\right)^2}, i = 1,2, \dots, n. \right)$$

3.5.8 Find the Cause and Effect Relationship

The next step is to utilize these values to calculate the prominence and relation, and then use them to calculate the cause-and-effect relationship. The relationship between the flaws and prominence is determined using the expectations values. The prominence values in the DEMATEL context show how important a fault is. Thus, a fault is more critical the greater its prominence value. Additionally, the connection r_i aids in classifying errors into groups that are either causes or effects. A fault is classified as a cause if its relation r_i value is more than zero. On the other hand, a fault is regarded as an effect if the value of relation r_i is less than zero.

3.5.9 Sketch Causal Diagram

The causal diagram is created based on the values of the expectation of prominence p_i and relation r_i. This diagram aids in illustrating the significance of the faults and ranking them into cause-and-effect groups. The vertical axis in the diagram represents r_i, which represents the fault kind, and the horizontal axis p_i, which represents the fault importance. To be more precise, the y-axis denotes the type of defect (cause or effect), while the x-axis illustrates the significance of faults. A better grasp of the fault linkages and the effects they have on the system is made possible by this visualization.

3.5.10 Draw Relationship Map

To visually depict the relationships between faults and highlight the most significant relationships among the faults that have been found, a relationship map is made. Based on sharp values obtained from the overall-relation matrix's expectation, this map is created. It can be depicted as follows; $T^* = \left[t_{ij}^*\right]_{n\times n}$ where $t_{ij}^* = Ex_{ij}^T$. The matrix obtained can be shown as,

$$T^* = \left[t_{ij}^*\right]_{n\times n} \tag{28}$$

$$T^* = \begin{bmatrix} t_{11}^* & \cdots & t_{1n}^* \\ \vdots & \ddots & \vdots \\ t_{n1}^* & \cdots & t_{nn}^* \end{bmatrix}$$

Drawing a connection map that incorporates every relationship may result in a complicated and esoteric map. A threshold value is established in order to simplify the relationship map and eliminate extraneous complexity. This threshold value aids in reducing the number of relationships that are deemed insignificant. It's crucial to remember that if the threshold value is set too high, numerous errors may be regarded as independent. On the other hand, if the threshold value is set too low, it may cause issues with data display. The following formula is used to determine the value of threshold:

$$\delta = \bar{t}_{ij} + \varphi \ (i, j = 1,2, \dots, n) \tag{29}$$

Here, δ represents the value of threshold, whereas $\bar{t}_{ij}$ and φ represent the matrix's mean and standard deviation T^* (Gao et al., 2021a)

CHAPTER 4. RESULTS AND DISCUSSIONS

4.1 GENERAL

In this chapter the application of proposed approach in industry is illustrated. The detailed execution of the approach as well as the results obtained from the application of the theory are jotted down in this section.

4.2 APPLICATION OF THE STUDY IN INDUSTRY

This study showcases the integration of cloud model theory and DEMATEL into practical applications. Through examining the connections between identified flaws related to textile manufacturing procedures, effective execution can result in enhancements to traditional FMEA techniques.

The aim of this research is to examine the relationship between the faults that reduce the production process's efficiency. The study will be put into practice in the textile production industry. The objective of this study is to evaluate how useful and practical the technique is. During the study, both technological and human-made mistakes will be taken into consideration and examined.

The figure given below provides additional clarity regarding the stages.

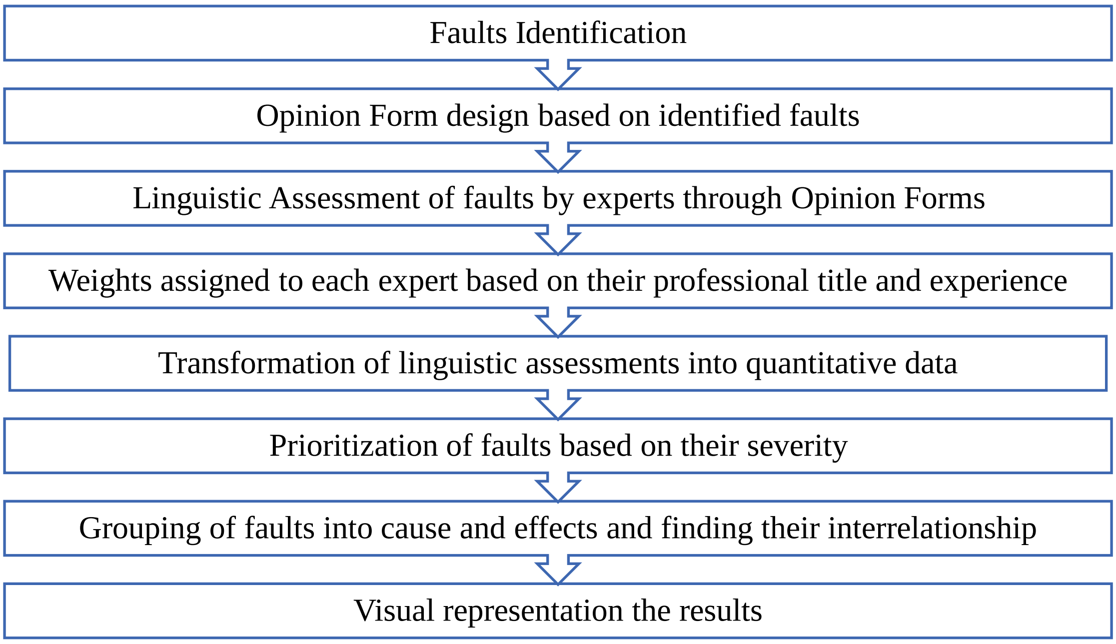

Figure 4-1 Stages of the Study

4.3 EXECUTION OF THE METHOD

The following stages shows how the method is applied in the industry

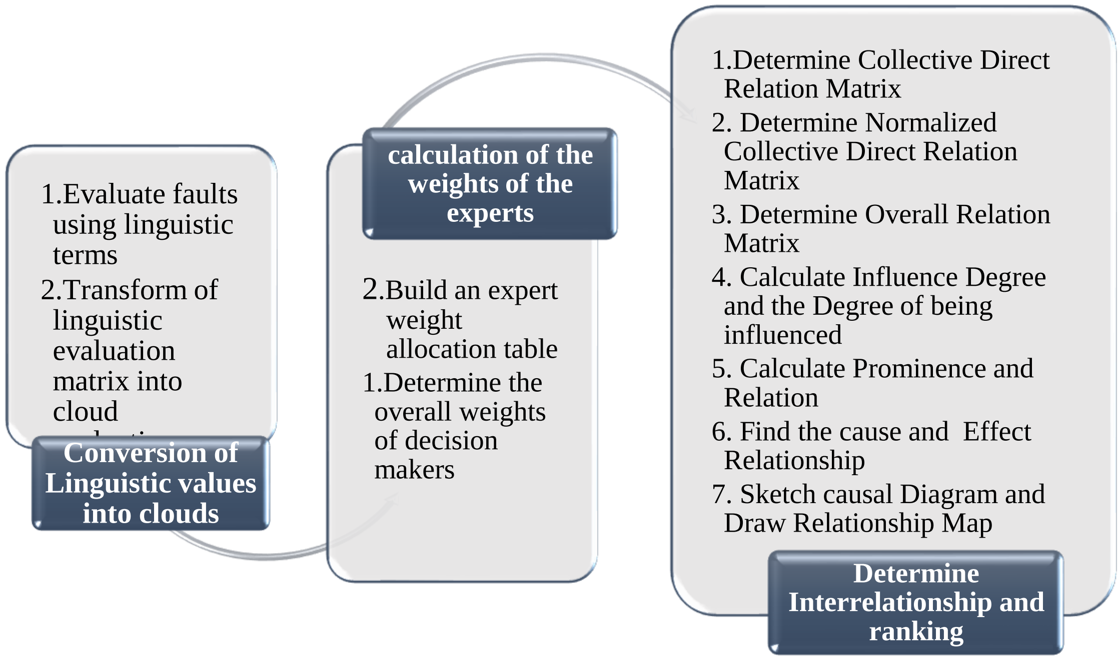

Figure 4-2 Steps of the Method

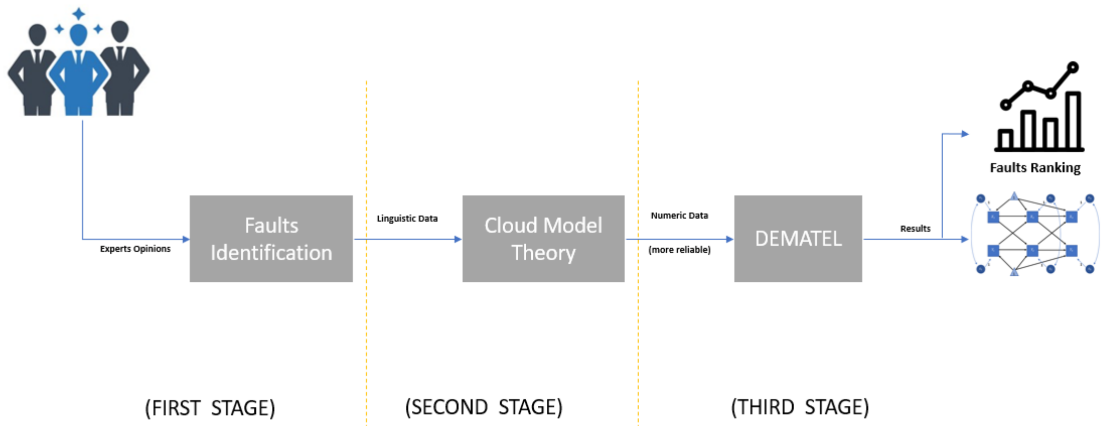

Figure 4-3 Research Process

4.3.1 Step 1 Identification of the Faults

To effectively evaluate system failures and the contributing faults, a comprehensive understanding of the system's functioning is essential. The transformation process from raw material to finished product can be complex and may require more effort and control than anticipated. Numerous inputs, controlled variable contributions, and uncontrolled variable data lines all influence assembly yields. Hence, the organization's standards and literature are utilized to identify corresponding risk factors within their hierarchy and evaluate each failure mode accordingly.

After the production process was examined, the 20 potential failure scenarios are displayed in the table 4-1,

Table 4-1 Identified faults in Production Line

Assigned Names	Identified Faults
F1	Needle Breakage
F2	Thread Breakage
F3	Bobin Thread Breakage
F4	Machine Jamming due to Thread Tension Issues
F5	Misalignment of Design
F6	Machine Skipping Stitches
F7	Machine Vibration
F8	Shittle Timing
F9	Motor Issues
F10	Fabric Rule
F11	Sensor Malfunction
F12	Lubrication Problems
F13	Uneven Stitching
F14	Puckering of Fabrics
F15	Bobin Tension Issues

F16	Head Not Working
F17	Thread Tangling
F18	Strange Noises
F19	Stitch Not Feeding
F20	Machine Runs but Needle does not Move

4.3.2 Step 2 Construction of the Opinion Form

In order to build an opinion form in response to the problems that were discovered, assistance from the relevant literature was sought. The DEMATEL technique required that the opinion form be designed in such a way that it could satisfy the standards that were laid forth for it. The feedback form took the form of a matrix created in Microsoft Excel, with discovered flaws listed along its horizontal and vertical rows and columns, respectively. The participants were given a list of linguistic phrases, and they were required to fill out a cell that corresponded to each cell in the survey.

4.3.3 Step 3 Selection of Respondents

The questionnaire was given in the shape of an excel-based opinion form to six different responders to complete up. This is due to the fact that both the FMEA and DEMATEL methods rely on the judgement of experts; hence, these two methods involve fewer but more expert respondents. These professionals have an extensive knowledge base in their field. They range widely in terms of their professional titles and levels of expertise. Within the opinion form, they were required to include information about their professional title and experience level in the opinion form. They were provided with concise description, along with the requirements of the opinion form, and instructions on how to fill out the opinion form. They are industry specialists; thus, it was not difficult for them to comprehend the nature of the dimension being asked for in the opinion form. In addition to this, students were given eleven linguistic terms to choose from so that they could keep the flexibility of their judgements.

4.3.4 Step 4 Calculation of the Weights of the Respondents

Respondents are assigned with weights. It is necessary to determine these weights utilizing either the subjective or objective weightage system. This phase involves two steps: first, construct a weight allocation table, second, allocation of overall weight to the respondents. The weight allocation system is based on an approach that is subject to interpretation, and it has two components: the seniority level and the experience level. The level of seniority is further subdivided into five classes, commencing with the subordinate level and working its way up to the senior level. In a similar manner, the experience level has an additional four classifications, ranging from a respondent with experience of less than five years to a respondent with more than twenty years of expertise. The formula for determining the communal weights is just the addition of these two scores.

Table 4-2 Weight Allocation Table

Aspect	Classes/Levels	Score
Level of Seniority	Senior level	5
	Sub-senior level	4
	Intermediate level	3
	Associate level	2
	Inferior level	1
Experience in industry	More than 20 years	4
	Between ten and nineteen years	3
	Between five and nine years	2
	Below five years	1

The weights are assigned to different respondents based on their understanding of a subject, their professional competencies, and their number of years of experience. Based on weights allocation table, the corresponding weights of the decision members are shown in table 4-3.

Table 4-3 Weight of the Decision Makers

Sr. No. of decision makers	Experience-based scoring	Professional title-based scoring	Cumulative scoring	Final weightage of decision makers (ω_k)
1	3	5	8	0.19047619
2	3	4	7	0.166666667
3	3	3	6	0.142857143
4	4	4	8	0.19047619
5	3	3	6	0.142857143
6	4	3	7	0.166666667

Overall weights of the respondents are calculated using the formula given below.

$$\mathrm{\omega_k} = \frac{\mathrm{H_k}}{\sum_{\mathrm{k=1}}^{\mathrm{n}} \mathrm{H_k}}, k = 1,2,3, \dots, n$$

Where k represents respondents, while n indicates the total number of respondents.

4.3.5 Conversion of Linguistic Values into Cloud Setting

The decision-makers employed a system of 9-point linguistic terms to denote the degree and existence of interdependencies among the discovered defects. The following are the terms used in CMT:

$L = \{l_0 = No\ Influence\ (NI), l_1 = Very\ Low\ (VL), l_2 = Low\ (L), l_3 = Medium\ Low\ (ML), l_4 = Medium\ (M), l_5 = Medium\ High\ (MH), l_6 = High(H), l_7 = Extremely\ High(EH), l_8 = Profound\ Influence\ (PI)\}$

Equations from 2-1 to 2-10 are employed to obtain the Numerical Clouds.

Below are the normal clouds that matched each of the nine linguistic points on the scale.

$\tilde{y}_0 = (2.61804, 0.87268, 0.20564)$

$\tilde{y}_1 = (3.1802669, 0.53932, 0.12709)$

$\tilde{y}_2 = (3.5277669, 0.3333, 0.07854)$

$\tilde{y}_3 = (4.09009, 0.20598, 0.04854)$

$\tilde{y}_4 = (5, 0.1723, 0.03)$

$\tilde{y}_5 = (5.9099, 0.20598, 0.0485)$

$\tilde{y}_6 = (6.47223, 0.3333, 0.07854)$

$\tilde{y}_7 = (6.819747, 0.53932, 0.12709)$

$\tilde{y}_8 = (7.38196, 0.87268, 0.20564)$

Where the range is $X_{min}, X_{max} = 0, 10$, and $He_4 = 0.03$

Expectation (Ex), Entropy (En), and Hyper-entropy form the collection of parameters that the cloud model theory uses to articulate conclusions.. In this theory, "expectation" denotes the central value within a cloud representation, reflecting the most likely or anticipated value within that cloud. It represents the predominant tendency of the data distribution within the cloud. Entropy, within the theory of cloud models, quantifies the degree of disorder or uncertainty present in a cloud. Higher entropy indicates greater uncertainty, while lower entropy suggests a more concentrated and predictable distribution of values. Hyper-entropy extends the concept of entropy and is used to characterize uncertainty in cloud spaces with multiple dimensions. It provides a quantitative analysis of the overall randomness and unpredictability within a cloud model when dealing with various qualities or variables. In essence, hyper-entropy determines the degree of uncertainty beyond entropy. Table 4-4 illustrates the corresponding values of Expectation, Entropy, and Hyper-entropy for all linguistic terms.

Table 4-4 Conversion of Linguistic Value into Cloud

Linguistic Terms	**Numerical Values (Ex, En, He)**
No Influence (NI)	$(2.61804, 0.87268, 0.20564)$
Very Low Influence (VL)	$(3.1802669, 0.53932, 0.12709)$
Low Influence (L)	$(3.5277669, 0.3333, 0.07854)$
Medium Low Influence (ML)	$(4.09009, 0.20598, 0.04854)$
Medium Influence (M)	$(5, 0.1723, 0.03)$
Medium High Influence (MH)	$(5.9099, 0.20598, 0.0485)$
High Influence (H)	$(6.47223, 0.3333, 0.07854)$
Extremely High Influence (EH)	$(6.819747, 0.53932, 0.12709)$
Profound Influence (PI)	$(7.38196, 0.87268, 0.20564)$

A subjective weighing scheme was used to determine the decision makers' respective weights. Equation 33 is utilized to ascertain the decision makers' respective weights.

4.3.6 Collective Direct Relation Matrix

Equation 11 is used to convert the cloud matrices into a collective direct-relation matrix $[\tilde{z}]_{20\times 20}$ once the decision makers have been assigned weights.

Table 4-5 Calculation of Direct Relation Matrix

		Effect of F10 on F11	Effect of F10 on F11	Collective direct Relation Matrix
Respondents	Weights (wk)	Linguistic terms	Cloud Values	$\left(\sum_{k=1}^{m} w_k Ex_{ij}^k, \sqrt{\sum_{k=1}^{m} w_k \left(En_{ij}^k\right)^2}, \sqrt{\sum_{k=1}^{m} w_k \left(He_{ij}^k\right)^2}\right)$

			(Ex, En, He)	
1	0.1904761	PI	(1.406, 0.1451, 0.008)	7.020537357, 0.67747675163, 0.15964376906 k shows decision makers, m=6, ij represents rows and columns, respectively.
2	0.1666667	PI	(1.23, 0.127, 0.007)	
3	0.1428571	EH	(0.974, 0.042, 0.002)	
4	0.1904761	EH	(1.298, 0.0554, 0.0031)	
5	0.1428571	EH	(0.974, 0.042, 0.0023)	
6	0.1666666	EH	(1.137, 0.048, 0.0027)	

4.3.7 Step 7 Normalized Collective Direct Relation Matrix

The Equation 12-15 is used to convert the collective direct-relation matrix into the normalized collective direct-relation matrix $[x_{ij}]_{20\times 20}$. Adding up each value in the row is the first step in calculating the normalized collective direct relation matrix. In the same manner, each value from the column is added to the total. The next step is to select the maximum value from each row and the maximum value from each column. After that, the value with the greatest difference between these two maximum values is the one that is used for dividing the data for expectation, entropy, and hyper-entropy.

Table 4-6 Calculation of Normalized Direct Relation Matrix

		$\frac{Ex_{ij}}{\alpha}, \frac{En_{ij}}{\beta}, \frac{He_{ij}}{\gamma}$
$\alpha = \left(max \left\{ max_{1 \le i \le n} \sum_{j=1}^{n} Ex_{ij}, max_{1 \le j \le n} \sum_{i=1}^{n} Ex_{ij} \right\} \right)$	127.77	For Effect of F10 on F11
$\beta = \left(max \left\{ max_{1 \le i \le n} \sum_{j=1}^{n} En_{ij}, max_{1 \le j \le n} \sum_{i=1}^{n} En_{ij} \right\} \right)$	14.857	
$\gamma = \left(max \left\{ max_{1 \le i \le n} \sum_{j=1}^{n} He_{ij}, max_{1 \le j \le n} \sum_{i=1}^{n} He_{ij} \right\} \right)$	3.501	0.00549466, 0.0455998, 0.04559947

Next, an overall-relation matrix is created using the normalized collective direct-relation matrix $T = [t_{ij}]_{n \times n}$ is constructed using equations 16-21.

Table 4-7 Calculation of Overall Relation Matrix

	Calculation of overall relation matrix for Ex	Calculation of overall relation matrix for En	Calculation of overall relation matrix for He
	$A(I-A)^{-1}$	$B(I-B)^{-1}$	$C(I-C)^{-1}$
Effect of F10 on F11	0.14261	0.19949	0.199543

The overall relation matrix is computed by taking the inverse of the normalized collective direct relation matrix. This process is carried out separately for the values of Expectation (Ex), Entropy (En), and Hyper-entropy (He).

4.3.8 Step 8 Influence degree and degree of being influenced

Consequently, the degree of influence P_i and the degree of being influenced R_j are computed using equations 22 and 23.

4.3.9 Step 9 Calculate prominence and relation

Afterwards, equations 24-27 are employed in the computation of the relation r_i and the prominence p_i.

4.3.10 Step 10 Prominence

If a fault is a cause, prominence denotes its vulnerability; if it is a cause, prominence denotes its severity. Put otherwise, a criterion's significance increases with its magnitude.

Table 4-8 Calculation of Prominence

Assigned Names	Actual Names	Prominence values	Rank
F4	Machine Jamming	6.136984223, 5.204771621, 5.204610242,	Higher
F7	Machine vibration	3.190092888, 4.887519419, 4.8873567565,	Lower

Similarly, prominence values for rest of the faults are calculated and show in the table below.

Table 4-9 Ranking based on Prominence Values in Descending Order

Identified Faults	Assigned Names	Prominence (Pi) Value	RANK
Machine jamming due to thread tension issues	F4	6.136984223	1
Sensor malfunction	F11	6.057223928	2
Shittle timing	F8	4.739867427	3
Bobin tension issues	F15	4.711355491	4

Needle breakage	F1	4.307370241	5
Stitch not feeding	F19	4.267689749	6
Bobin Thread Breakage	F3	4.243928372	7
Machine skipping stitches	F6	4.207805065	8
Head not working	F16	4.149458832	9
Misalignment of design	F5	4.135433688	10
Thread breakage	F2	4.126550247	11
Uneven stitching	F13	4.0827826	12
Motor issues	F9	3.993354506	13
Puckering of fabrics	F14	3.950910898	14
Thread tangling	F17	3.819750676	15
Lubrication problems	F12	3.795806083	16
Fabric rule	F10	3.644626713	17
Machine runs but needle does not move	F20	3.586759852	18
Strange noises	F18	3.43256847	19
Machine vibration	F7	3.190092888	20

The relation values assign faults to either a cause group or an impact group depending on their nature. It is determined to be a cause of a fault if the size of the relation r_i is bigger than zero for the fault in question. It is determined to be an effect rather than a fault if the size of the relation r_i is negative and greater than zero.

All faults are ranked into cause-and-effect groups on the basis of relation values and relationship map will further display their mutual relationships in the following tables.

Table 4-10 Cause Group and ranking of the faults

Assigned Names	Identified Faults	ri Values	Group Name	Rank
F7	Machine vibration	0.259174062	Cause	1
F12	Lubrication problems	0.213577867	Cause	2
F1	Needle breakage	0.197158401	Cause	3
F2	Thread breakage	0.196699535	Cause	4
F16	Head not working	0.156883578	Cause	5
F5	Misalignment of design	0.1553033	Cause	6
F20	Machine runs but needle does not move	0.13147322	Cause	7
F4	Machine jamming due to thread tension issues	0.035930815	Cause	8

Table 4-11 Effect Group and Ranking of the Faults

Assigned Name	Identified Faults	Relation (ri) Values	Group Name	Rank
F9	Motor issues	-0.024294929	Effect	1
F14	Puckering of fabrics	-0.051452143	Effect	2
F10	Fabric rule	-0.056357822	Effect	3
F6	Machine skipping stitches	-0.057170832	Effect	4
F8	Shittle timing	-0.090949007	Effect	5
F11	Sensor malfunction	-0.111050296	Effect	6
F3	Bobin thread breakage	-0.115420989	Effect	7
F18	Strange noises	-0.155126381	Effect	8
F17	Thread tangling	-0.164377416	Effect	9

F15	Bobin tension issues	-0.24168501	Effect	10
F19	Stitch not feeding	-0.272595943	Effect	11

Table 4-12 Neutral Fault

Assigned Name	Identified Fault	ri Value	Group Name	pi Value
F13	Uneven Stitching	zero	Neutral	4.0827826

4.3.11 Construct Causal Diagram

The predicted prominence and relation values are then used to create a causal diagram, as seen in figures 4-4 and 4-5. The x- and y-axes, with their corresponding positive and negative values, make up the causal diagram. The horizontal axis in the causal diagram represents the prominence values, which indicate the importance of errors. On the other hand, the relation is represented by the vertical axis, which shows the kinds of errors. The kind of defects is shown by the link between the two axes.

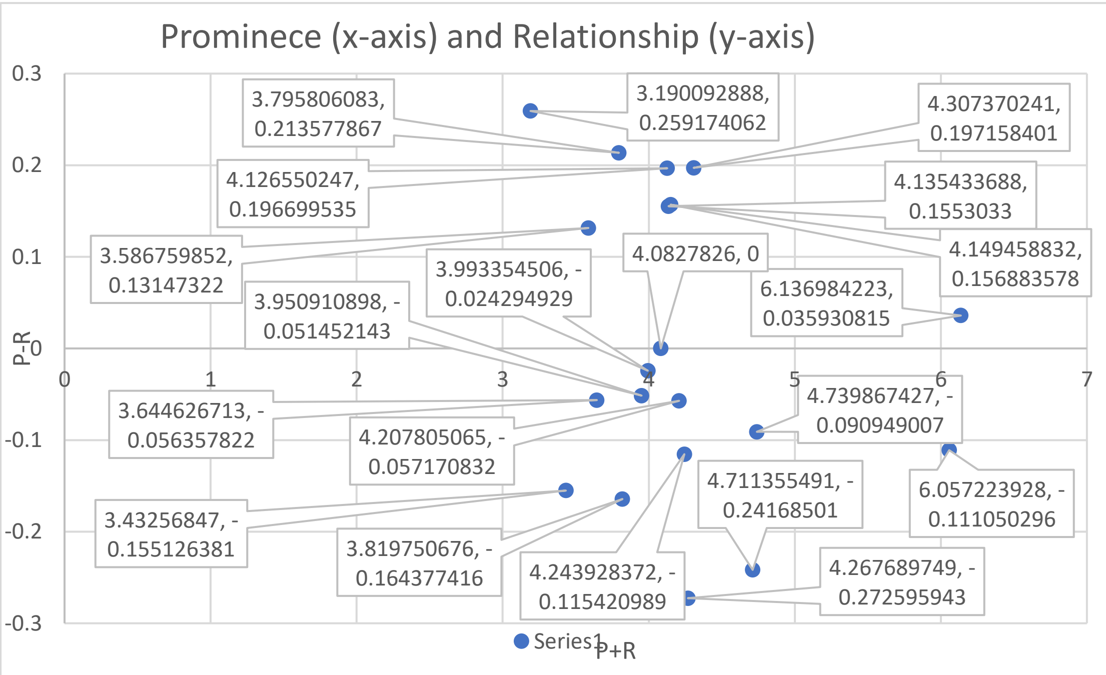

Figure 4-4 Causal Diagram with Values

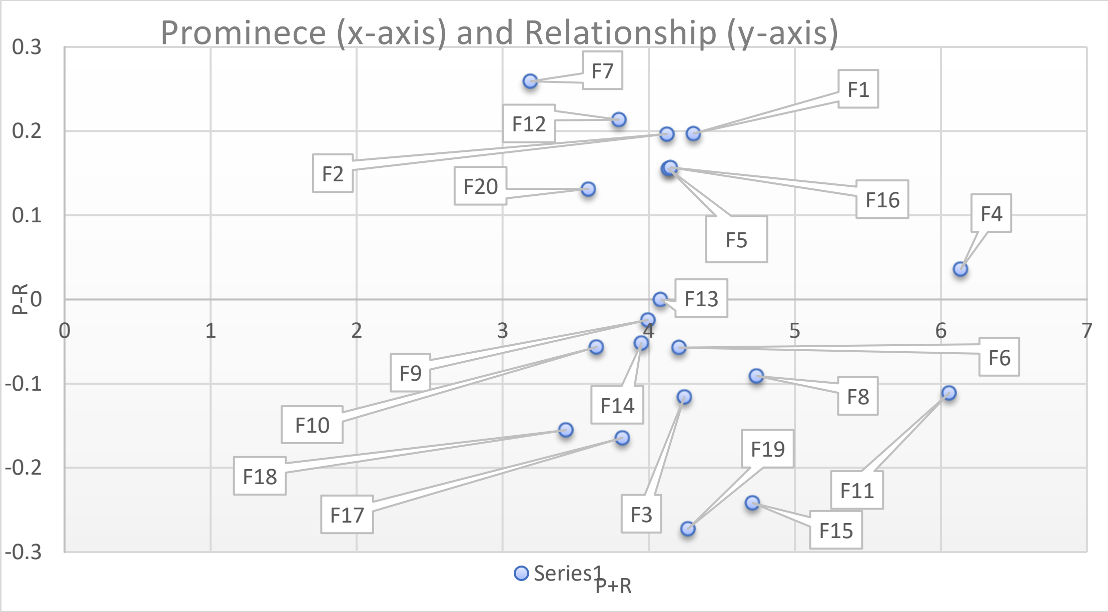

Figure 4-5 Causal Diagram with Fault Names

4.3.12 Step 12 Construct a Relationship Map

To calculate the relationship map, the first step is to compute the Effect matrix. The Effect matrix is derived by removing values from cells that are less than the threshold value, which in this case is 1.03007919780384. Upon examining the Effect matrix, it becomes evident that the effect of fault F20 is on fault F9 is 0.3, surpassing the threshold value. This indicates that F20 (cause) influences F9 (effect). Such relationships can be visualized in the relationship map provided below. This method allows us to ascertain the interrelationships among the remaining faults.

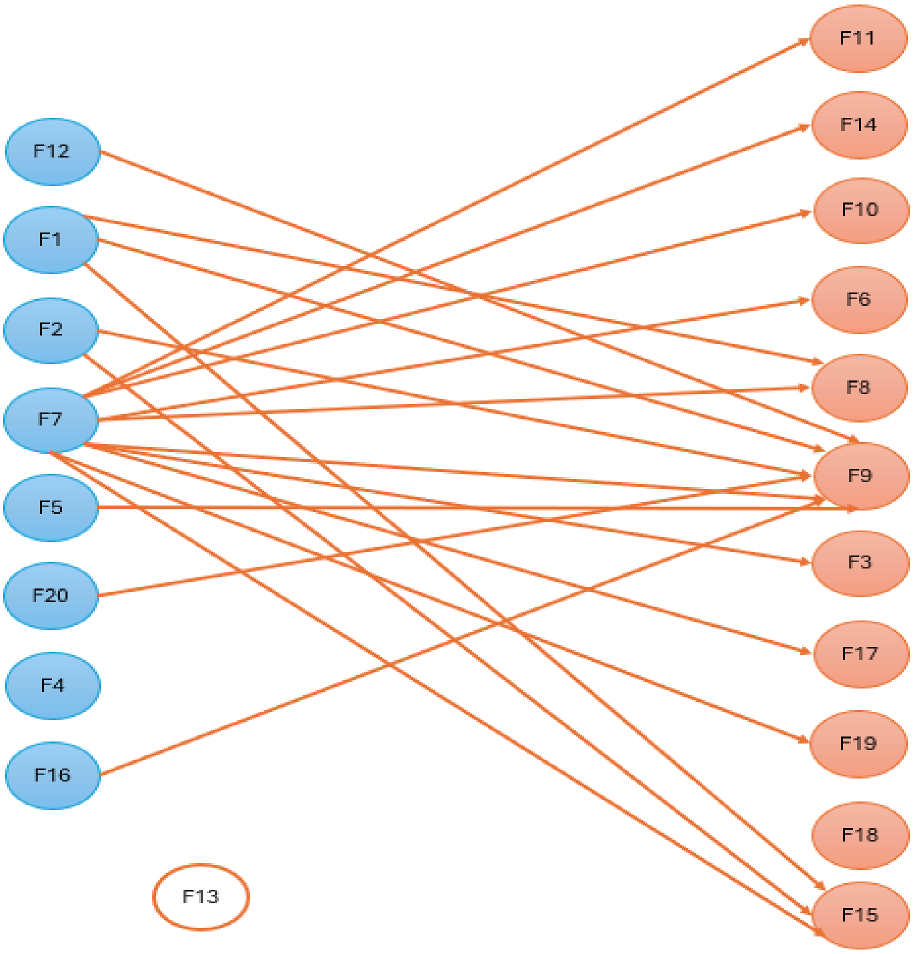

Figure 4-6 Relationship Map

4.4 DISCUSSION ON RESULTS

Table 4-1 shows the ranking of the identified problems based on the importance levels. The prominence values in DEMATEL show that defects are ranked higher for larger values of prominence and lower for lesser values of prominence. Looking at table 4-9, it's evident that machine jamming due to thread tension issues tops the list with the highest prominence value, securing the first position. This highlights it as the most significant fault. Following closely are sensor malfunction and shuttle timing. Conversely, strange noises and machine vibration, with their lower prominence values, find themselves at the bottom of the ranking in table 4-9, showing that they are very least significant among all the faults that are identified.

As shown in tables 4-10, 4-11, and 4-12, the relation values also aid in the grading and classification of discovered defects into cause-and-effect groupings. In DEMATEL, if a fault's relation value is less than zero, it is considered an effect. Conversely, if the value of relation is greater than zero, it serves as a cause. Following the DEMATEL theory, tables 4-10, 4-11 and 4-12 delineate these cause-and-effect groups. Faults categorized as effects exhibit negative relation values, while those categorized as causes display positive relation values. However, faults with a relation value of zero are allocated to a separate group termed the neutral group, as depicted in table 4-12. This classification arises from their lack of positive or negative relation values.

The following insights are produced by aggregating the results of the prominence and relation values in tables 4-10, 4-11, and 4-12. Firstly, machine jamming due to thread tension issues exhibits a negative relation value and the highest prominence value, positioning it as the most critical fault. Likewise, within the effect group, stitch not feeding occupies the bottom rank, indicating it as the least affected effect. This is attributed to its negative relation value and minimal prominence compared to other effects. Similar assessments can be made for the cause group.

The causal diagrams, which are shown in figures 4-4 and 4-5, provide a visual depiction of errors according to their importance and relationship values. The prominence value is represented by the x-axis, while the relationship value is shown by the y-axis. Faults with negative correlations below the x-axis zero line are classified as consequences, while those above the x-axis (representing positive correlation) are considered causes. The fault's distance from zero on the x-axis indicates its importance. For example, a cause-effect analysis would indicate that fault F9 is below the x-axis zero line, indicating its status as Effect. Additionally, the position farthest from zero shows the importance of the effect. Likewise, the F7 fault is located above the zero line of the x-axis and has the largest distance to the zero line in its group, not only showing its role as a result, but also showing a very significant impact. Furthermore, the x-axis malfunction (F13, for instance) is not associated with either the cause or the effect group. Its limited relevance among defects is further indicated by its prominence value and placements on the x-axis.

Furthermore, figure 4-6 illustrates the relationship map, offering insights into the interconnectedness between causes and effects. This map highlights the most significant problems and offers useful information on their dependencies. It helps to visualize the main flaws as well as how they relate to one another. Only values surpassing the predetermined threshold value, set at 0.134672174861413, are included in the relationship map, obtained from the crisp form of the overall relation matrix. The mean value of matrix T^* stands at 0.105725399934155, with a standard deviation of 0.0289467749272581. Faults depicted within blue circles represent causes, while those within red circles signify effects. At the bottom of the relationship map are faults that show no inclination toward either cause or effect. The quantity of lines that emerge from or merge onto a fault indicates how prominent it is. Therefore, faults with a greater number of lines demonstrate heightened severity. In the relationship map, the tail of arrows denotes causes, while the head represents effects. Analysis of the map reveals that the highest number of arrows originates from F7, indicating its status as the most significant cause. Similarly, F9 demonstrates the maximum number of incoming arrows, suggesting it as the most impacted effect. However, faults such as F4 (Machine Jamming) and F18 (Strange Noises), despite falling into the cause and effect groups, respectively, lack interdependence due to their values in the overall relation matrix falling below the threshold. Therefore, despite their categorization, they are disregarded in the relationship map due to their insignificant prominence. This approach allows for a clear observation of the relationships among the remaining causes and effects.

The method utilized in this study holds significant potential for applications in diverse fields such as energy and development sectors, safety systems, analysis of the environments, and business intelligence, among others. By adapting and employing this established method in our research, we have effectively bridged disciplinary barriers and demonstrated its efficacy in revealing previously unexplored facets of processes within the manufacturing industry. The study represents an innovative contribution to the manufacturing sector, highlighting the versatility of the methodology beyond its traditional domains. Embracing a cross-disciplinary approach has led to the emergence of fresh perspectives and enhanced understanding of the manufacturing industry, thus underscoring the adaptability of this methodology. While not the pioneering application of this method, our study stands out as a notable instance of successful integration into the manufacturing and production domain. It is an invaluable resource for upcoming studies aiming at enhancing its potential in this field.

CHAPTER 5. CONCLUSION AND FUTURE RESEARCH

5.1 GENERAL

This chapter encompasses a summary of the study, outlining both its theoretical and practical contributions, as well as limitations encountered during the research process. Solutions to address these limitations are offered, alongside future recommendations for researchers in the field.

5.2 SUMMARY OF THE STUDY

The negative consequences of the defects within a production process extend beyond mere operational disruptions, affecting the quality of resulting items. Beyond mere identification and prioritization, it's crucial to deeply analyse the interconnectedness among these flaws. These interconnections create a complex web where their effects intertwine and mutually influence one another. This study endeavours to provide a comprehensive analysis to effectively mitigate the consequences stemming from these errors. The primary objective of this study is to explore the interconnections among various defects impacting production processes in the manufacturing industry, establishing a hierarchical ranking of these faults. To achieve this goal, two techniques are employed. The cloud model theory is utilized to address the challenge of managing uncertainty in decision-making processes arising from differences in decision makers' cognitive capacities and background knowledge. Additionally, the DEMATEL approach is extended to integrate the cloud model framework, enabling the identification of critical flaws and analysis of their interdependencies. The proposed model categorizes discovered problems into distinct groups based on their causes and effects and reveals the interdependence among these flaws. Furthermore, it determines a comprehensive rating of the faults, irrespective of their grouping. These results are visually represented through diagrams and maps. This research underscores the innovation of integrating cloud model theory with DEMATEL to enhance traditional FMEA and broaden its applicability in manufacturing operations. The implementation of this study has notably increased production efficiency within the industry, attributed to a significant reduction in losses resulting from interconnected defects. In the nutshell, this study employs an integrated methodology to identify and analyze flaws and their linkages, thereby improving the efficiency of production processes in the textile manufacturing sector. It does this by combining cloud model theory with the DEMATEL method.

5.2 CONTRIBUTION

5.2.1 Practical Contribution of the study

The successful application of this methodology is to pinpoint areas within a system or process that require increased focus and examination. Identified as trouble spots, these areas are prone to disruptions or negative outcomes. Once these critical areas are identified, they can undergo comprehensive corrective actions and treatments aimed at mitigating potential consequences. By embracing the insights and recommendations derived from this study, the sector stands to achieve substantial improvements in the overall quality of its output. These enhancements extend beyond product quality, encompassing significant strides in increasing production quantity. This objective is achieved by strategically minimizing downtime resulting from machine component failures or malfunctions during the production process. The effective implementation of this methodology not only serves as a proactive strategy to anticipate and prevent prospective problems but also acts as a catalyst for enhancing both the quality and quantity of production. The study functions as a potent instrument for augmenting operational efficiency, thereby contributing significantly to the industry's competitive advantage and long-term viability.

5.2.2 Theoretical Contribution of the study

This study introduces advancements in Failure Modes and Effects Analysis (FMEA) methodology across several critical domains. These advancements encompass key areas, each contributing significantly to the improvement of FMEA practices. Firstly, a major contribution lies in the reduction of FMEA result duplication. By employing novel evaluation and examination methods, redundant or overlapping results are minimized. This reduction in duplicative efforts enhances FMEA workflow efficiency and optimizes resource allocation. Moreover, traditional FMEA struggles with managing real-world uncertainty and ambiguity. To address this limitation, this study expands the theoretical basis of FMEA. The framework becomes adaptable and resilient to dynamic and unexpected circumstances through the inclusion of uncertainty and ambiguity management strategies. This enhancement enhances the utility of FMEA across various industry domains. Additionally, this study delves into understanding the complex network of reciprocal linkages between failure modes, which is another theoretical contribution. While traditional FMEA focuses on specific failure modes and TOPSIS treats faults as independent entities, this study identifies and analyses interdependencies and feedback loops among failure modes. This holistic perspective provides insights into how failure modes interact and cascade, thereby improving decision-making and risk management in the industry. In conclusion, this study's theoretical contributions significantly expand FMEA capabilities by addressing crucial challenges such as result duplication, adaptation in uncertain environments, and reciprocal failure mode linkages. These contributions enhance FMEA's effectiveness, efficiency, relevance, and applicability in navigating a rapidly changing and complex industrial landscape, positioning it as a valuable tool for proactive risk assessment and management across various industry domains.

5.3 LIMITATIONS OF THE STUDY

This approach has limits, despite the fact that it greatly aids business managers in identifying and analysing important defects and their interconnections. First off, because of their restricted cognitive capacity, decision makers could find it difficult to offer all evaluation data. As a result, certain sections of the assessment matrix may remain unfilled, prompting the need for additional research on generating appropriate instructions for completing the matrix. Moreover, decision makers come from diverse backgrounds and possess varying cognitive skill sets. Therefore, a tool designed for displaying judgments at a more general level may not suffice. Improvements to the weighting mechanism could enhance the efficiency of this method. Additionally, one drawback of DEMATEL is that respondents require more information as the number of components increases, leading to potential validity and accuracy issues if respondents become disinterested or bored with lengthy questionnaires. Therefore, in order to guarantee the validity and accuracy of the data, efforts should be made to alleviate respondent weariness brought on by long questionnaires.

5.4 FUTURE DIRECTIONS

Incorporating the Analytical Network Process theory into this study offers the chance to assess the strength or robustness of relationships between identified causes and effects. Combining the Grey hypothesis with DEMATEL could be a useful way to address problems like survey fatigue and declining respondent engagement.

Additionally, offering respondents multiple options to fill the form is advisable, considering their diverse backgrounds and cognitive capacities. Options such as HFLTS, PLTS, LHFS, and ILIFTS could be provided. Respondents might articulate significant preferences for specific options or attributes in a highly ambiguous manner using HFLTS, indicating a strong affiliation with their chosen selections. It is recommended that when asked about their preferences, respondents give more complex answers that permit partial membership to a number of traits or possibilities. This suggests that people have varied degrees of inclination to favor different solutions. In these situations, respondents are likely to express their preferences using a range of fuzzy sets, showing varying degrees of liking across different options or traits, from low level to high level. Respondents can express a range of fuzzy preferences with ILIFTS by using intervals rather than a single point, which allows for greater flexibility in their selections.

REFERNCES

Abu Dabous, S., Ibrahim, F., Feroz, S., & Alsyouf, I. (2021). Integration of failure mode, effects, and criticality analysis with multi-criteria decision-making in engineering applications: Part I – Manufacturing industry. *Engineering Failure Analysis*, *122*, 105264. https://doi.org/10.1016/j.engfailanal.2021.105264

Agrawal, V., Seth, N., & Dixit, J. K. (2022). A combined AHP–TOPSIS–DEMATEL approach for evaluating success factors of e-service quality: An experience from Indian banking industry. *Electronic Commerce Research*, *22*(3), 715–747. https://doi.org/10.1007/s10660-020-09430-3

Ahsan, F., Naseem, A., Ahmad, Y., & Sajjad, Z. (2023). Evaluation of manufacturing process in low variety high volume industry with the coupling of cloud model theory and TOPSIS approach. *Quality Engineering*, *35*(2), 222–237. https://doi.org/10.1080/08982112.2022.2107934

Alvand, A., Mirhosseini, S. M., Ehsanifar, M., Zeighami, E., & Mohammadi, A. (2023). Identification and assessment of risk in construction projects using the integrated FMEA-SWARA-WASPAS model under fuzzy environment: A case study of a construction project in Iran. *International Journal of Construction Management*, *23*(3), 392–404. https://doi.org/10.1080/15623599.2021.1877875

Boral, S., Chaturvedi, S. K., Howard, I. M., McKee, K., & Naikan, V. N. A. (2020). An Integrated Approach for Fuzzy Failure Mode and Effect Analysis Using Fuzzy AHP and Fuzzy MARCOS. *2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 395–400. https://doi.org/10.1109/IEEM45057.2020.9309790

Büyüközkan, G., & Çifçi, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. *Expert Systems with Applications*, *39*(3), 3000–3011. https://doi.org/10.1016/j.eswa.2011.08.162
Chakraborty, S. (2022). TOPSIS and Modified TOPSIS: A comparative analysis. *Decision Analytics Journal*, *2*, 100021. https://doi.org/10.1016/j.dajour.2021.100021

Chang, K.-H., Chang, Y.-C., & Lee, Y.-T. (2014). Integrating TOPSIS and DEMATEL Methods to Rank the Risk of Failure of FMEA. *International Journal of Information Technology & Decision Making*, *13*(06), 1229–1257. https://doi.org/10.1142/S0219622014500758

Chen, Y., Cui Ye, Bingdong Liu, & Rui Kang. (2012). Status of FMECA research and engineering application. *Proceedings of the IEEE 2012 Prognostics and System Health Management Conference (PHM-2012 Beijing)*, 1–9. https://doi.org/10.1109/PHM.2012.6228914

Chen, Y.-T. (2016a). Applying the DEMATEL approach to identify the focus of library service quality: A case study of a Taiwanese academic library. *The Electronic Library*, *34*(2), 315–331. https://doi.org/10.1108/EL-08-2014-0134

Chen, Y.-T. (2016b). Applying the DEMATEL approach to identify the focus of library service quality: A case study of a Taiwanese academic library. *The Electronic Library*, *34*(2), 315–331. https://doi.org/10.1108/EL-08-2014-0134

Chiozza, M. L., & Ponzetti, C. (2009). FMEA: A model for reducing medical errors. *Clinica Chimica Acta*, *404*(1), 75–78. https://doi.org/10.1016/j.cca.2009.03.015

Dinçer, H., & Yüksel, S. (2018). Financial Sector-Based Analysis of the G20 Economies Using the Integrated Decision-Making Approach with DEMATEL and TOPSIS. In N. Ozatac & K. K. Gökmenoglu (Eds.), *Emerging Trends in Banking and Finance* (pp. 210–223). Springer International Publishing. http://link.springer.com/10.1007/978-3-030-01784-2_13

Du, Y.-W., & Zhou, W. (2019). New improved DEMATEL method based on both subjective experience and objective data. *Engineering Applications of Artificial Intelligence*, *83*, 57–71. https://doi.org/10.1016/j.engappai.2019.05.001

Fabis-Domagala, J., Domagala, M., & Momeni, H. (2021). A Concept of Risk Prioritization in FMEA Analysis for Fluid Power Systems. *Energies*, *14*(20), 6482. https://doi.org/10.3390/en14206482

Fattahi, R., & Khalilzadeh, M. (2018). Risk evaluation using a novel hybrid method based on FMEA, extended MULTIMOORA, and AHP methods under fuzzy environment. *Safety Science*, *102*, 290–300. https://doi.org/10.1016/j.ssci.2017.10.018

Garg, C. P. (2021). Modeling the e-waste mitigation strategies using grey-theory and DEMATEL framework. *Journal of Cleaner Production*, *281*, 124035. https://doi.org/10.1016/j.jclepro.2020.124035

Ghoushchi, S. J., Yousefi, S., & Khazaeili, M. (2019). An extended FMEA approach based on the Z-MOORA and fuzzy BWM for prioritization of failures. *Applied Soft Computing*, *81*, 105505. https://doi.org/10.1016/j.asoc.2019.105505

Gong, X., Yu, C., & Min, L. (2021). A cloud theory-based multi-objective portfolio selection model with variable risk appetite. *Expert Systems with Applications*, *176*, 114911. https://doi.org/10.1016/j.eswa.2021.114911

Gul, M., Yucesan, M., & Celik, E. (2020). A manufacturing failure mode and effect analysis based on fuzzy and probabilistic risk analysis. *Applied Soft Computing*, *96*, 106689. https://doi.org/10.1016/j.asoc.2020.106689

Han, Y., & Deng, Y. (2018). An enhanced fuzzy evidential DEMATEL method with its application to identify critical success factors. *Soft Computing*, *22*(15), 5073–5090. https://doi.org/10.1007/s00500-018-3311-x

Hassan, A., Purnomo, M. R. A., & Anugerah, A. R. (2019). Fuzzy-analytical-hierarchy process in failure mode and effect analysis (FMEA) to identify process failure in the warehouse of a cement industry. *Journal of Engineering, Design and Technology*, *18*(2), 378–388. https://doi.org/10.1108/JEDT-05-2019-0131

Hassan, S., Wang, J., Kontovas, C., & Bashir, M. (2022). Modified FMEA hazard identification for cross-country petroleum pipeline using Fuzzy Rule Base and approximate reasoning. *Journal of Loss Prevention in the Process Industries*, *74*, 104616. https://doi.org/10.1016/j.jlp.2021.104616

Karamoozian, A., & Wu, D. (2020). A hybrid risk prioritization approach in construction projects using failure mode and effective analysis. *Engineering, Construction and Architectural Management*, *27*(9), 2661–2686. https://doi.org/10.1108/ECAM-10-2019-0535

Kumar, M. B., & Parameshwaran, R. (2020). A comprehensive model to prioritise lean tools for manufacturing industries: A fuzzy FMEA, AHP and QFD-based approach. *International Journal of Services and Operations Management*, *37*(2), 170. https://doi.org/10.1504/IJSOM.2020.110337

Li, H., Díaz, H., & Guedes Soares, C. (2021). A failure analysis of floating offshore wind turbines using AHP-FMEA methodology. *Ocean Engineering*, *234*, 109261. https://doi.org/10.1016/j.oceaneng.2021.109261

Li, J., Wu, C.-H., Chen, C.-W., Huang, Y.-F., & Lin, C.-T. (2020). Apply Fuzzy DEMATEL to Explore the Decisive Factors of the Auto Lighting Aftermarket Industry in Taiwan. *Mathematics*, *8*(7), 1187. https://doi.org/10.3390/math8071187

Liu, H.-C., Li, Z., Song, W., & Su, Q. (2017). Failure Mode and Effect Analysis Using Cloud Model Theory and PROMETHEE Method. *IEEE Transactions on Reliability*, *66*(4), 1058–1072. https://doi.org/10.1109/TR.2017.2754642

Liu, H.-C., Liu, L., & Liu, N. (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert Systems with Applications*, *40*(2), 828–838. https://doi.org/10.1016/j.eswa.2012.08.010

Liu, H.-C., Wang, L.-E., Li, Z., & Hu, Y.-P. (2019a). Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method. *IEEE Transactions on Fuzzy Systems*, *27*(1), 84–95. https://doi.org/10.1109/TFUZZ.2018.2861719

Liu, H.-C., Wang, L.-E., Li, Z., & Hu, Y.-P. (2019b). Improving Risk Evaluation in FMEA With Cloud Model and Hierarchical TOPSIS Method. *IEEE Transactions on Fuzzy Systems*, *27*(1), 84–95. https://doi.org/10.1109/TFUZZ.2018.2861719

Lo, H.-W., & Liou, J. J. H. (2018). A novel multiple-criteria decision-making-based FMEA model for risk assessment. *Applied Soft Computing*, *73*, 684–696. https://doi.org/10.1016/j.asoc.2018.09.020

Lo, H.-W., Shiue, W., Liou, J. J. H., & Tzeng, G.-H. (2020). A hybrid MCDM-based FMEA model for identification of critical failure modes in manufacturing. *Soft Computing*, *24*(20), 15733–15745. https://doi.org/10.1007/s00500-020-04903-x

Ly, T. H., Roh, S., & Jang, H. (2021). Selection of Functional Logistics Service Providers: AHP and DEMATEL Application. *The Korean Data Analysis Society*, *23*(4), 1517–1534. https://doi.org/10.37727/jkdas.2021.23.4.1517

Mirmousa, S., & Dehnavi, H. D. (2016). Development of Criteria of Selecting the Supplier by Using the Fuzzy DEMATEL Method. *Procedia - Social and Behavioral Sciences*, *230*, 281–289. https://doi.org/10.1016/j.sbspro.2016.09.036

Moreira, A. C., Ferreira, L. M. D. F., & Silva, P. (2021). A case study on FMEA-based improvement for managing new product development risk. *International Journal of Quality & Reliability Management*, *38*(5), 1130–1148. https://doi.org/10.1108/IJQRM-06-2020-0201

Nguyen, H. T., & Chu, T.-C. (2023). Ranking Startups Using DEMATEL-ANP-Based Fuzzy PROMETHEE II. *Axioms*, *12*(6), 528. https://doi.org/10.3390/axioms12060528
Ostadi, B., & Masouleh, M. S. (2019). Application of FEMA and RPN techniques for man-machine analysis in Tobacco Company. *Cogent Engineering*, *6*(1), 1640101. https://doi.org/10.1080/23311916.2019.1640101

Pandey, M., Litoriya, R., & Pandey, P. (2019). Application of Fuzzy DEMATEL Approach in Analyzing Mobile App Issues. *Programming and Computer Software*, *45*(5), 268–287. https://doi.org/10.1134/S0361768819050050

Peeters, J. F. W., Basten, R. J. I., & Tinga, T. (2018). Improving failure analysis efficiency by combining FTA and FMEA in a recursive manner. *Reliability Engineering & System Safety*, *172*, 36–44. https://doi.org/10.1016/j.ress.2017.11.024

Po-Heng Tsou & Hsin-Yao Hsu. (2022). Applications of Fishbone Diagram and DEMATEL Technique for Improving Warehouse Operation—A Case Study on YMT Overseas Imported Components. *China-USA Business Review*, *21*(4). https://doi.org/10.17265/1537-1514/2022.04.001

Qin, J., Xi, Y., & Pedrycz, W. (2020). Failure mode and effects analysis (FMEA) for risk assessment based on interval type-2 fuzzy evidential reasoning method. *Applied Soft Computing*, *89*, 106134. https://doi.org/10.1016/j.asoc.2020.106134

S. Parsana, T., & T. Patel, M. (2014). A Case Study: A Process FMEA Tool to Enhance Quality and Efficiency of Manufacturing Industry. *Bonfring International Journal of Industrial Engineering and Management Science*, *4*(3), 145–152. https://doi.org/10.9756/BIJIEMS.10350

Sadeghi, B., Sodagari, M., Nematollahi, H., & Alikhani, H. (2021). FMEA and AHP Methods in Managing Environmental Risks in Landfills: A Case Study of Kahrizak, Iran. *Environmental Energy and Economic Research*, *5*(2). https://doi.org/10.22097/eeer.2020.253735.1172

Sagnak, M., Kazancoglu, Y., Ozkan Ozen, Y. D., & Garza-Reyes, J. A. (2020). Decision-making for risk evaluation: Integration of prospect theory with failure modes and effects analysis (FMEA). *International Journal of Quality & Reliability Management*, *37*(6/7), 939–956. https://doi.org/10.1108/IJQRM-01-2020-0013

Shi, Y., Zhang, A., Gao, X., & Tan, Z. (2008). Cloud model and its application in effectiveness evaluation. *2008 International Conference on Management Science and*

Engineering 15th Annual Conference Proceedings, 250–255. https://doi.org/10.1109/ICMSE.2008.4668924

Si, S.-L., You, X.-Y., Liu, H.-C., & Zhang, P. (2018). DEMATEL Technique: A Systematic Review of the State-of-the-Art Literature on Methodologies and Applications. *Mathematical Problems in Engineering*, *2018*, 1–33. https://doi.org/10.1155/2018/3696457

Spreafico, C., Russo, D., & Rizzi, C. (2017). A state-of-the-art review of FMEA/FMECA including patents. *Computer Science Review*, *25*, 19–28. https://doi.org/10.1016/j.cosrev.2017.05.002

Sulaman, S. M., Beer, A., Felderer, M., & Höst, M. (2019). Comparison of the FMEA and STPA safety analysis methods–a case study. *Software Quality Journal*, *27*(1), 349–387. https://doi.org/10.1007/s11219-017-9396-0

Tazi, N., Châtelet, E., & Bouzidi, Y. (2017). Using a Hybrid Cost-FMEA Analysis for Wind Turbine Reliability Analysis. *Energies*, *10*(3), 276. https://doi.org/10.3390/en10030276

Tsai, S.-B., Zhou, J., Gao, Y., Wang, J., Li, G., Zheng, Y., Ren, P., & Xu, W. (2017). Combining FMEA with DEMATEL models to solve production process problems. *PLOS ONE*, *12*(8), e0183634. https://doi.org/10.1371/journal.pone.0183634

Tseng, M.-L., & Lin, Y. H. (2009). Application of fuzzy DEMATEL to develop a cause and effect model of municipal solid waste management in Metro Manila. *Environmental Monitoring and Assessment*, *158*(1–4), 519–533. https://doi.org/10.1007/s10661-008-0601-2

Vinodh, S., & Santhosh, D. (2012). Application of FMEA to an automotive leaf spring manufacturing organization. *The TQM Journal*, *24*(3), 260–274. https://doi.org/10.1108/17542731211226772

Wang, G., Xu, C., & Li, D. (2014). Generic normal cloud model. *Information Sciences*, *280*, 1–15. https://doi.org/10.1016/j.ins.2014.04.051

Wang, K.-Q., Liu, H.-C., Liu, L., & Huang, J. (2017). Green Supplier Evaluation and Selection Using Cloud Model Theory and the QUALIFLEX Method. *Sustainability*, *9*(5), 688. https://doi.org/10.3390/su9050688

Wang, L., Yan, F., Wang, F., & Li, Z. (2021). FMEA-CM based quantitative risk assessment for process industries—A case study of coal-to-methanol plant in China. *Process Safety and Environmental Protection*, *149*, 299–311. https://doi.org/10.1016/j.psep.2020.10.052

Wang, W., Liu, X., Chen, X., & Qin, Y. (2019). Risk assessment based on hybrid FMEA framework by considering decision maker's psychological behavior character. *Computers & Industrial Engineering*, *136*, 516–527. https://doi.org/10.1016/j.cie.2019.07.051

Xiao, N., Huang, H.-Z., Li, Y., He, L., & Jin, T. (2011). Multiple failure modes analysis and weighted risk priority number evaluation in FMEA. *Engineering Failure Analysis*, *18*(4), 1162–1170. https://doi.org/10.1016/j.engfailanal.2011.02.004

Xie, S., Dong, S., Chen, Y., Peng, Y., & Li, X. (2021). A novel risk evaluation method for fire and explosion accidents in oil depots using bow-tie analysis and risk matrix analysis method based on cloud model theory. *Reliability Engineering & System Safety*, *215*, 107791. https://doi.org/10.1016/j.ress.2021.107791

Xu, Q., Zhang, Y. B., Zhang, J., & Lv, X. G. (2015). Improved TOPSIS Model and its Application in the Evaluation of NCAA Basketball Coaches. *Modern Applied Science*, *9*(2), p259. https://doi.org/10.5539/mas.v9n2p259

Yazdi, M., Daneshvar, S., & Setareh, H. (2017). An extension to Fuzzy Developed Failure Mode and Effects Analysis (FDFMEA) application for aircraft landing system. *Safety Science*, *98*, 113–123. https://doi.org/10.1016/j.ssci.2017.06.009

Yazdi, M., Khan, F., Abbassi, R., & Rusli, R. (2020). Improved DEMATEL methodology for effective safety management decision-making. *Safety Science*, *127*, 104705. https://doi.org/10.1016/j.ssci.2020.104705

Yousefi, S., Alizadeh, A., Hayati, J., & Baghery, M. (2018). HSE risk prioritization using robust DEA-FMEA approach with undesirable outputs: A study of automotive parts industry in Iran. *Safety Science*, *102*, 144–158. https://doi.org/10.1016/j.ssci.2017.10.015

Zhang, Z., & Chu, X. (2011). Risk prioritization in failure mode and effects analysis under uncertainty. *Expert Systems with Applications*, *38*(1), 206–214. https://doi.org/10.1016/j.eswa.2010.06.046

Zhou, H., & Chen, J. (2018). Research on Influencing Factors of Usage Intension to Use Mobile Intelligent Wearable Device. *Proceedings of the 8th International Conference on Management and Computer Science (ICMCS 2018)*. 8th International Conference on Management and Computer Science (ICMCS 2018), Shenyang, China. https://doi.org/10.2991/icmcs-18.2018.8

Appendix – I Cloud Conversion

Sr. NO.	y	Linguistic Value	EX	EN	HE
1	y0	NI	2.61804	0.87268	0.20564
2	y1	VL	3.1802	0.5393	0.12709
3	y2	L	3.527767	0.33333	0.07854
4	y3	ML	4.09009	0.20598	0.04854
5	y4	M	5.0000	0.1723	0.03
6	y5	MH	5.9099	0.20598	0.0485
7	y6	H	6.47223	0.3333	0.07854
8	y7	EH	6.819747	0.53932	0.12709
9	y8	PI	7.38196	0.87268	0.20564

Appendix – II Weight Allocation Table

Professional Title	Scores by PT	Work Experience in industry	Score by WE		$\mathbf{w}k = \frac{Hk}{\sum_{k=1}^{l} Hk}$
Senior Technician	5	12 Years	3	8	0.19047619
Machine Master	4	19 Years	3	7	0.166666667
Junior Supervisor	3	15 Years	3	6	0.142857143
Senior Supervisor	4	21 Years	4	8	0.19047619
Electrical Engineer	3	10 Years	3	6	0.142857143
Manager in Department	3	25 Years	4	7	0.166666667
				42	1

Appendix – III Weighted Matrices

Sr #	Failure Modes	1 needle breakage	2 thread breakage	3 bobin thread breakage	4 machine jamming	5 misallignment of design	6 machine skipping stitches	7 machine vibration	8 shittle timing	9 motor issues	10 fabric rule	11 sensor malfunction	12 lubrication problems	13 uneven sttitching	14 puckering of fabrics	15 bobin tension issues	16 head not working	17 thread tangling	18 strange noises	19 stitch not feeding	20 machine runs but needle not
1	needle breakage	0	3.149592	6.16819	7.30164	2.69836	4.74003	2.778676	6.85553	5.15165	3.09995	7.02053736	2.69835813	3.2381836	4.1614098	6.00362	3.2961	6.08786	6.08786	4.97833	5.49828
2	thread breakage	3.287826	0	7.158296	7.30164	2.69836	4.74003	2.778676	6.16819	2.71174	2.69836	7.02053736	2.71174448	2.7251308	4.39339333	6.91345	6.00362	4.31306	3.00624	6.91345	2.71174
3	bobin thread breakage	3.149592	3.149592	0	7.30164	2.71174	3.15787	2.778676	7.1583	2.69836	3.09995	6.9842781	2.69835813	4.6380293	4.39339333	7.06459	2.72513	5.70032	3.00624	7.07798	2.79206
4	machine jamming	7.207942	7.064594	7.301644	0	7.1583	7.30164	2.792063	7.1583	7.05121	6.95751	7.07798026	7.19455567	7.3016439	7.15829641	7.06459	7.06459	7.30164	3.56357	7.07798	7.07798
5	misallignment of design	3.398643	2.698358	2.698358	7.30164	0	6.7701	2.792063	6.00362	2.71174	6.53015	7.22132771	2.61804	6.5739299	4.87001286	6.21784	4.52338	4.82668	2.69836	2.71174	2.71174
6	machine skipping stitches	2.711744	2.711744	2.698358	7.30164	6.7701	0	2.778676	6.16819	2.69836	6.00362	7.11423952	2.69835813	6.217835	4.1614098	4.78968	5.49828	4.24174	2.71174	2.80545	2.71174
7	machine vibration	5.45495	4.09177	3.760512	2.69836	4.84835	2.69836	0	2.87238	6.3356	3.15787	2.61804	6.21783505	3.2381836	2.9125398	3.2961	3.39781	2.71174	5.23005	2.79206	2.71174
8	shittle timing	6.631849	6.913449	6.631849	7.30164	3.09995	5.77991	2.778676	0	3.23818	2.71174	7.11423952	3.09994877	5.4982771	6.21783505	7.06459	3.33989	2.71174	3.56357	6.84603	2.69836
9	motor issues	2.711744	2.698358	2.698358	7.1583	2.69836	2.61804	6.16819	2.69836	0	4.63803	7.07798026	6.63184936	2.805449	2.81883532	6.91345	3.33989	2.61804	6.91345	4.24174	2.61804
10	fabric rule	2.698358	3.478124	3.571845	7.1583	2.71174	2.69836	2.778676	2.79206	6.57393	0	7.02053736	3.47812404	2.8188353	3.09994877	2.81884	2.80545	2.61804	3.42021	6.00362	2.69836
11	sensor malfunction	7.064594	7.064594	7.301644	7.1583	7.1583	7.30164	2.698358	7.1583	7.05121	7.10085	0	2.61804	7.3016439	7.15829641	7.20794	7.06459	7.30164	3.23818	6.98428	6.7701
12	lubrication problems	3.478124	3.149592	3.238184	7.30164	2.69836	3.15787	6.57393	3.09995	6.35022	3.62149	6.44154243	0	2.805449	2.89915345	3.62149	4.24174	2.61804	6.91345	3.09995	5.99414
13	uneven sttitching	2.698358	2.698358	2.698358	7.30164	6.91345	6.7701	2.778676	5.49828	2.69836	2.71174	7.1008535	2.69835813	0	6.57979479	5.49828	3.15787	4.82668	2.61804	3.23818	2.61804
14	puckering of fabrics	3.149592	3.149592	2.711744	7.30164	4.63803	4.74003	2.698358	6.00362	3.23818	2.71174	7.20794169	2.61804	6.6318494	0	5.3033	3.15787	3.62149	2.79206	2.71174	2.71174
15	bobin tension issues	3.621487	3.621487	6.770102	7.30164	5.49828	5.77991	2.778676	7.30164	3.62149	2.69836	7.06459424	5.28163571	4.2417417	3.09994877	0	3.47812	4.24174	4.82668	5.77991	2.69836
16	head not working	6.631849	6.16819	5.324964	7.30164	4.473	4.18307	3.099949	3.33989	4.24174	3.23818	7.05120822	4.00975813	3.478124	3.1802669	2.80545	0	3.2961	3.86639	5.84249	4.82668
17	thread tangling	5.671594	3.207508	3.441884	7.30164	4.33476	4.18307	2.698358	3.57184	3.26234	2.69836	7.19455567	2.69835813	3.0999488	3.47812404	2.81884	2.72513	0	3.2961	3.23818	3.23818
18	strange noises	3.287826	2.711744	3.099949	3.09995	2.69836	2.69836	2.792063	3.00624	6.53015	4.24174	4.99999857	6.91344917	2.805449	2.81883532	3.62149	3.15787	2.71174	0	2.69836	2.61804
19	stitch not feeding	3.149592	6.913449	3.238184	7.1583	2.71174	2.69836	2.872381	6.57393	2.69836	2.69836	7.19455567	2.61804	2.8188353	3.0507746	6.53015	6.00362	3.86639	3.43946	0	2.79206
20	machine runs but needle not move	6.631849	3.136205	6.631849	3.57184	2.71174	2.69836	2.698358	3.23818	2.71174	3.09995	7.1008535	3.62148742	2.8188353	2.9125398	4.24174	4.78968	3.33989	2.69836	6.00362	0

Weighted Expectation Matrix

Sr #	Failure Modes	1 needle breakage	2 thread breakage	3 bobin thread breakage	4 machine jamming	5 misallignment of design	6 machine skipping stitches	7 machine vibration	8 shittle timing	9 motor issues	10 fabric rule	11 sensor malfunction	12 lubrication problems	13 uneven sttitching	14 puckering of fabrics	15 bobin tension issues	16 head not working	17 thread tangling	18 strange noises	19 stitch not feeding	20 machine runs but needle not
1	needle breakag	0	0.5766	0.2934	0.8333	0.8333	0.1539	0.7919	0.5825	0.1434	0.5984	0.6775	0.8333	0.5108	0.2188	0.2321	0.4806	0.2762	0.2762	0.1599	0.1951
2	thread breakag	0.485	0	0.7682	0.8333	0.8333	0.1539	0.7919	0.2934	0.8265	0.8333	0.6775	0.8265	0.8197	0.1835	0.6077	0.2321	0.2086	0.6607	0.6077	0.8265
3	bobin thread breakag	0.5766	0.5766	0	0.8333	0.8265	0.5728	0.7919	0.7682	0.8333	0.5984	0.6667	0.8333	0.1847	0.1835	0.7154	0.8197	0.2321	0.6607	0.7232	0.7848
4	machine jamming	0.7848	0.7154	0.8333	0	0.7682	0.8333	0.7848	0.7682	0.7075	0.6497	0.7232	0.7776	0.8333	0.7682	0.7154	0.7154	0.8333	0.36	0.7232	0.7232
5	misallignment of design	0.7848	0.8333	0.8333	0.8333	0	0.515	0.7848	0.2321	0.8265	0.3756	0.7919	0.8727	0.4421	0.1412	0.3343	0.1967	0.173	0.8333	0.8265	0.8265
6	machine skipping stitches	0.8265	0.8265	0.8333	0.8333	0.515	0	0.7919	0.2934	0.8333	0.2321	0.7331	0.8333	0.3343	0.2188	0.1962	0.1951	0.1951	0.8265	0.7776	0.8265
7	machine vibratio	0.1712	0.354	0.3961	0.8333	0.1712	0.8333	0	0.7407	0.5825	0.5728	0.8727	0.3343	0.5108	0.7176	0.4806	0.4517	0.8265	0.3957	0.7848	0.8265
8	shittle timing	0.4748	0.6077	0.4748	0.8333	0.5984	0.1967	0.7919	0	0.5108	0.8265	0.7331	0.5984	0.1951	0.3343	0.7154	0.4837	0.8265	0.36	0.6362	0.8333
9	motor issues	0.8265	0.8333	0.8333	0.7682	0.8333	0.8727	0.2934	0.8333	0	0.1847	0.7232	0.4748	0.7776	0.7704	0.6077	0.4837	0.8727	0.6077	0.1951	0.8727
10	fabric rule	0.8333	0.3698	0.354	0.7682	0.8265	0.8333	0.7919	0.7848	0.4421	0	0.6775	0.3698	0.7704	0.5984	0.7704	0.7776	0.8727	0.4083	0.2321	0.8333
11	sensor malfunction	0.7154	0.7154	0.8333	0.7682	0.7682	0.8333	0.8333	0.7682	0.7075	0.7254	0	0.8727	0.8333	0.7682	0.7848	0.7154	0.8333	0.5108	0.6667	0.515
12	lubrication problem	0.3698	0.5766	0.5108	0.8333	0.8333	0.5728	0.4421	0.5984	0.4246	0.3157	0.3563	0	0.7776	0.7254	0.3157	0.1951	0.8727	0.6077	0.5984	0.2546
13	uneven sttitchin	0.8333	0.8333	0.8333	0.8333	0.6077	0.515	0.7919	0.1951	0.8333	0.8265	0.7254	0.8333	0	0.4083	0.1951	0.5728	0.173	0.8727	0.5108	0.8727
14	puckering of fabrics	0.5766	0.5766	0.8265	0.8333	0.1847	0.1539	0.8333	0.2321	0.5108	0.8265	0.7848	0.8727	0.4748	0	0.1579	0.5728	0.3157	0.7848	0.8265	0.8265
15	bobin tension issues	0.3157	0.3157	0.515	0.8333	0.1951	0.1967	0.7919	0.8333	0.3157	0.8333	0.7154	0.156	0.1951	0.5984	0	0.3698	0.1951	0.173	0.1967	0.8333
16	head not working	0.4748	0.2934	0.1599	0.8333	0.2839	0.2174	0.5984	0.4837	0.1951	0.5108	0.7075	0.2286	0.3698	0.5393	0.7776	0	0.4806	0.2989	0.2459	0.173
17	thread tangling	0.3454	0.55	0.4672	0.8333	0.4217	0.2174	0.8333	0.354	0.7682	0.8333	0.7776	0.8333	0.5984	0.3698	0.7704	0.8197	0	0.4806	0.5108	0.5108
18	strange noises	0.485	0.8265	0.5984	0.5984	0.8333	0.8333	0.7848	0.6607	0.3756	0.1951	0.1539	0.6077	0.7776	0.7704	0.3157	0.5728	0.8265	0	0.8333	0.8727
19	stitch not	0.5766	0.6077	0.5108	0.7682	0.8265	0.8333	0.7407	0.4421	0.8333	0.8333	0.7776	0.8727	0.7704	0.6464	0.3756	0.2321	0.2989	0.4402	0	0.7848
20	machine runs but needle not	0.4748	0.5862	0.4748	0.354	0.8265	0.8333	0.8333	0.5108	0.8265	0.5984	0.7254	0.3157	0.7704	0.7176	0.1951	0.1962	0.4837	0.8333	0.2321	0

Weighted Entropy Matrix

Sr #	Failure Modes	1 needle breakage	2 thread breakage	3 bobin thread breakage	4 machine jamming	5 misallignment of design	6 machine skipping stitches	7 machine vibration	8 shittle timing	9 motor issues	10 fabric rule	11 sensor malfunction	12 lubrication problems	13 uneven sttitching	14 puckering of fabrics	15 bobin tension issues	16 head not working	17 thread tangling	18 strange noises	19 stitch not feeding	20 machine runs but needle not
1	needle breakag	0	0.1359	0.0691	0.1964	0.1964	0.0363	0.1866	0.1373	0.0338	0.141	0.1596	0.1964	0.1204	0.0516	0.0547	0.1132	0.0651	0.0651	0.0377	0.0459
2	thread breakag	0.1143	0	0.181	0.1964	0.1964	0.0363	0.1866	0.0691	0.1948	0.1964	0.1596	0.1948	0.1932	0.0433	0.1432	0.0547	0.0491	0.1557	0.1432	0.1948
3	bobin thread breakag	0.1359	0.1359	0	0.1964	0.1948	0.135	0.1866	0.181	0.1964	0.141	0.1571	0.1964	0.0435	0.0433	0.1686	0.1932	0.0547	0.1557	0.1704	0.1849
4	machine jamming	0.1849	0.1686	0.1964	0	0.181	0.1964	0.1849	0.181	0.1667	0.1531	0.1704	0.1832	0.1964	0.181	0.1686	0.1686	0.1964	0.0848	0.1704	0.1704
5	misallignment of	0.1849	0.1964	0.1964	0.1964	0	0.1213	0.1849	0.0547	0.1948	0.0885	0.1866	0.2056	0.1042	0.0333	0.0788	0.0463	0.0408	0.1964	0.1948	0.1948
6	machine skipping	0.1948	0.1948	0.1964	0.1964	0.1213	0	0.1866	0.0691	0.1964	0.0547	0.1727	0.1964	0.0788	0.0516	0.0462	0.0459	0.046	0.1948	0.1832	0.1948
7	machine vibratio	0.0403	0.0834	0.0933	0.1964	0.0403	0.1964	0	0.1745	0.1373	0.135	0.2056	0.0788	0.1204	0.1691	0.1132	0.1064	0.1948	0.0932	0.1849	0.1948
8	shittle timing	0.1119	0.1432	0.1119	0.1964	0.141	0.0463	0.1866	0	0.1204	0.1948	0.1727	0.141	0.0459	0.0788	0.1686	0.114	0.1948	0.0848	0.1499	0.1964
9	motor issues	0.1948	0.1964	0.1964	0.181	0.1964	0.2056	0.0691	0.1964	0	0.0435	0.1704	0.1119	0.1832	0.1815	0.1432	0.114	0.2056	0.1432	0.046	0.2056
10	fabric rule	0.1964	0.0871	0.0834	0.181	0.1948	0.1964	0.1866	0.1849	0.1042	0	0.1596	0.0871	0.1815	0.141	0.1815	0.1832	0.2056	0.0962	0.0547	0.1964
11	sensor malfunction	0.1686	0.1686	0.1964	0.181	0.181	0.1964	0.1964	0.181	0.1667	0.1709	0	0.2056	0.1964	0.181	0.1849	0.1686	0.1964	0.1204	0.1571	0.1213
12	lubrication problem	0.0871	0.1359	0.1204	0.1964	0.1964	0.135	0.1042	0.141	0.1	0.0744	0.084	0	0.1832	0.1709	0.0744	0.046	0.2056	0.1432	0.141	0.06
13	uneven sttitchin	0.1964	0.1964	0.1964	0.1964	0.1432	0.1213	0.1866	0.0459	0.1964	0.1948	0.1709	0.1964	0	0.0962	0.0459	0.135	0.0408	0.2056	0.1204	0.2056
14	puckering of fabrics	0.1359	0.1359	0.1948	0.1964	0.0435	0.0363	0.1964	0.0547	0.1204	0.1948	0.1849	0.2056	0.1119	0	0.0372	0.135	0.0744	0.1849	0.1948	0.1948
15	bobin tension issues	0.0744	0.0744	0.1213	0.1964	0.0459	0.0463	0.1866	0.1964	0.0744	0.1964	0.1686	0.0367	0.046	0.141	0	0.0871	0.046	0.0408	0.0463	0.1964
16	head not	0.1119	0.0691	0.0377	0.1964	0.0669	0.0512	0.141	0.114	0.046	0.1204	0.1667	0.0539	0.0871	0.1271	0.1832	0	0.1132	0.0704	0.0579	0.0408
17	thread tangling	0.0814	0.1296	0.1101	0.1964	0.0994	0.0512	0.1964	0.0834	0.181	0.1964	0.1832	0.1964	0.141	0.0871	0.1815	0.1932	0	0.1132	0.1204	0.1204
18	strange noises	0.1143	0.1948	0.141	0.141	0.1964	0.1964	0.1849	0.1557	0.0885	0.046	0.0363	0.1432	0.1832	0.1815	0.0744	0.135	0.1948	0	0.1964	0.2056
19	stitch not	0.1359	0.1432	0.1204	0.181	0.1948	0.1964	0.1745	0.1042	0.1964	0.1964	0.1832	0.2056	0.1815	0.1523	0.0885	0.0547	0.0704	0.1037	0	0.1849
20	machine runs but needle not	0.1119	0.1381	0.1119	0.0834	0.1948	0.1964	0.1964	0.1204	0.1948	0.141	0.1709	0.0744	0.1815	0.1691	0.046	0.0462	0.114	0.1964	0.0547	0

Weighted Hyper-entropy Matrix