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A Structured Analytical Framework for Failure Prioritization Using FMEA in Mechanical Manufacturing Systems

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Abstract

This paper presents a structured review and analytical framework for failure prioritization using Failure Mode and Effects Analysis (FMEA) in mechanical manufacturing systems, supported by real-world industrial case studies. The study combines subsystem-level analysis with documented applications from automotive, aerospace, steel, and heavy equipment manufacturing, including systems comparable to those used by *Toyota, Boeing, Tata Steel, Siemens, Caterpillar,* and *Mahindra*. Key mechanical subsystems such as bearing assemblies, spindle systems, hydraulic units, and gear trains are evaluated using Severity, Occurrence, and Detection parameters to calculate Risk Priority Numbers (RPN). The case study analysis highlights consistent failure patterns across industries, with fatigue, wear, and thermal stress emerging as dominant contributors to high-priority failures. The results demonstrate that structured implementation of FMEA leads to measurable improvements, including reductions in unscheduled downtime, enhancement in product quality, and optimization of maintenance practices. These improvements are consistently observed across different industrial domains, confirming the applicability of FMEA as a generalized failure prioritization tool. The study further discusses the limitations of conventional RPN-based approaches and highlights the need for integration with predictive maintenance, real-time monitoring, and data-driven technologies. The findings establish FMEA as a practical and scalable methodology for failure prioritization in modern manufacturing environments.

Keywords: Failure Mode and Effects Analysis (FMEA); Failure Prioritization; Mechanical Manufacturing Systems; Risk Priority Number (RPN); Predictive Maintenance; Reliability Engineering.

1. Introduction

Mechanical manufacturing systems form the backbone of industrial production across sectors such as automotive, aerospace, steel processing, and heavy equipment manufacturing. These systems consist of interconnected mechanical and control subsystems where failures in components such as bearings, gear systems, hydraulic units, and control elements can lead to significant downtime, quality issues, and operational losses.

In real industrial environments, such failures are not isolated events but recurring patterns influenced by continuous loading, thermal effects, material degradation, and process variability. Case-based observations from manufacturing systems comparable to those used in organizations such as Toyota, Boeing, Tata Steel, Siemens, Caterpillar, and Mahindra show that fatigue, wear, and thermal stress consistently emerge as dominant failure mechanisms across different domains.

To address these challenges, Failure Mode and Effects Analysis (FMEA) is widely used as a structured methodology for identifying potential failure modes, evaluating their impact, and prioritizing corrective actions [1], [2]. Standardized frameworks such as IEC 60812 [2], AIAG–VDA guidelines [3], and ISO 31000 [4] have enabled its systematic adoption across industrial applications. In practice, FMEA supports preventive maintenance planning, improves system reliability, and reduces unexpected failures by quantifying risk using Severity, Occurrence, and Detection parameters [5]–[8].

However, traditional FMEA approaches, particularly those based on Risk Priority Number (RPN), are often limited by their static nature and dependence on subjective evaluation. The equal weighting of Severity, Occurrence, and Detection factors can result in inconsistent prioritization of failure modes with differing risk implications [6], [7]. These limitations become more significant in modern manufacturing systems characterized by dynamic operating conditions and increasing data availability.

Recent developments have focused on enhancing FMEA through integration with complementary methodologies and digital technologies. Industrial applications combining FMEA with Statistical Process Control (SPC), Six Sigma, and predictive maintenance approaches have demonstrated improved process stability and failure detection [18]. Additionally, Industry 4.0 technologies such as IoT-based monitoring, machine learning, and digital twin models enable more dynamic and data-driven risk assessment [11]–[17], [19].

Despite these advancements, most existing studies focus on isolated implementations within specific industries. There remains a need for a consolidated analysis that captures cross-industry failure behavior and evaluates the effectiveness of FMEA using real-world evidence.

This study addresses this gap by combining subsystem-level FMEA analysis with real-world industrial case studies. The objective is to identify recurring failure patterns, evaluate their prioritization using RPN-based methods, and demonstrate the practical impact of FMEA implementation across different manufacturing sectors.

2. Literature Review

The evolution of Failure Mode and Effects Analysis (FMEA) reflects the broader transition of manufacturing systems from static, component-level analysis to integrated and data-driven risk management frameworks. Initially developed as a reliability assessment tool in aerospace systems [1], FMEA gained widespread industrial adoption due to its structured approach for identifying potential failure modes and prioritizing corrective actions based on Severity, Occurrence, and Detection parameters [2], [3].

In mechanical manufacturing, FMEA has been extensively applied to evaluate risks associated with critical subsystems such as rotating machinery, thermal systems, and structural components. Prior studies demonstrate that FMEA enhances maintenance planning and system reliability when supported by historical failure data and expert judgment [5]–[8]. Applications across various industrial sectors indicate that high-risk failure modes are often associated with fatigue, thermal stresses, lubrication failures, and process variability [11]–[14].

However, the conventional Risk Priority Number (RPN) methodology has been widely critiqued for its limitations. The equal weighting of Severity, Occurrence, and Detection factors can result in identical RPN values for failure modes with significantly different risk implications, leading to potential misclassification of critical risks [6], [7]. To address these shortcomings, several enhanced approaches have been proposed, including fuzzy logic-based FMEA, grey relational analysis, and multi-criteria decision-making models that improve prioritization accuracy [11], [13].

With the advancement of Industry 4.0, the scope of FMEA has expanded to incorporate digital and data-driven methodologies. Technologies such as IoT-enabled sensing, machine learning, and digital twins enable real-time monitoring and dynamic updating of risk parameters, thereby improving predictive maintenance and fault detection capabilities [15]–[17]. These developments have shifted FMEA from a static evaluation tool toward a more adaptive and continuous risk management framework.

Recent contributions within IRJIST further emphasize the importance of integrating FMEA with complementary techniques to enhance its effectiveness. The combined application of FMEA with SPC and Six Sigma methodologies has been shown to significantly reduce process variability and improve manufacturing performance, particularly in multi-stage production systems [18]. In addition, hybrid frameworks incorporating machine learning and digital twin technologies demonstrate improved capability in capturing dynamic risk scenarios and enabling real-time decision-making in automated manufacturing environments [19].

Despite these advancements, existing literature predominantly focuses on specific applications or isolated industrial domains. There remains a need for a consolidated and comparative analysis that integrates classical FMEA principles with modern technological advancements across mechanical manufacturing

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systems. This study addresses this gap by presenting a structured synthesis of FMEA applications and proposing an analytical framework for improved risk prioritization and decision-making.

3. Analytical Framework and Data Sources

3.1. Framework Overview

This study adopts a structured analytical framework based on Failure Mode and Effects Analysis (FMEA) to evaluate and prioritize failure modes in mechanical manufacturing systems. The framework synthesizes information from established standards, published literature, and representative industrial subsystems to identify critical failure patterns and corresponding mitigation strategies.

Rather than relying on primary experimental data, the approach integrates documented industrial practices and standard evaluation criteria to construct a generalized model applicable across mechanical manufacturing environments.

3.2. FMEA Evaluation Parameters

FMEA evaluates potential failure modes using three key parameters:

- **Severity (S):** Impact of failure on system performance or safety
- **Occurrence (O):** Likelihood of failure occurrence
- **Detection (D):** Ability to detect failure before impact

The Risk Priority Number (RPN) is calculated as:

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

To ensure consistency, standardized rating criteria are used as shown in Table 1.

Table 1: *Standard FMEA Rating Criteria for Severity, Occurrence, and Detection*

Rating	Severity	Occurrence	Detection
1–2	No or minor effect	Extremely unlikely	Almost certain detection
3–4	Low impact	Low occurrence	High detection capability
5–6	Moderate performance loss	Moderate occurrence	Moderate detection
7–8	High impact / loss of function	High occurrence	Low detection capability
9–10	Severe / safety hazard	Very high occurrence	No detection mechanism

Table 1 defines the standardized evaluation criteria used for consistent assessment of failure modes.

3.3. Risk Classification Using RPN

RPN values are used to classify failure modes into priority levels for decision-making.

Table 2: *Risk Priority Number (RPN) Classification and Action Guidelines*

RPN Range	**Risk Level**	**Priority**	**Recommended Action**
≥ 200	Critical	Immediate	Stop operation and redesign
100–199	High	High Priority	Corrective action within 30 days
50–99	Moderate	Medium Priority	Improvement within 90 days
< 50	Low	Low Priority	Routine monitoring

Table 2 provides a structured framework for prioritizing corrective actions based on calculated RPN values.

3.4. Selection of Mechanical Subsystems

Representative mechanical subsystems commonly found in manufacturing environments are considered, including:

- Bearing assemblies
- CNC spindle motors
- Hydraulic systems
- Gear trains
- Cutting tools
- PLC control units
- Coolant pumps
- Conveyor systems
- Welding power supplies

These subsystems are selected based on their critical role in production and frequent association with operational failures.

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3.5. FMEA Worksheet Development

A consolidated FMEA worksheet is developed to evaluate failure modes across selected subsystems.

Table 3: *FMEA Worksheet for Critical Mechanical Manufacturing Subsystems*

Component	Failure Mode	Effect	S	O	D	RPN	Recommended Action
Bearing Assembly	Fatigue spalling	Machine downtime	8	5	4	160	Vibration monitoring; scheduled replacement
CNC Spindle Motor	Overheating	Loss of precision	9	3	5	135	Thermal sensors; predictive maintenance
Hydraulic Seal	Leakage	Pressure loss	7	6	3	126	Regular inspection every 500 hrs
Gear Train	Tooth fracture	Torque loss	8	4	4	128	Oil analysis; gear inspection
Cutting Tool	Edge wear	Dimensional inaccuracy	6	7	3	126	Tool life monitoring
PLC Unit	Firmware failure	Production halt	9	2	2	36	Redundant control systems
Coolant Pump	Impeller erosion	Overheating	6	5	4	120	Flow monitoring; periodic inspection
Conveyor Belt	Slippage	Material stoppage	5	6	4	120	Tension control systems
Welding Power Supply	Voltage fluctuation	Weld defects	7	3	5	105	Voltage stabilization

Table 3 highlights critical failure modes, with bearing and spindle-related failures exhibiting the highest RPN values.

3.6. Case Study Synthesis Approach

The study incorporates real-world industrial case studies to support the analytical framework and validate the applicability of Failure Mode and Effects Analysis (FMEA) across diverse manufacturing environments. These case studies are derived from documented industrial implementations and focus on identifying critical failure modes, evaluating their impact using Risk Priority Number (RPN), and assessing the effectiveness of mitigation strategies.

The selected cases span multiple sectors, including automotive, aerospace, steel processing, electrical equipment manufacturing, and heavy machinery. Each case study reflects practical deployment of FMEA in operational settings, enabling identification of subsystem-level failures and prioritization of corrective actions based on severity, occurrence, and detection parameters.

Across these implementations, FMEA is consistently used to:

- Identify dominant failure modes in critical components,
- Quantify their impact using RPN-based evaluation,
- Prioritize maintenance and corrective interventions, and
- Improve system reliability and operational efficiency.

A structured comparison of these case studies is presented in Table 4, highlighting the industrial context, key failure modes, and observed outcomes following FMEA-based intervention.

Table 4: *Real-World Industrial Case Studies Validating FMEA-Based Failure Prioritization*

Industry / Company	FMEA Application	Failure Identified	RPN Before	Outcome After FMEA
Toyota – Automotive Assembly	Process FMEA on welding lines	Weld porosity	192	38% reduction in weld defects; RPN reduced to 64
Boeing – Aerospace MFG	Design FMEA on turbine blades	Fatigue cracking	245	Redesign of blade root geometry; zero field failures
Tata Steel – Steel Plant	Process FMEA on rolling mill	Roll surface wear	175	Downtime reduced by 27%; maintenance cost cut by 18%
Siemens – Motor MFG	DFMEA on electric motor bearings	Bearing spalling	160	Predictive maintenance adopted; MTBF increased by 40%
Caterpillar – Heavy Equip.	PFMEA on hydraulic cylinders	Seal leakage	126	Redesigned seal grove; warranty claims dropped 31%
Mahindra – Tractor MFG (India)	System FMEA on gearboxes	Gear tooth fracture	128	Material grade upgrade; field failure rate fell 45%

Table 4 demonstrates consistent improvement in reliability across industries using FMEA.

Across the analyzed case studies, recurring patterns indicate that mechanical stress, thermal loading, and process variability are the primary contributors to high-priority failures. These observations reinforce the consistency and applicability of FMEA-based failure prioritization across different manufacturing domains.

3.7. Comparative Analysis of Risk Assessment Methods

Table 5: *Comparison of FMEA with Other Risk Assessment Methods*

Method	Scope	Strength	Limitation
FMEA	Component level	Systematic, structured	Static analysis
FTA	System level	Cause-effect analysis	Complex modeling

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Method	Scope	Strength	Limitation
HAZOP	Process level	Detailed deviation analysis	Time-consuming
RCM	Maintenance strategy	Optimizes maintenance planning	Requires extensive data

Table 5 shows that FMEA is most effective for component-level analysis and is often complemented by other methods.

4. Results and Discussion

4.1. Analysis of Failure Modes and RPN Distribution

The FMEA results presented in Table 3 provide a systematic evaluation of failure modes across key mechanical subsystems. The calculated RPN values indicate a broad distribution of failure criticality, reflecting variations in severity, likelihood of occurrence, and detectability across components.

Mechanical elements subjected to continuous loading and wear, such as bearing assemblies and gear systems, exhibit comparatively higher RPN values. These failures are primarily driven by fatigue, lubrication deficiencies, and material degradation. In contrast, control-related failures, although potentially severe, tend to have lower RPN values due to higher detectability and lower occurrence rates. This distribution highlights that risk prioritization in mechanical systems is strongly influenced by the combined effect of operational stress and detection capability, rather than severity alone.

4.2. Dominant Failure Mechanisms

The evaluated failure modes can be broadly categorized into three dominant mechanisms:

i. Wear and Fatigue-Related Failures

Components such as bearings, gears, and cutting tools are highly susceptible to progressive wear and fatigue. These failures occur due to cyclic loading, insufficient lubrication, and prolonged operation, resulting in gradual degradation and eventual system inefficiency.

ii. Thermal and Operational Overload

Failures associated with thermal effects—such as overheating in spindle systems or coolant inefficiencies-affect both performance and product quality. These conditions often arise from excessive operational loads or inadequate heat dissipation mechanisms.

iii. Control and Electrical Failures

Failures in PLC systems, sensors, and power supply units exhibit high severity but relatively lower RPN values due to effective detection systems. This indicates that improved monitoring can significantly reduce overall risk impact, even for critical systems.

4.3. Interpretation of RPN-Based Prioritization

The classification framework presented in Table 2 enables structured prioritization of failure modes based on their RPN values. High-priority failures require immediate corrective actions, while moderate-risk failures are addressed through scheduled maintenance and monitoring.

The results indicate that a significant proportion of failure modes fall within the high-risk category, emphasizing the importance of proactive maintenance strategies and continuous monitoring systems in mechanical manufacturing environments.

4.4. Cross-Industry Validation Through Case Studies

The real-world case studies summarized in Table 4 provide empirical validation of the analytical framework. Despite differences in industry type and application, consistent trends are observed across all cases.

Failure modes associated with fatigue, wear, and process variability repeatedly exhibit higher RPN values, indicating their dominant role in manufacturing system failures. For instance, component-level failures in rotating systems and thermally stressed components show similar risk patterns across automotive, aerospace, and heavy equipment sectors.

Furthermore, the implementation of FMEA-based corrective measures across these case studies has resulted in measurable improvements in system performance, including reductions in defect rates, improved reliability, and enhanced maintenance efficiency. These findings demonstrate that FMEA provides a robust and transferable methodology for failure

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prioritization, capable of delivering consistent results across diverse industrial contexts.

4.5. Limitations of Conventional FMEA

Despite its effectiveness, several limitations of traditional FMEA are identified:

- Equal weighting of Severity, Occurrence, and Detection may lead to inaccurate risk representation
- Static evaluation does not account for dynamic operating conditions
- Dependence on expert judgment introduces subjectivity

These limitations suggest the need for enhanced methodologies that incorporate real-time data and adaptive evaluation mechanisms.

4.6. Implications for Modern Manufacturing Systems

The results indicate that integrating FMEA with modern technologies can significantly enhance its effectiveness. Predictive maintenance systems, IoT-based monitoring, and data-driven analytics can improve failure detection and reduce occurrence rates.

Such integration enables a transition from static risk evaluation to dynamic and continuous risk management, aligning with the requirements of modern Industry 4.0 manufacturing systems.

4.7. Comparative Effectiveness of Risk Assessment Methods

The comparison presented in Table 5 indicates that FMEA is particularly effective for component-level failure analysis due to its structured and systematic approach. However, it is most effective when used in conjunction with complementary methods such as Fault Tree Analysis (FTA), Hazard and Operability Study (HAZOP), and Reliability-Centered Maintenance (RCM). This highlights the importance of adopting a hybrid risk assessment approach to achieve comprehensive evaluation of manufacturing systems.

5. Conclusion

This study examined the practical effectiveness of Failure Mode and Effects Analysis (FMEA) in mechanical manufacturing through real-world case studies and subsystem-level analysis. The results show that when FMEA is applied systematically, it leads to clear and measurable improvements. Across the analyzed cases, reductions in unscheduled downtime of 27%–38%, improvements in product quality of 31%–45%, and maintenance cost reductions of 18%–22% were consistently observed.

A key takeaway is the consistency of failure patterns across industries. Failures related to fatigue, wear, and thermal stress dominate in systems ranging from automotive and aerospace to steel and heavy equipment manufacturing. This reinforces that FMEA is not industry-specific but broadly applicable wherever structured failure analysis is required.

At the same time, the study highlights that conventional RPN-based FMEA remains largely static. As manufacturing systems become more data-driven, there is a clear need to extend FMEA through integration with predictive maintenance, real-time monitoring, and advanced analytical tools. Approaches such as digital twins, machine learning-based prediction, and the AIAG–VDA Action Priority framework can make risk prioritization more dynamic and effective.

Overall, FMEA continues to be a reliable foundation for failure prioritization, but its future lies in combining its structured methodology with modern data-driven technologies.

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