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Enhanced Approach for Prioritisation of Failures in Failure Mode and Effects Analysis Under Uncertainty

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ABSTRACT

The industrial development and economic growth have provided a conducive environment for manufacturing process improvements. However, this progress also poses several challenges to remain competitive and improve efficiency as well as productivity. Failure mode and effect analysis is a systematic approach that is used extensively in the field of risk management to enhance quality and efficiency in different sectors, including the manufacturing and healthcare sectors. In this paper, a novel approach to enhance the failure mode and effects analysis was proposed. The approach can address the inherent uncertainty involved in assigning numerical values to represent the severity, occurrence and detection of each failure. A case study from a small-scale factor was assessed to ensure the applicability and effectiveness of the proposed approach.

Keywords: failure mode and effect analysis, risk priority number, uncertainty, risk management.

INTRODUCTION

With the advancement of technology and lean methodology, manufacturing industries have made remarkable progress that have resulted in major expansions of investment and market reach. However, despite this progress, there are also challenges raised, such as intensified competition [1], as well as constant changes in customers' needs and requirements. To overcome such challenges, the operations managers need to centre their concerns on eliminating wastes and risks while simultaneously maximising productivity and market share [2, 3]. Failure mode and effects analysis (FMEA) is a popular tool for analysing activities in different production and manufacturing stages [4].

FMEA is a technique that evaluates the system design, process, or service to identify all failures that might occur [5]. At the beginning, all potential failure modes are identified. Then, for each failure, an estimation of its severity of the effect of the failure, the probability of occurrence, and dedication of each failure are determined using a 10-point scale for establishing the risk of each factor, with 10 being the most frequent, most severe, or least detectable. Finally, the measure of failure risk, i.e. risk priority number (RPN) is obtained [6]. FMEA has been applied in different sectors where safety is important, such as healthcare [7, 8], automotive industry [9, 10], manufacturing [11, 12], and maintenance management [13, 14].

In general, FMEA is a well-structured technique that can be used for quality improvement and risk assessment to rank potential failures and prepare control plans to reduce the probability of failure occurrence [15]. However, FMEA has several weaknesses and limitations, such as: use of ordinal ranking numbers as numeric quantities

[16], the risk factors i.e. severity, occurrence, and detection are assumed to have the same weight and importance. In addition, FMEA does not quantify the factors that contribute to the risk [17].

To date, several studies have investigated the FMEA method in order to improve quality in different sectors. Franceschini and Galetto [18] proposed a novel method to calculate the risk priority level for the failure mode in FMEA. The presented method has the ability to manage different importance levels for the failure mode component indices, and allow a more flexible structure for combining the index importance. Van Tilburg et al. [19] investigated the validity of the health care failure mode and effect analysis for proactive analysis of the prescription up to and including administration of chemotherapy in a paediatric oncology setting using a hazard scoring matrix. The authors used the decision matrix to determine which failure mode recommendations must be done. To assess the risk of potential failure mode [20] proposed a novel method where 2-tuple and ordered weighted averaging (OWA) were combined in a product when conducting design failure mode effects analysis (DFMEA). According to the authors, the proposed approach can help decision makers to find the most critical causes of failure and assign limited resources to the serious risks by providing accurate risk ranking. Geum et al. [21] presented a systematic framework for identifying and evaluating potential failures using a service-specific failure mode and effect analysis as well as grey relational analysis. A construction of service-specific FMEA was proposed to incorporate the service specific characteristics to the traditional failure mode effect analysis. Then, grey relational analysis was applied to calculate the risk priority of each failure mode. Fahmy et al. [22] examined the impact of quality risk management in prioritizing the number of experiments needed to identify the critical quality attributes (CQA). The authors used failure mode effect analysis and Plackett Burman design of experiments in the identification of "main factors" in the formulation and process design space for roller-compacted ciprofloxacin hydrochloride immediate-release tablets. The results show the use of failure mode and effect analysis and screening designs, such as the Plackett Burman, can rationally guide the process of reducing the number of experiments to a manageable level. Tooranloo and Sadat Ayatollah [1] introduced a novel model for failure mode and effect analysis based on the intuitionistic fuzzy approach. The proposed model has the ability to deal with vague concepts and insufficient data. The authors tested the model in a case study that examines FMEA for the quality of internet banking services. They concluded that the use of intuitionistic fuzzy TOPSIS technique provides a strong basis for dealing with uncertain and ambiguous factors, which is common in business environments, hence provides important insight for decision makers.

Huang et al. [23] applied linguistic distribution and TODIM (an acronym in Portuguese of interactive and multi-criteria decision making) approach to evaluate as well as rank failure mode and effect analysis by quantify the risk ratings of failure modes against each risk factor. According to the authors, the presented method can deal with the uncertainty and diversity of assessment information, including the psychological behaviour of the experts in the risk analysis process.

Liu et al. [24] developed a robust FMEA model by integrating interval-valued intuitionistic fuzzy sets (IVIFSs) and the multi-attributive border approximation area (MABAC) method to determine the risk priorities of failure modes. The authors found that the presented method is more flexible and precise to deal with linguistic terms; in addition, it can obtain more rational ranking results of failure mode. Liu et al. [25] provided a comprehensive review of the FMEA studies using multi criteria decision making (MCDM) approaches for evaluation and prioritisation of failure modes with respect to the most popular MCDM approach for FMEA, the most influential studies, the publication dates, the published journals, the national context of articles, and the application areas. The authors also highlighted the risk factors, risk factor weighting methods, and risk assessment methods used in the reviewed studies. Huang et al. [26] conducted a systematic review of the journal articles on the FMEA topic during the years between 1998 and 2018. The authors provided a statistical analysis to highlight the publication distribution across time and journals as well as a bibliometric analysis to identify the most influential authors, institutions and areas, and reveal the research hotspots. The authors also identified research gaps and opportunities on the improvement of FMEA. Sader et al. [27] developed a novel approach to enhance FMEA using multiclass classification by developing four machine learning models using auto machine learning. To do so, the authors used a dataset that includes a one-year registry of 1532 failure models to predict the values of severity, occurrence, and detectability. The results show that the proposed work can enhance consistency and minimize the processing time.

In this paper, a new approach for failure mode and effect analysis was shown, dealing with the uncertainty and inaccuracy of human decisions. The presented approach aims at dealing with the FMEA weaknesses by using three values for each of FMEA: optimistic, most likely and pessimistic. This can provide more rational ranking of the failure modes.

METHODOLOGY

The FMEA method measures the risk of each failure mode with respect to the three risk factors severity, occurrence and detection, where each factor is expressed using single value. However, decision maker judgments are inherently subjective and vague under many conditions. They are often incapable of assessing and ranking failures adequately using a single value. Therefore, it is more convenient to express FMEA factors i.e. severity, occurrence and detection using multiple values for each. This section delineates the steps of the proposed methodology.

The presented methodology comprises three primary phases. In the first phase, decision makers identify all possible failure modes. In the second phase, each decision maker is asked to assess the risk of each failure mode based on the severity (S), occurrence (O), and detection (D) using three values that represent optimistic, pessimistic, and most likely scenarios using the following equation:

$$\mathrm{S, O, D} = \frac{(O_i + 4 \cdot ML_i + P_i)}{6} \tag{1}$$

where: O_i – optimistic value with respect to each failure, ML_i – most likely value with respect to each failure; P_i – pessimistic value with respect to each failure.

Where all $(10 \geq O_i, L_i, P_i \geq 1)$. Failures $\in \{1,2,\ldots,n\}$.

Then, the risk priority number (RPN) = severity×occurrence×detection is obtained for each decision maker, with respect to each failure. Later, the values of the RPN are aggregated by calculating the average of inputs provided by all decision-makers. According to the results, the

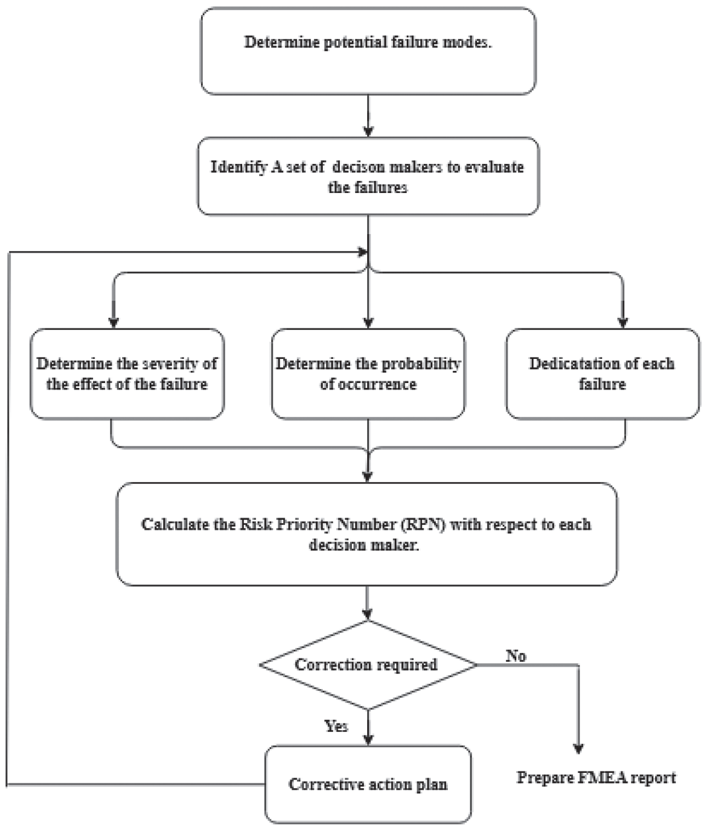

Figure 1. The proposed methodology

Table 1. Failure types and RPN values with respect to one decision maker

No.	Type of failure	Risk description	Severity			Occurrence			Detectability			RPN
			P	ML	O	P	ML	O	P	ML	O	
1	Production	Machine breakdown	1	9	8	3	2	1	10	9	8	162
2		Shortage of raw material	9	8	7	3	2	1	9	8	7	128
3		Deficiency in skilled labour	8	6	4	5	4	3	7	5	3	120
4	Loading / unloading	Unauthorized employee enter the loading/unloading area	5	3	2	8	6	4	5	4	3	76
5		Storing and stacking the cargo improperly	7	6	5	4	2	1	7	6	5	78
6		Workers sustain injuries due to inefficient practices.	8	6	4	4	2	1	8	6	4	78
7	Technology	System outages due to hardware or software failures	10	9	8	5	3	2	9	8	7	228
8		Inadequate technology training	9	8	7	5	4	3	5	4	3	128
9		Lack of predictive maintenance implementation	7	6	5	7	5	2	4	3	2	87

risks with the highest value are revised and required modifications are obtained. Figure 1 illustrates the proposed methodology.

Case study

In this section, the proposed approach was used to assess the failure in a small-scale factory in Jordan, where there are many hazards that might have a negative impact on the productivity and efficiency of the factory. Therefore, it is necessary for the factory to carefully review the different operations and assess the risks, then prepare an action plan to reduce these risks. Thus, a team of experts were assigned to define all the potential failures across three distinct aspects: production, loading/unloading processes, and technology. Next, the decision makers determine the severity of each failure, the probability of occurrence, and the detection of risk based on a scale of 1–10 using equations 1, 2, and 3, respectively.

Table 1 shows the potential failures rate with respect to severity, occurrence and detection from the perspective of a single decision maker across three distinct aspects: production, loading/unloading processes, and technology for the small scale factory used in this case study.

Table 2 shows the results from the aggregation of ratings provided by the team of decision makers assigned to evaluate the failures. On the basis of the rating acquired from the decision makers, the results indicate that the shortage of raw material has the highest potential of failure followed by Inadequate Technology Training, and Machine breakdown, respectively.

Comparative analysis of the proposed models

In order to evaluate the developed approach, the RPN results in the original method are compared against the resulting RPN from the proposed approach, where the same set of experts rated the potential failure based on the original failure mode and effect analysis method, where each of severity, occurrence and detection are presented using single value. RPN values are obtained by multiplying the severity, occurrence and detection to determine whether there is a significant difference in how they rank the failures. Table 3 illustrates the RPN results in the original method and RPN from the proposed approach

A hypothesis testing (Wilcoxon signed rank test) is carried out on the outcomes of the two approaches in terms of RPN values. The applied Wilcoxon signed rank test takes the

Table 2. The risk priority number of each failure after aggregation

No.	Potential risks	RPN
1	Shortage of raw material	147.58
2	Inadequate technology training	133.25
3	Machine breakdown	123.93
4	System outages due to hardware or software failures	123.53
5	Deficiency in skilled labor	118.92
6	Storing and stacking the cargo improperly	72.32
7	Lack of predictive maintenance Implementation	71.25
8	Workers sustain injuries due to inefficient practices	60.58
9	Unauthorized employee enter the loading/unloading area	60.38

Table 3. The comparison between the values of RPN

Potential failures	RPN (original method)	RPN (proposed method)
Machine breakdown	125.0	123.9
Shortage of raw material	144.7	147.5
Deficiency in skilled labor	118.7	118.9
Unauthorized employee enter the loading/unloading area	54.7	60.4
Storing and stacking the cargo improperly	68.0	72.3
Workers sustain injuries due to inefficient practices.	57.0	60.5
System outages due to hardware or software failures	116.0	123.5
Inadequate technology training	131.7	133.2
Lack of predictive maintenance implementation	69.0	71.3

paired score differences and ranks them in ascending order by absolute value in order to find out whether it is significant or not [28]. The confidence interval for the difference between the two variables is considered 95%. The test is performed using SPSS 16.0, as follows:

$$\begin{cases} H_0: \text{There is no difference between the two methods} \\ H_1: \text{There is difference between the two methods} \end{cases}$$

According to the results listed in Table 4, Wilcoxon signed-rank test suggests that there is a statistically significant difference in rankings between the two methods. Therefore, the null hypothesis is rejected; there is difference between the proposed procedure and the original one, and it might be assumed that the proposed procedure can provide more reliable and accurate rankings in the presence of uncertainty.

Table 4. The results of Wilcoxon signed-rank test

Ranks	N	Mean rank	Sum of ranks
Negative ranks	8	5.38	43.00
Positive ranks	1	2.00	2.00
Ties	0		
Total	9		
Test statistic	Var0001 – Var0002		
Z	-2.43		
Asymp. Sig. (2-tailed)	0.015		

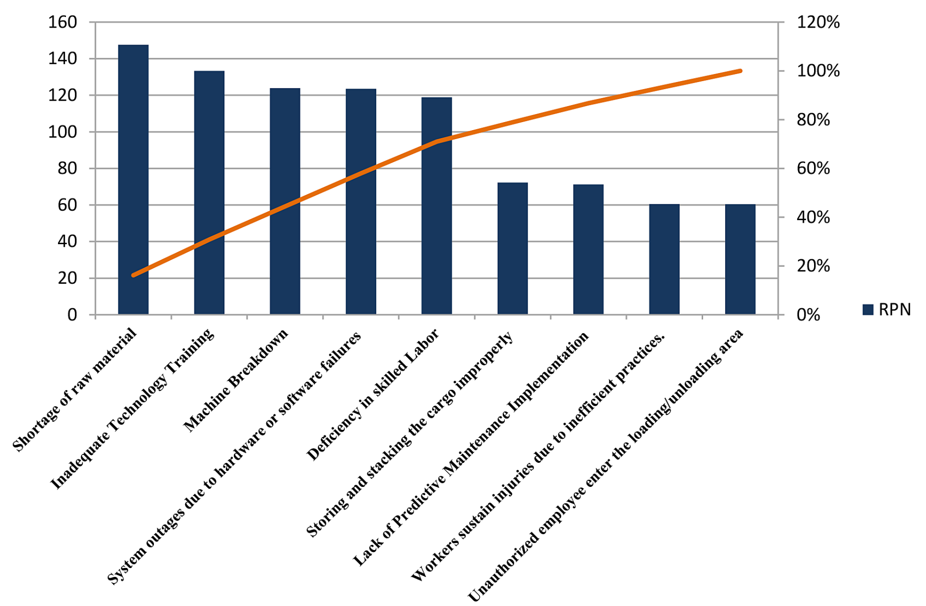

Figure 2. Pareto chart of potential risks

Pareto analysis

Pareto analysis was performed to determine the vital failures that affect the performance of the factory. Pareto analysis is a tool used to select the limited number of tasks that has the most effect in decision making [29]. The technique is based on identifying the 20% of the causes that needed to be addressed to solve 80% of the problem [30]. Potential failures with more than 80% of cumulative frequency are considered vital failures that require preparing an action plan to reduce the risk for the failure and mitigate the consequences, such as diversifying supply sources, deploying inventory management systems, providing training and educational courses and etc. In turn, failures with less than or equal to 80% cumulative frequency are considered as vital. After that, the RPN value will be calculated again, if the value is still not tolerable, the failure must be eliminated.

The vital failures for the small-scale factory examined (Figure 2) mainly included shortage of raw material, inadequate technology training, machine breakdown, system outages due to hardware or software failures and deficiency in skilled labour. The project manager needs to prepare an action plan to reduce or eliminate the likelihood of failure.

CONCLUSIONS

In the paper, a new approach was tested for assessing the potential risks considering the uncertainty the experts may encounter during risk assessments. The approach can address the uncertainty in assigning values to the severity, occurrence and detection of each failure. To test the approach, a case study from manufacturing environment was presented, where the type of failure was classified into three primary categories: production, loading/unloading, and technology. The results suggested that the presented methodology not only provides more accurate results but also effectively addresses the uncertainty associated with human decision-making. Moreover, the presented approach reduced the influence of subjective judgment, thereby enhancing the reliability and consistency of outcomes. This improvement is particularly vital in fields where precision is very critical, as it offers a more objective and systematic process to decision-making.

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