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ORIGINAL PAPER

FUZZY FAILURE MODE AND EFFECT ANALYSIS MODEL FOR OPERATIONAL SUPPLY CHAIN RISKS ASSESSMENT: AN APPLICATION IN CANNED TUNA MANUFACTURER IN THAILAND

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ABSTRACT. Background: This study proposes a multi-criterion decision-making (MCDM) framework for operational supply chain risks assessment based on fuzzy failure mode effect analysis model. The proposed framework attempts to overcome some weaknesses and disadvantages of the traditional FMEA in many aspects such as (i) considering "degree of difficulty to eliminate risks" in the assessment process, (ii) using MCDM ranking methodology instead of a risk priority number, (iii) taking both subjective and objective weights of risk criteria into account. Application of the proposed framework used canned tuna production in Thailand as a case study.

Methods: In this study, the operational supply chain risks assessment is treated as fuzzy MCDM problem. Subjective weights of risk criteria are determined by experts' judgements. Objective weights are derived by Shannon entropy method. VIKOR approach is employed to prioritize the failure modes. A sensitivity analysis is performed to examine the robustness of the proposed framework.

Results and conclusions: The findings from this study indicates that the most three critical FMs are "risk of product deterioration" followed by "risk of volatility raw materials supplied" and "risk of variabilities in production processes", respectively. It recommends that the practitioners in canned tuna industry should give the priority to mitigate these risks. Although the present study focuses on canned tuna industry, the other similar industries can apply this proposed framework to assess their operational supply chain risks in the same way.

Keywords: Operational supply chain risks; FMEA; MCDM; Shannon entropy; VIKOR

INTRODUCTION

The rapidly changing business environment causes manufacturers to encounter various risks and uncertainties in managing their supply chain activities, such as variations in the lead time of incoming raw materials, demand volatility, unexpected machines and equipment breakdown, labour shortage and IT disruption [Wu et al. 2019]. These risks adversely affect not only the efficiency of supply chain operations but also the desired performance outcomes of manufactures. Organizations that seek only high performance and neglect risk management are doomed to failure in today's turbulent business environment [Fan et al. 2016]. Risks may arise from natural disasters or man-made problems and it should have a negative impact on industries in the form of financial and operational difficulties that could lead to business disruption [da Silva et al. 2020].

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Principally, the sources of supply chain risks can arise from both inside and outside of organizations [Moktadir et al. 2018]. However, most manufacturers have internal risk management and often overlook significant risks throughout their supply chains. Although some risks are inevitable, organizations should seek proactive mechanisms to monitor, control and manage them to alleviate their affection [Mohamed and Youssef 2017]. Hence, supply chain risk management (referred as SCRM) becomes an essential part of operations management [Shan et al. 2020]. SCRM can be described as the identification, assessment of risks and development of an effective risk mitigation plan [Butdee and Phuangsalee 2019]. Proper risk management has a positive effect on supply chain efficiency and it can help manufactures be more resilient in the face of major disruptions. Supply chain risks can be classified by the source of risk as (i) disruption risk and (ii) operational risk. Disruption risks come from human-made and natural disasters such as terrorist attacks, economic crises, earthquakes, pandemics, storms, and floods [Nakandala et al.2017]. While, operation risks arise from the execution of business processes or activities in supply chain [Heckmann et al. 2015]. Major sources of operational risks are demand uncertainties, supply chain volatility, market price fluctuation, and machine and equipment breakdown [Shen et al. 2020]. These risks pose a disturbance in the supply chain and require an appropriate assessment to develop risk mitigation strategies [Junaid et al. 2020]. In order to prevent the deterioration in profitability, supply chains management is able to accurately assess risks and fast respond to the risk events. Hence, risk assessment is one of the important processes in risk management [Fan et al. 2016]. There are many risk assessment approaches reported in the literature. Failure Mode and Effect Analysis (FMEA) is one of the most wildly used tools in risk management [Panchal et al. 2018]. The aim of the FMEA method is to proactively manage risks against potential future risk events. The basic concept of FMEA is to determine risk priority number (RPN). There are three quantified risks criteria as severity (S), probability of occurrence (O), and probability of detection (D), then multiply them as a risk priority number (RPN) [Yazdi 2019]. Eliminating or mitigating potential risks will be planned and implemented based on RPN prioritization manner [Liu et al., 2018]. The FMEA calculation procedure can be divided into three main components: (i) determining the critical risk threshold, (ii) calculating the RPN, and (iii) capturing data uncertainty [Scheu et al. 2019]. As can be seen from various studies in literature, the risk assessment and failure modes prioritization procedures for FMEA can be considered as multi-criteria decision making (MCDM) problem [Fattahi and Khalilzadeh 2018]. In addition, fuzzy set theory (FST) is commonly used to deal with imprecise information in decision-making processes [Shaker et al. 2019]. A recent example of the application of MCDM-based FST approaches in FMEA are summarized in Table 1.

Although FMEA technique is applied in many real-world decision-making problems, there has been little research on supply chain risk assessment, especially in seafood supply chain such as tuna industry. The tuna industry has a complex supply chain and is highly volatile in both demand and supply. This could increase the operational risk of the supply chain. Comprehensive operational supply chain risk assessment in tuna industry has not been fully explored from existing literature. To the best of the author's knowledge, no studies so far have assessed the operational risk of the supply chain in tuna industry. To bridge the gap, this study proposes a new multi-criteria decision-making framework based on FMEA model to assess operational supply chain risk under uncertain environment. To validate the proposed framework, canned tuna industry in Thailand is therefore used as a case study.

Table 1. Recent examples of the application of MCDM-based FST approaches in FMEA

No.	Authors and year of publication	FMEA problems	MCDM Methodology used
1	Karatop et al. (2021)	Renewable energy investment	Fuzzy AHP-EDAS
2	Rathore et al. (2021)	Evaluation of risks in foodgrains supply chain	Fuzzy VIKOR
3	Yener and Can (2021)	Risk assessment of air insulated metal shielded cells production	Fuzzy AHP- MABAC
4	Nabizadeh and Khalilzadeh (2021)	Health, safety and environment risks assessment	Fuzzy goal Programming-VIKOR
5	Pourmadadkar et al. (2020)	Healthcare services risk assessment and quality enhancement	Fuzzy TOPSIS
6	Sagnak et al. (2020)	Evaluation of manufacturing equipment failure in hot-dip galvanizing production process	Fuzzy AHP-TODIM
7	Yazdi et al. (2020)	Risk analysis on a supercritical water gasification	Fuzzy best-worst method-Data Envelopment Analysis
8	Yan et al. (2019)	Risk assessment for construction of urban rail transit projects	Fuzzy matter-element model
9	Wang et al. (2019)	Evaluating and prioritizing risk the potential failure modes of steam valve system	Fuzzy Choquet integral-TODIM
10	Mete (2019)	Assessing occupational risks in pipeline construction	Fuzzy AHP- MOORA

RESEARCH HIGHLIGHTS AND CONTRIBUTIONS

This study attempts to overcome some weaknesses and drawbacks of the traditional FMEA method by proposing a new approach to operational supply chain risk assessment. The highlights of this paper and the contributions to the literature on supply chain risk assessment and FMEA model can be summarized as follows:

- The conventional FMEA is restricted to using only three risk criteria as S, O and D for the FMs rating, lacking consideration of the difficulties in eliminating any risk exposure. In this study, a new risk factor namely "degree of difficulty to eliminate risks" (E) is included to analyze FMEA.
- RPN values are normally used to measure FMs risks level in traditional FMEA. However, the mathematical foundation for computing RPN (S*O*D) is controversial because it is not rational and highly sensitive to variations in results. Because the different combination values of S, O, and D may produce the same RPN values, but the different FMs can have different risk levels. In this study, a compromise programming (CP) approach as VIsekriterijumska optimizacija i KOmpromisno Resenje (VIKOR) approach is used instead of RPN values to assess the operational supply chain risk. The main reasons for using VIKOR in this study are that (i) it is able to assess and identify gaps of FMs performance leading to further improvements (ii) it is straightforward and uncomplicated in computation.
- The classical FMEA assumes risk criteria have equal important weights in risk criteria rating which may not be realistic in various problems in the real-world problems. The advantage of using VIKOR method is that the important weight of risk criteria can be altered in the assessment process.
- Most of the previous research used either subjective weights (purely based on the opinion of decision-makers) or objective weights (based on information gathered from criteria but ignoring opinions from decision-makers) to determine the important weights of risk criteria. In this study, the subjective and objective weights are combined to make the important weights of risk criteria more reliable.
- The proposed framework of this paper will help the practitioners and managers in canned tuna industry to effectively assess the operational risks and prioritize the failure modes in supply chain. Although this study focuses on the canned

tuna industry, the proposed framework can be applied to other industries in a similar procedure.

The present study is organized as follows: a brief of mathematical preliminaries is included in the second part. The proposed framework for operational supply chain risks assessment is presented in the third part of the study. The fourth part illustrates the application of the proposed framework of this study. Finally, the conclusions and future research are drawn in the fifth part.

MATHEMATICAL PRELIMINARIES FUZZY SET THEORY

Fuzzy set theory (FST) was proposed by Zadeh [1965] to logically map linguistic variables to crisp variables in the decision-making processes of human judgement. FST is wildly used to deal with uncertain and imprecise information in fuzzy multi-criteria decision-making (FMCDM) problems. The main concept of FST is defined as linguistic variables based on a specific type of fuzzy set. A fuzzy set is generally represented by a membership function that assigns a degree of membership within the range [0,1] known as fuzzy number to each linguistic variable belonging to the fuzzy set. A fuzzy set can be mathematically defined in terms of fuzzy numbers as: N = $\{(x), \mu_N(x), x \in R\}$; where $\mu_N(x)$ is a degree of membership within the range [0,1].

TRAPEZOIDAL FUZZY NUMBERS (TrFN)

There are different types of fuzzy numbers such as Triangular Fuzzy Number (TFN), Trapezoidal Fuzzy Number (TrFN), and Gaussian Fuzzy Number (GFN). In this study, TrFN is used to address uncertain and imprecise information because it is a comprehensive computation and broadly used in various problems. A pictorial TrFN is shown in figure 1 and the mathematical membership function can be denoted as follows [Wang et al. 2019]:

$$\mu_N(x) = \begin{cases} (x-l)/(m_1-l), & x \in [l, m_1] \\ 1 & x \in [m_1, m_2] \\ (r-x)/(r-m_2), & x \in [m_2, r] \\ 0 & ; otherwise \end{cases} \quad (1)$$

*where $\{(l, m_1, m_2, r) | l, m_1, m_2, r \in R;\ l \leq m_1 \leq m_2 \leq r\}$.

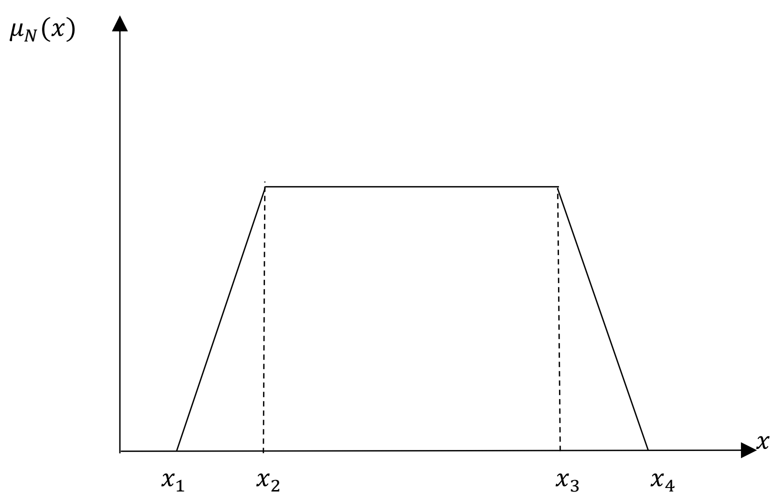

Fig. 1 Trapezoidal fuzzy number

COMPUTING THE SUBJECTIVE WEIGHTS OF RISK

The fuzzy rating for subjective weight of j^{th} criterion is given by the expert k^{th} be $\widetilde{w}_{jk}^{s} = \{(w_{jk1}^{s}, w_{jk2}^{s}, w_{jk3}^{s}, w_{jk4}^{s}) | j = 1,2,..,n\}$. Hence, the fuzzy rating for subjective weights (w_j^s) from all experts are aggregated into group as [Shemshadi et al. 2011]:

$$w_j^s = \begin{cases} w_{j1}^s = \min_k\{w_{jk1}^s\} \\ w_{j2}^s = \frac{1}{k}\sum_{k=1}^{k} w_{jk2}^s \\ w_{j3}^s = \frac{1}{k}\sum_{k=1}^{k} w_{jk3}^s \\ w_{j4}^s = \max_k\{w_{jk4}^s\} \end{cases} \quad (2)$$

*where $w_j^s = [w_{j1}^s, w_{j2}^s, w_{j3}^s, w_{j4}^s]$ is the subjective weight of j^{th} risk criterion.

CONSTRUCT AGGREGATED FUZZY RATING MATRIX

The fuzzy rating score collected from expert k^{th} for i^{th} alternative regarding j^{th} criterion is denoted as $\tilde{x}_{ijk} = (x_{ijk1}, x_{ijk2}, x_{ijk3}, x_{ijk4})$. Then, the fuzzy rating scores from all experts are aggregated into a group as [Shemshadi et al. 2011]:

$$\tilde{X}_{ij} = \begin{cases} x_{ij1} = \min_k\{x_{ijk1}\} \\ x_{ij2} = \frac{1}{K}\sum_{k=1}^{K} x_{ijk2} \\ x_{ij3} = \frac{1}{K}\sum_{k=1}^{K} x_{ijk3} \\ x_{ij4} = \max_k\{x_{ijk4}\} \end{cases}$$

(3)

Thus, the aggregated fuzzy rating matrix $(\tilde{R})$ is constructed as:

$$\widetilde{D} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (4)$$

*where $x_{ij} = (x_{ij1}, x_{ij2}, x_{ij3}, x_{ij4})$

DEFUZZIFY THE AGGREGATED FUZZY RATING MATRIX

Each element in the aggregated fuzzy rating matrix $(\tilde{R})$ is defuzzified into crisp values as [Shemshadi et al. 2011]:

$$\text{Defuzz}(x_{ij}) = \frac{\int \mu(x).xdx}{\int \mu(x)dx} \quad (5)$$

$$= \frac{\int_{x_{ij1}}^{x_{ij2}}\left(\frac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right)\cdot xdx + \int_{x_{ij2}}^{x_{ij3}} xdx + \int_{x_{ij3}}^{x_{ij4}}\left(\frac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right)\cdot xdx}{\int_{x_{ij1}}^{x_{ij2}}\left(\frac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right)dx + \int_{x_{ij2}}^{x_{ij3}} dx + \int_{x_{ij3}}^{x_{ij4}}\left(\frac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right)dx}$$

$$= \frac{-x_{ij1}x_{ij2} + x_{ij3}x_{ij4} + \frac{1}{3}(x_{ij4} - x_{ij3})^2 - \frac{1}{3}(x_{ij2} - x_{ij1})^2}{-x_{ij1} - x_{ij2} + x_{ij3} + x_{ij4}}$$

SHANNON ENTROPY APPROACH

Shannon [2001] introduced the entropy approach to measure the uncertainty inherited in information and explain it with probability theory. In this study, entropy is employed to determine the objective weights of risk criteria. The entropy procedure is presented as follows [Lee and Chang, 2018]:

Step 1: Normalize the evaluation of the decision matrix

Based on the defuzzify aggregated fuzzy rating matrix, all elements are normalized to render the evaluation criteria become dimensionless as:

$$P_{ij} = \frac{P_{ij}}{\sum_j P_{ij}} \quad (6)$$

Step 2: Calculate entropy measuring values of criteria

The entropy measuring values (e_j) of the evaluation criteria are calculated as:

$$e_j = -k \sum_{j=1}^{n} P_{ij} \ln (P_{ij}) \quad (7)$$

*where k = $(\ln(m))^{-1}$ and m is the number of alternatives.

Step 3: Determine the divergence values

The divergence values (d_j) of evaluation criteria are determined as:

$$d_j = 1 - e_j \quad (8)$$

Step 4: Compute the normalized weights of criteria

The normalized weights of evaluation criteria are computed as:

$$w_j = \frac{div_j}{\sum_j div_j} \quad (9)$$

FUZZY VIKOR

VIKOR is one of MCDM techniques that help decision-makers prioritize the alternatives with respect to assessment criteria. The basic concept of this technique is that the location of the best alternative is close to the ideal solution. In other words, the best one has the shortest distance from the ideal solution. In this study, fuzzy VIKOR is employed to prioritize the failure modes. The computation procedure of fuzzy VIKOR is illustrated as follows [Shemshadi et al. 2011]:

Step 1: Normalize the aggregated fuzzy rating matrix

Based on the aggregated fuzzy rating matrix $(\tilde{R})$, all elements are normalized to make them can be comparable. Then, the normalized the aggregated fuzzy rating matrix $\left(U = [u_{ij}]_{m\times n}\right)$ is constructed as:

$$u_{ij} = \left\{\left(\frac{x_{ij1}}{x_{ij1}^-}, \frac{x_{ij2}}{x_{ij1}^-}, \frac{x_{ij3}}{x_{ij1}^-}, \frac{x_{ij4}}{x_{ij1}^-}\right)\right\} \text{ for cost criterion} \quad (10)$$

$$u_{ij} = \left\{\left(\frac{x_{ij1}}{x_{ij4}^+}, \frac{x_{ij2}}{x_{ij4}^+}, \frac{x_{ij3}}{x_{ij4}^+}, \frac{x_{ij4}}{x_{ij4}^+}\right)\right\} \text{for benefit criterion} \quad (11)$$

*where $x_{ij4}^+ = \max_i\{x_{ij4}\}$ for benefit criterion, while $x_{ij1}^- = \min_i\{x_{ij1}\}$ for cost criterion.

Step 2: Calculate the overall performance rating

The overall performance ratings values of alternatives (f_{ij}) are calculated as [Shemshadi et al. 2011]:

$$F = [f_{ij}]_{m\times n}$$

$$f_{ij} = defuzz\left(u_{ij} \otimes w_j^s\right) \quad (12)$$

$$f_{ij} = \frac{\int \mu(x).x dx}{\int \mu(x) dx}$$

$$f_{ij} = \frac{\int_{u_{ij1}w_{j1}^s}^{u_{ij2}w_{j2}^s}\left(\frac{x - w_{j1}^s}{u_{ij2}w_{j2}^s - u_{ij1}w_{j1}^s}\right)\cdot xdx + \int_{u_{ij2}w_{j2}^s}^{u_{ij3}w_{j3}^s} xdx + \int_{u_{ij3}w_{j3}^s}^{u_{ij4}w_{j4}^s}\left(\frac{u_{ij4}w_{j4}^s - x}{u_{ij4}w_{j4}^s - u_{ij3}w_{j3}^s}\right)\cdot xdx}{\int_{u_{ij1}w_{j1}^s}^{u_{ij2}w_{j2}^s}\left(\frac{x - u_{ij1}w_{j1}^s}{u_{ij2}w_{j2}^s - u_{ij1}w_{j1}^s}\right)dx + \int_{u_{ij2}w_{j2}^s}^{u_{ij3}w_{j3}^s} dx + \int_{u_{ij3}w_{j3}^s}^{u_{ij4}w_{j4}^s}\left(\frac{u_{ij4}w_{j4}^s - x}{u_{ij4}w_{j4}^s - u_{ij3}w_{j3}^s}\right)dx}$$

$$f_{ij} = \frac{-(u_{ij1}u_{ij2})\left(w_{j1}^s w_{j2}^s\right)+(u_{ij3}u_{ij4})\left(w_{j3}^s w_{j4}^s\right)+\frac{1}{3}\left(u_{ij4}w_{j4}^s - u_{ij3}w_{j3}^s\right)^2 - \frac{1}{3}(u_{ij2}w_{j2}^s - u_{ij1}w_{j1}^s)^2}{-u_{ij1}w_{j1}^s - u_{ij2}w_{j2}^s + u_{ij3}w_{j3}^s + u_{ij4}w_{j4}^s}$$

where $w^s = \left[w_{j1}^s, w_{j2}^s, w_{j3}^s, w_{j4}^s\right]$ is the subjective weights of risk criterion.

Step 3: Determine the best ideal and the worst ideal values

The best ideal value $\left(f_j^*\right)$ and the worst ideal values $\left(f_j^-\right)$ of the overall performance rating values of alternatives (f_{ij}) can be defined as:

$$f_i^* = \max_i\{f_{ij}\} \quad (13)$$

$$f_i^- = \min_i\{f_{ij}\} \quad (14)$$

Step 4: Calculate the values of utility measure S_i and regret measure R_i for each alternative

The value of S_i and R_i for each alternative can be calculated by using LP-matric $\left(L_{P,i}\right)$ as an aggregating function to determine the compromise raking of the alternative. According to LP-matric, $L_{1,i}$ and $L_{\infty,i}$ are used to compute S_i and R_i as follows:

$$L_{P,i} = \left\{\sum_{j=1}^{n}\left[w_j\left(r_j^* - r_{ij}\right)/\left(r_j^* - r_j^-\right)\right]^p\right\}^{1/p} \quad (15)$$

$$S_i = \sum_{j=1}^{n}\frac{w_j^o(f_i^* - f_{ij})}{(f_i^* - f_i^-)} \quad (16)$$

$$R_i = \max_i\left(\frac{w_j^o(f_i^* - f_{ij})}{(f_i^* - f_i^-)}\right) \quad (17)$$

*where w_j^o the objective weight of risk criterion obtained from Shannon entropy.

Step 5: Compute the values of Q_i for failure modes

The value of Q_i for each failure mode can be computed as:

$$Q_i = \frac{\upsilon(S_i - S^*)}{S^- - S^*} + \frac{(1-\upsilon)(R_i - R^*)}{R^- - R^*} \quad (18)$$

*where

$$S^- = \max_i\{S_i\} \quad (19)$$

$$S^* = \min_i\{S_i\} \quad (20)$$

$$R^- = \max_i\{R_i\} \quad (21)$$

$$R^* = \min_i\{R_i\} \quad (22)$$

υ stands for weight for the strategy of maximum group utility, while $1 - \upsilon$ stands for the weight of the individual regret. In this study, the υ value is 0.5.

Step 6: Prioritize the failure modes

The failure modes are prioritized based on S_i, R_i, and Q_i in ascending order.

Step 7: Examine the condition of the compromise solution

In this step, the condition of the compromise solution is examined. Considering the minimum value of Q_i, the failure mode $FM^{(1)}$ is the first ranked if the following two conditions are fulfilled.

Condition #1: Acceptable advantage: $Q\left(FM^{(2)} - FM^{(1)}\right) \geq DQ$ where $FM^{(2)}$ is the second-ranked list by Q_i and $DQ = {}^{1}/_{J-1}$.

Condition #2: Acceptable stability in the decision making. The failure mode $FM^{(1)}$ must be the first priority ranked by S_i or/and R_i . It indicates that the compromise solution is stable in decision-making process (when $\upsilon > 0.5$ is required, or "by experts' consensus" $\upsilon \approx 0.5$, or "by veto" $\upsilon < 0.5$).

If one of the conditions cannot be met, then a set of compromise solutions is assigned as follows:

- Failure mode $FM^{(1)}$ and $FM^{(m)}$ if only if "Condition# 2" is not met, or
- Failure mode $FM^{(1)\cdot}$, $FM^{(2)\cdot}$,... , $FM^{(m)\cdot}$ If only if "Condition# 1" is not met; $FM^{(m)}$ is defined by the relation $Q\left(FM^{(\mathrm{m})} - FM^{(1)}\right) \geq DQ$ for maximum M.

PROPOSED FRAMEWORK FOR OPERATIONAL SUPPLY CHAIN RISKS ASSESSMENT

This study proposed eight phases framework for operational supply chain risks assessment based on fuzzy FMEA as: Phase I-Identify potential operational supply chain risks based on FMEA, Phase II-Define risk criteria and measuring scale, Phase III-Compute the subjective weights of risk criteria, Phase IV: Construct aggregated fuzzy rating matrix of FMs, Phase V- Defuzzify the aggregated fuzzy rating matrix of FMs, Phase VI-Compute the objective weights of risk criteria, Phase VII-Prioritize the FMs, and Phase VIII-Perform a sensitivity analysis. The schematic diagram of the proposed framework is illustrated in figure 2.

APPLICATION OF THE PROPOSED FRAMEWORK

CASE STUDY

The proposed framework is validated by using one of the leading canned tuna manufacturers in Thailand. This manufacturer is regarded as the largest producer of ready-to-eat canned tuna products in Southeast Asia with annual sales exceeding US$ 3.2 billion in the year 2020. The company operates as an original brand manufacturer (OBM). In the past few years, this company encounters various risks causing an interruption in the supply chain. Company executive staffs need to proactively develop an effective plan to mitigate those risks. To do this, a panel of experts consists of six experts with more than ten years of experience including plant manager, logistics manager, quality assurance manager, risk management manager, procurement manager and academician. Therefore, the proposed framework in this study is used as a tool to assist a panel of experts to identify, assess and prioritize the risks inherited in supply chain operations.

RESULTS

Phase I: Identify potential operational supply chain risks based on FMEA

The experts are invited to investigate the potential failure modes (FMs) of operation supply chain risks for case manufacturing. After several rounds of discussions, eleven FMs are identified as presented in Table 2.

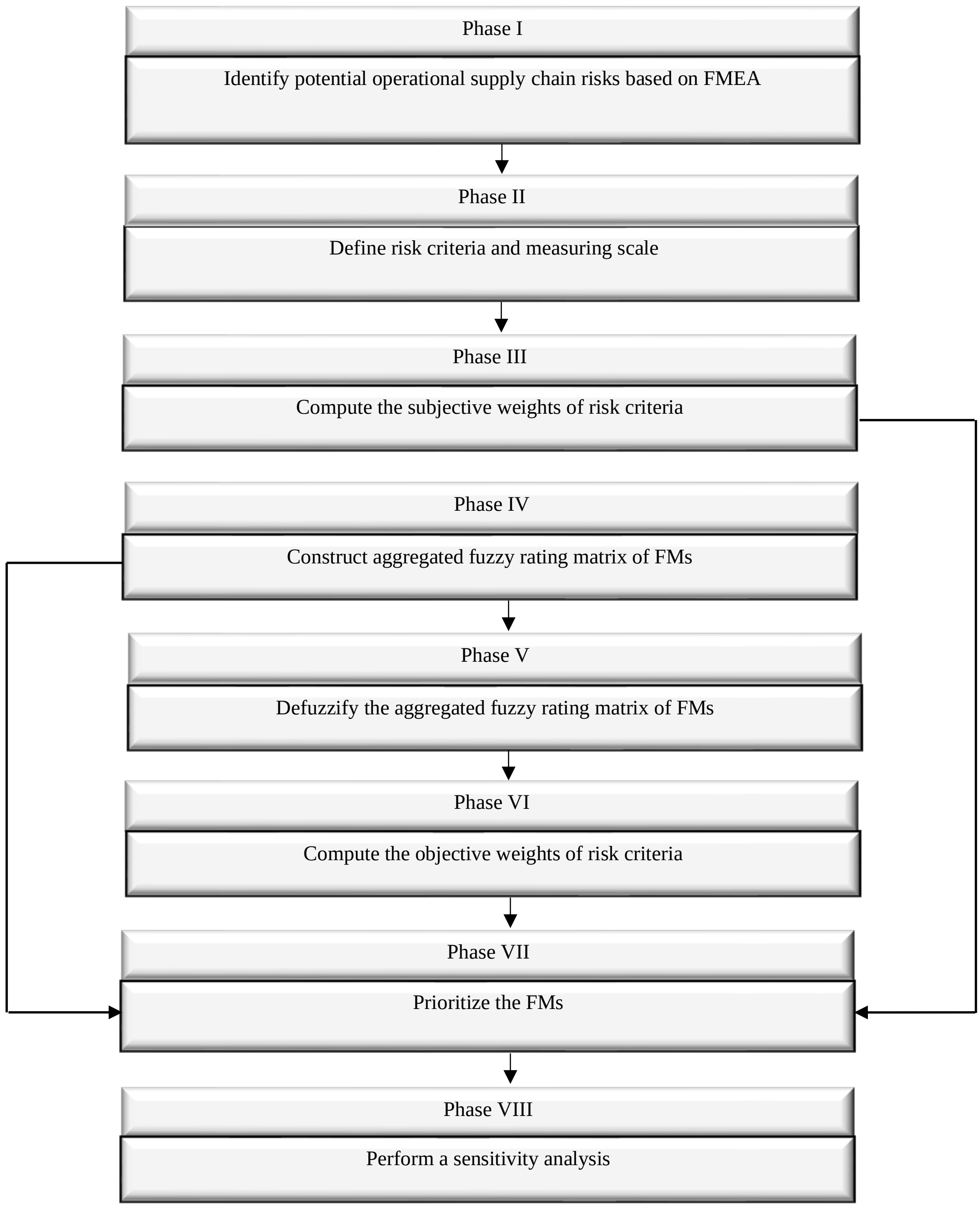

Fig. 2. The proposed framework

Table 2. The identification of potential FMs for case manufacturing

Code	***Failure Mode of operational supply chain risks***	***Effect***
FM1	Risk of volatility raw materials supplied	Manufacturers face a shortage of raw materials and/or raw materials that do not meet the requirements. This results in excess lead times and unacceptable quality levels of the raw materials supplied.
FM2	Risk of relying on a few major suppliers	Manufacturers have low bargaining power with suppliers as their dependence on a few major suppliers results in high raw material costs.
FM3	Risk of product deterioration	Manufacturers face deterioration and spoilage of tuna products caused by the use of improper temperatures. Disease and contamination in transport activities This results in higher cost of quality and loss of business reputation.
FM4	Risk of variabilities in production processes.	Manufacturers face variability in the production process, resulting in higher production costs, loss of productivity and non-conforming finished products.
FM5	Risk of improper inventory management	Manufacturers face higher inventory costs, inventory shortage and obsolete inventory due to keeping too low or too high inventory.
FM6	Risk of failing to comply with industrial standard	Manufactures face revocation of required industry standard certificates such as Good Manufacturing Practice: GMP, Hazard Analysis and Critical Control Point: HACCP resulting in production halts and damage to business reputation.
FM7	Risk of inefficient traceability system across supply chain processes.	Manufacturers do not meet the security requirements for record storage and counterfeit detection. This results in ongoing problems that are difficult for manufactures to deal with in the event of a nonconforming product recall.
FM8	Risk of a shortage of skilled workers	Manufacturers face a shortage of skilled workers. This can lead to a competitive disadvantage in the seafood market.
FM9	Risk of products damage and contamination during transportation.	Manufacturers face damage and product contamination during transportation. This results in higher reverse logistics costs for nonconforming products and customer complaints.
FM10	Risk of technological innovation change.	Manufacturers cannot keep up with the rapid changes of technological innovations. This could lead to a competitive disadvantage in the seafood market.
FM11	Risk of failure in information technology (IT) system	Manufacturers face disruptions in their businesses including sales, production and cash flow in the supply chain due to IT system failure.

Phase II: Define risk criteria and measuring scale.

Through brainstorming session, the experts define the four risks of FMs as "severity" (S), "probability of occurrence" (O), "probability of detection" (D) and "degree of difficulty to eliminate risks" (E). Also, the measurement scales in linguistic terms for subjective important weights of risk criteria, and for assessment of FMs are provided in Table 3 and Table 4, respectively.

Phase III: Compute the subjective weights of risk criteria

The experts evaluate the subjective weights of risk criteria (S, O, D, E) by using linguistics terms in Table 3 and the results are shown in Table 5. The linguistic terms are converted to their corresponding fuzzy numbers as shown in Table 6. The subjective weights of risk criteria (w_j^s) are computed by aggregating the fuzzy numbers by equation (2) and the results are shown in Table 7.

Table 3. The measurement scales for subjective important weights of risk criteria

Linguistic terms	*Abbreviation*	*Fuzzy number*
Very low	VL	(0.0,0.0,0.1,0.2)
Low	L	(0.1,0.2,0.2,0.3)
Medium low	ML	(0.2,0.3,0.4,0.5)
Medium	M	(0.4,0.5,0.5,0.6)
Medium high	MH	(0.5,0.6,0.7,0.8)
High	H	(0.7,0.8,0.8,0.9)
Very high	VH	(0.8,0.9,1.0,1.0)

Table 4. The measurement scales for assessment FMs

Severity (S)	*Occurrence* (O)	*Detection* (D)	*Degree of difficulty to eliminate risks* (E)	*Trapezoidal fuzzy numbers (TFN)*
No (N)	Almost Never (AN)	Almost Certain (AC)	Almost no difficulty (N)	(0,0,1,2)
Very Slight (VS)	Remote (RS)	Very High (VH)	Remote (R)	(0,1,2,3)
Slight (S)	Very Slight (VS)	High (H)	Low (L)	(1,2,3,4)
Minor (M)	Slight (S)	Moderately High (MH)	Relative Low (RL)	(2,3,4,5)
Moderate (MO)	Low (L)	Medium (M)	Moderate (M)	(3,4,5,6)
Significant (SI)	Medium (M)	Low (L)	Moderate High (MH)	(4,5,6,7)
Major (M)	Moderate High (MH)	Slight (S)	High (H)	(5,6,7,8)
Extreme (E)	High (H)	Very Slight (VS)	Very High (VH)	(6,7,8,9)
Serious (SE)	Very High (VH)	Remote (R)	Extremely High (EH)	(7,8,9,10)
Hazardous (H)	Almost Certain (AC)	Almost Impossible (AI)	Almost Impossible (AI)	(8,9,10,10)

Table 5: The evaluation of subjective weights in linguistic terms

Experts	S	O	D	E
E_1	VH	MH	M	H
E_2	VH	H	ML	MH
E_3	H	MH	M	H
E_4	VH	MH	M	H
E_5	VH	MH	ML	MH
E_6	H	MH	M	H

Table 6. The evaluation of subjective weights in fuzzy numbers

Experts	*Risk criteria*															
	S				*O*				*D*				*E*			
E_1	0.8	0.9	1.0	1.0	0.5	0.6	0.7	0.8	0.4	0.5	0.5	0.6	0.7	0.8	0.8	0.9
E_2	0.8	0.9	1.0	1.0	0.7	0.8	0.8	0.9	0.2	0.3	0.4	0.5	0.5	0.6	0.7	0.8
E_3	0.7	0.8	0.8	0.9	0.5	0.6	0.7	0.8	0.4	0.5	0.5	0.6	0.7	0.8	0.8	0.9
E_4	0.8	0.9	1.0	1.0	0.5	0.6	0.7	0.8	0.4	0.5	0.5	0.6	0.7	0.8	0.8	0.9
E_5	0.8	0.9	1.0	1.0	0.5	0.6	0.7	0.8	0.2	0.3	0.4	0.5	0.5	0.6	0.7	0.8
E_6	0.7	0.8	0.8	0.9	0.5	0.6	0.7	0.8	0.4	0.5	0.5	0.6	0.7	0.8	0.8	0.9

Table 7. The subjective weights of risk criteria (w_j^s)

Subjective weights	S				O				D				E			
w_j^s	0.700	0.867	0.933	1.000	0.500	0.633	0.717	0.900	0.200	0.433	0.467	0.600	0.500	0.733	0.767	0.900

Phase IV: Construct aggregated fuzzy rating matrix of FMs

The experts employ the linguistic terms in Table 4 to evaluate eleven FMs with respect to risk criteria and the results are shown in Table 8. The elements in Table 8 are then converted into corresponding fuzzy numbers. Using equations (3)-(4), the aggregated fuzzy rating matrix of FMs is constructed as shown in Table 9.

Phase V: Defuzzify the aggregated fuzzy rating matrix of FMs into crisp numbers

According to the aggregated fuzzy rating matrix Table 9, all elements are defuzzified into crisp numbers by using equation (5). The subjective weights can be obtained from Phase III. Table 10 shows the crisp numbers of FMs rating matrix.

Table 8. The evaluation of eleven FMs in linguistic terms

No.	S	O	D	E
FM1	SE,SE,SE,SE,SE,E	H,VH,H,VH,H,VH	M,MH,MH,MH,M,MH	H,MH,MH,M,M,MH
FM2	E,MA,MA,SI,SI,MA	M,M,MH,H,H,MH	H,H,H,VH,VH,H	MH,MH,H,H,MH,VH
FM3	SE,SE,SE,SE,SE,E	H,VH,H,VH,H,VH	H,H,H,MH,H,MH	VH,EH,EH,VH,VH,EH
FM4	SI,MA,MA,SI,MA,MA	H,VH,H,VH,H,VH	H,MH,H,MH,MH,H	H,MH,MH,M,MH,H
FM5	SI,MA,MA,MA,MA,SI	M,M,L,L,M,MH	H,H,MH,H,MH,MH	H,H,MH,MH,M,M
FM6	SE,SE,SE,SE,SE,E	M,L,L,L,M,L	H,H,H,VH,H,VH	H,H,MH,H,VH,VH
FM7	SI,SI,MA,MA,SI,MA	MH,MH,M,H,MH,M	H,M,MH,MH,M,MH	MH,MH,H,H,MH,M
FM8	E,E,SE,MA,MA,E	H,H,VH,MH,H,MH	H,VH,H,VH,H,VH	H,H,H,VH,MH,MH,H
FM9	E,SE,SE,E,E,SE	M,L,L,L,L,M	L,L,S,VS,S,M	H,VH,VH,MH,H,MH
FM10	MA,MA,E,MA,MA,MA	M,H,MH,MH,MH,MH	H,H,H,VH,M,VH	H,MH,MH,H,MH,MH
FM11	E,E,MA,MA,E,MA	L,L,S,M,M,M	H,H,VH,MH,V,M	MH,MH,M,M,MH,H

Table 9. The aggregated evaluation decision matrix of FMs

	S				O				D				E			
	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4
FM1	6.000	7.833	8.833	10.000	6.000	7.500	8.500	10.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000
FM2	4.000	5.833	6.833	9.000	4.000	6.000	7.000	9.000	4.000	6.000	7.000	9.000	4.000	5.667	6.667	9.000
FM3	6.000	7.833	8.833	10.000	6.000	7.500	8.500	10.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000
FM4	4.000	5.667	6.667	8.000	6.000	7.500	8.500	10.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000
FM5	4.000	5.667	6.667	8.000	3.000	4.833	5.833	8.000	3.000	4.833	5.833	8.000	3.000	5.000	6.000	8.000
FM6	6.000	7.833	8.833	10.000	3.000	4.333	5.333	7.000	3.000	4.333	5.333	7.000	4.000	6.167	7.167	9.000
FM7	4.000	5.500	6.500	8.000	4.000	5.500	6.500	8.000	4.000	5.500	6.500	8.000	3.000	5.167	6.167	8.000
FM8	5.000	6.833	7.833	10.000	5.000	7.167	8.167	10.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000
FM9	6.000	7.500	8.500	10.000	3.000	4.333	5.333	7.000	4.000	6.000	7.000	9.000	4.000	5.667	6.667	9.000
FM10	5.000	6.167	7.167	9.000	4.000	6.000	7.000	9.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000
FM11	6.000	7.833	8.833	10.000	6.000	7.500	8.500	10.000	6.000	7.500	8.500	10.000	5.000	6.167	7.167	9.000

Table 10. The crisp numbers of FMs rating matrix

Failure mode	S	O	D	E
FM1	8.133	8.000	5.438	6.867
FM2	6.435	6.500	2.067	6.370
FM3	8.133	8.000	5.933	6.867
FM4	6.067	8.000	5.933	6.867
FM5	6.067	5.435	3.000	5.500
FM6	8.133	4.933	2.067	6.565
FM7	6.000	6.000	3.565	5.565
FM8	7.435	7.565	2.000	6.500
FM9	8.000	4.933	6.000	6.500
FM10	6.867	6.500	2.810	5.933
FM11	7.000	4.630	2.937	5.435

Phase VI: Compute the objective weights of risk criteria

In this study, Shannon entropy method is employed to compute the objective weights of risk criteria. Based on Table 10, the elements in FMs rating matrix are normalized using equation (6). The entropy measuring values (e_j) the divergence values (d_j) of risk criteria are computed using equation (7) and equation (8), respectively. The objective weights (w_j) of risk criteria can be obtained by using equation (9). Table 11 shows the results of objective weights computation. It can be seen that the objective weights of risk criteria be *S* (0.253) = *E* (0.253)> *O* (0.251)>*D* (0.242).

Phase VII: Prioritize the FMs

In this study, fuzzy VIKOR is applied to prioritize the FMs. Based on aggregated fuzzy rating matrix in Table 9, the elements are normalized using equation (10) for cost criterion (S, O, E) and equation (11) for benefit criterion (D). Table 12 shows the normalized aggregated fuzzy rating matrix. Then, the overall performance rating (f_{ij}) of each FM with respect to risk criteria is calculated using equation (12), as shown in Table 13. Based on Table 13, the best ideal value (f_j^*) and the worst ideal value (f_j^-) of FMs are determined by using equation (13) and equation (14), respectively. The values of utility measure S_i, and regret measure R_i for each FM are obtained using equations (15)-(17), respectively. Based on the objective weights obtained from Phase VI, the Q_i value for each FM is computed by using equations (18)-(22). In this study, the υ value is defined as 0.5. Table 1 shows the values of S_i, R_i and Q_i. Two conditions of compromise solution are examined and the results of both conditions are satisfied as shown in Table 14. Based on the results from Table 13 and Table 14, FMs are ranking, according to their Q_i values in ascending order (the smaller value is the higher the ranking). The results show that $FM3 > FM1 > FM4 > FM9 > FM8 > FM10 > FM6 > FM2 > FM7 > FM11 > FM5$. Therefore, *FM3* is the most critical failure mode and the tuna industry should give the first priority to proactively manage risks.

Table 11. The object weights of risk criteria

	S	O	D	E
e_j	5.733	5.703	5.538	5.741
d_j	-4.733	-4.703	-4.538	-4.741
w_j	0.253	0.251	0.242	0.253

Table 12. The normalized aggregated fuzzy rating matrix

	S				*O*				*D*				*E*			
	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4
FM1	1.500	1.958	2.208	2.500	3.000	3.750	4.250	5.000	0.222	0.537	0.648	1.000	1.667	2.056	2.389	3.000
FM2	1.000	1.458	1.708	2.250	2.000	3.000	3.500	4.500	0.000	0.185	0.296	0.444	1.333	1.889	2.222	3.000
FM3	1.500	1.958	2.208	2.500	3.000	3.750	4.250	5.000	0.444	0.593	0.704	0.889	1.667	2.056	2.389	3.000
FM4	1.000	1.417	1.667	2.000	3.000	3.750	4.250	5.000	0.444	0.593	0.704	0.889	1.667	2.056	2.389	3.000
FM5	1.000	1.417	1.667	2.000	1.500	2.417	2.917	4.000	0.111	0.278	0.389	0.556	1.000	1.667	2.000	2.667
FM6	1.500	1.958	2.208	2.500	1.500	2.167	2.667	3.500	0.000	0.185	0.296	0.444	1.333	2.056	2.389	3.000
FM7	1.000	1.375	1.625	2.000	2.000	2.750	3.250	4.000	0.111	0.352	0.463	0.667	1.000	1.722	2.056	2.667
FM8	1.250	1.708	1.958	2.500	2.500	3.583	4.083	5.000	0.000	0.167	0.278	0.444	1.333	2.000	2.333	3.000
FM9	1.500	1.875	2.125	2.500	1.500	2.167	2.667	3.500	0.333	0.611	0.722	1.000	1.333	2.000	2.333	3.000
FM10	1.250	1.542	1.792	2.250	2.000	3.000	3.500	4.500	0.000	0.222	0.333	0.667	1.333	1.778	2.111	2.667
FM11	1.250	1.625	1.875	2.250	1.000	2.167	2.667	3.500	0.000	0.259	0.370	0.667	1.000	1.611	1.944	2.667

Table 13. The overall performance rating (f_{ij}) of each FM

Failure mode	S	O	D	E	S_i	R_i	Q_i	***Prioritization***		
								S_i	R_i	Q_i
FM1	1.817	2.812	0.338	1.729	0.060	0.060	0.153	2	2	2
FM2	1.457	2.316	0.124	1.631	0.626	0.240	0.829	7	4	8
FM3	1.817	2.812	0.410	1.729	0.000	0.000	0.000	1	1	1
FM4	1.367	2.812	0.410	1.729	0.245	0.245	0.622	3	6	3
FM5	1.367	1.916	0.184	1.423	0.880	0.245	0.983	11	6	11
FM6	1.817	1.721	0.124	1.678	0.530	0.250	0.794	6	7	7
FM7	1.352	2.115	0.217	1.438	0.802	0.253	0.955	9	8	9
FM8	1.674	2.718	0.121	1.662	0.394	0.242	0.703	5	5	5
FM9	1.787	1.721	0.385	1.662	0.340	0.250	0.686	4	7	4
FM10	1.539	2.316	0.172	1.506	0.639	0.199	0.757	8	3	6
FM11	1.569	1.713	0.178	1.407	0.833	0.253	0.973	10	8	10

Table 14. The condition of compromise solution

	Condition	*Check*	*Result*
Condition I	Acceptable advantage	$Q\,(FM1) - Q(FM3) \geq 1/(m-1)$ $0.153 - 0.000 \geq 1/10$ $0.153 \geq 0.1$	Satisfied
Condition II	Acceptable stability in decision making	*FM3* is the best ranking indicated by Q_i, S_i and R_i	Satisfied

Phase VIII: Perform a sensitivity analysis

To evaluate the robustness of the proposed FMEA model, the sensitivity analysis of the decision is conducted by altering the different values of weights for the strategy of maximum group utility (ν). The objective is to examine whether the FMs changes (according Q_i values) when the ν value changes. In this study, a total of different eleven scenarios are analyzed by varying ν values to 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0. The results of sensitivity analysis are shown in Table 15 and figure 3. It can be seen that *FM3* is the most critical failure mode followed by *FM2* in all scenarios. Moreover, the overall ranking of FMs is remained unchanged when ν = 0.4, 0.5 and 0.6, but it is sensitive at other ν values. It implies that the selection of ν values is necessary to balance between utility measure (S_i)

and regret measure (R_i) plays an important role for implementing the proposed model. Thus, the implementation of the proposed framework should apply $\nu = 0.5$, which means the failure modes are evaluated in a consensus way.

Table 15. The results of sensitivity analysis

Q_i											
Scenario	1	2	3	4	5	6	7	8	9	10	11
υ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
FM1	0.238	0.221	0.204	0.187	0.170	0.153	0.136	0.119	0.102	0.086	0.069
FM2	0.946	0.923	0.899	0.876	0.852	0.829	0.806	0.782	0.759	0.735	0.712
FM3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FM4	0.966	0.897	0.828	0.760	0.691	0.622	0.553	0.484	0.416	0.347	0.278
FM5	0.966	0.969	0.973	0.976	0.980	0.983	0.986	0.990	0.993	0.997	1.000
FM6	0.985	0.947	0.909	0.870	0.832	0.794	0.755	0.717	0.679	0.640	0.602
FM7	0.998	0.990	0.981	0.972	0.964	0.955	0.946	0.937	0.929	0.920	0.911
FM8	0.957	0.906	0.855	0.804	0.753	0.703	0.652	0.601	0.550	0.499	0.448
FM9	0.985	0.925	0.865	0.806	0.746	0.686	0.626	0.566	0.506	0.446	0.386
FM10	0.787	0.781	0.775	0.769	0.763	0.757	0.751	0.745	0.739	0.733	0.726
FM11	1.000	0.995	0.989	0.984	0.979	0.973	0.968	0.963	0.957	0.952	0.947

Table 16. The priority of FMs in each scenario

Priority of FMs											
Scenario	1	2	3	4	5	6	7	8	9	10	11
υ	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
FM1	2	2	2	2	2	2	2	2	2	2	2
FM2	4	6	7	8	8	8	8	8	8	8	7
FM3	1	1	1	1	1	1	1	1	1	1	1
FM4	6	4	4	3	3	3	3	3	3	3	3
FM5	6	9	9	10	11	11	11	11	11	11	11
FM6	8	8	8	7	7	7	7	6	6	6	6
FM7	10	10	10	9	9	9	9	9	9	9	9
FM8	5	5	5	5	5	5	5	5	5	5	5
FM9	8	7	6	6	4	4	4	4	4	4	4
FM10	3	3	3	4	6	6	6	7	7	7	8
FM11	11	11	11	11	10	10	10	10	10	10	10

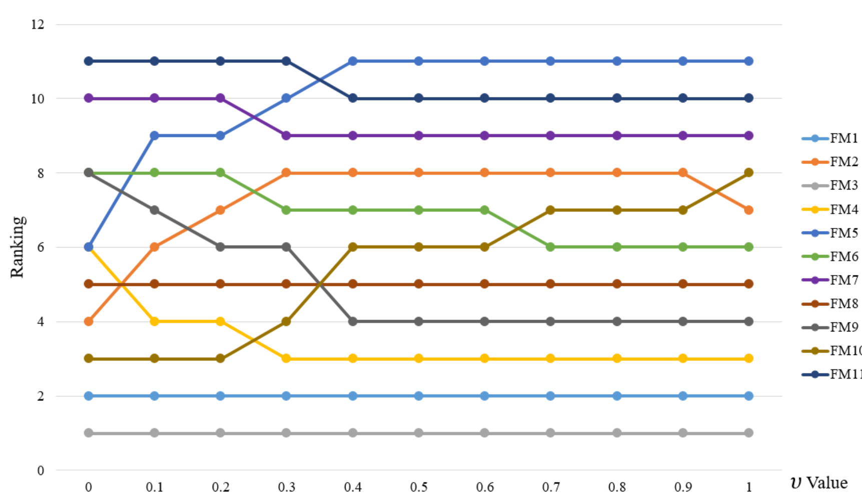

Fig. 3. Sensitivity analysis of eleven scenarios

CONCLUSIONS AND FUTURE RESEARCH

In this study, a new FMEA based on MCDM approach is proposed to assess operational supply chain risks. The proposed framework can mitigate the disadvantages of conventional FMEAs in a number of ways. This study distinguishes from previous researches in many aspects. First, the fuzzy set theory under trapezoidal fuzzy number is used to deal with the uncertain and imprecise information in decision-making processes. Second, the eleven failure modes of operational supply chain risks are identified by a panel of experts. Third, the new risk criteria namely "degree of difficulty to eliminate risks" includes risk assessment. Forth, the important weights of risk criteria are determined by combining subjective weights and objective weights. The subjective weights are obtained by opinion of experts, while the objective weights are derived obtained by Shannon entropy method. Next, fuzzy VIKOR is employed to prioritize failure modes instead of a risk priority number (RPN). Finally, a sensitive is performed and the results indicate that the proposed framework provides the stability and robustness for failure modes ranking. A validation of the framework presented here uses the canned tuna industry in Thailand as a case study. The findings from this study indicates that the most three critical FMs are "risk of product deterioration" (*FM3*) followed by "risk of volatility raw materials supplied" (*FM1*) and "risk of variabilities in production processes" (*FM4*), respectively. The outcomes of this study enable tuna industry practitioners to proactively assess the operational supply chain risks. Moreover, the proposed framework can be applied to other seafood industries in the same procedure. Further research may extend from this framework by investigating the interaction between risk criteria using DEMATEL approach. Apart from that, the other MCDM methods such as CRITIC can be utilized to determine the objective weights. Also future research should include the sustainability dimensions of the supply chain in identifying failure modes.

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