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A perceptual computing-based method to prioritize failure modes in failure mode and effect analysis and its application to edible bird nest farming

Kok Chin Chai [a,*], Chian Haur Jong [b], Kai Meng Tay [a], Chee Peng Lim [c]

[a] *Faculty of Engineering, Universiti Malaysia Sarawak, Sarawak, Malaysia*
[b] *University College of Technology Sarawak, Malaysia*
[c] *Institute for Intelligent Systems Research and Innovation, Deakin University, Australia*

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ABSTRACT

A failure mode and effect analysis (FMEA) procedure that incorporates a novel Perceptual Computing (Per-C)–based Risk Priority Number (RPN) model is proposed in this paper. The proposed model considers linguistic uncertainties and vagueness of words, because it is more natural to use words, instead of numerals, for an FMEA user to express his/her knowledge when he/she provides an assessment. Therefore, it is important to consider the inherited uncertainties in words used by humans for assessment as an additional risk factor in the entire FMEA reasoning process. As such, we propose to use Per-C to analyze the uncertainties in words provided by different FMEA users. There are three potential sources of risks. Firstly, the risk factors of Severity (S), Occurrence (O), and Detection (D) are graded using words by each FMEA user, and indicated as interval type-2 fuzzy sets (IT2FSs). Secondly, the relative importance of S, O, and D are reflected by the weights given by each FMEA user in words, which are indicated as IT2FSs. Thirdly, the expertise level of each FMEA user is reflected by words, which are expressed as IT2FSs too. The proposed Per-C-RPN model allows these three sources of risks from each FMEA user to be considered and combined in terms of IT2FSs. A case study related to edible bird nest farming in Borneo Island is reported. The results indicate the effectiveness of the proposed model. In summary, this paper contributes to a new Per-C-RPN model that utilizes imprecise assessment grades pertaining to group decision making in FMEA.

1. Introduction

Failure Mode and Effect Analysis (FMEA) is an effective methodology for determining the postulated component failures/errors of a process, system, or design [1]. In manufacturing processes, FMEA is useful to define, identify, and reduce the potential failures of a process prior to their occurrence by eliminating their root causes, thereby improving safety, reliability, and quality of the operations [1,2]. Among the successful applications of FMEA include automotive [1], aerospace [3], agriculture [4], chemical [5], health care and hospital [6,7], manufacturing [8], mechanical [9], nuclear [10], electronic and semiconductor [11] and ocean engineering [12]. Traditionally, the Risk Priority Number (RPN) is used to determine the risk associated with a failure. To obtain the RPN score, one can simply multiply three risk factors, i.e., Severity (S), Occurrence (O), and Detection (D). As such, RPN = $S \times O \times D$ [2], where S and O are the seriousness and frequency of a failure mode, respectively, while D is the effectiveness of the existing measures in detecting a failure before it affects the customers [1]. While the conventional RPN model is straightforward, it has a number of limitations [2,13–17]: (i) the RPN score does not consider the relative importance pertaining to S, O, and D; (ii) while the same RPN score can be produced by different combinations of S, O, and D, the underlying risk implication can be different; (iii) it is not easy to precisely assess S, O, and D; (iv) the method for computing the RPN score (i.e., by multiplying S, O, and D) is open to discussion, as it is not robust in terms of evaluating critical factors.

Many solutions have been proposed to tackle the shortcomings of the conventional RPN model [2]. A search in the literature reveals that two popular research trends pertaining to FMEA, which are also the focus of this paper, are: (i) imprecise assessment grades [13–17], and (ii) group decision behaviours [2,13–17,18]. The first trend suggests the use of uncertain, imprecise, and vague words for assessing S, O, and D, because it is more natural for one to

* Corresponding author.
E-mail address: kcchai@live.com (K.C. Chai).

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express his/her knowledge in such way [13–17,19]. The second trend suggests that FMEA is a cross-functional team activity, and different FMEA users provide different opinions because of varying expertise and background [2,13–17,19]. A challenge in the abovementioned two research trends is the possibility of linguistic uncertainty among FMEA users. In this paper, it is argued that the inherent uncertainties in words have to be carefully handled in order to avoid unnecessary loss of information as well as to enhance the validity and applicability in risk analysis. This challenge often occurs in FMEA activity [17,20]. Therefore, the aim of this paper focuses on utilizing IT2FS representation and the relevant techniques for tackling the abovementioned challenge.

With reference to fuzzy set theory, intra- and inter- uncertainties are two existing uncertainties in using words to express one's knowledge [20–27]. The former is concerned with the uncertainty of words used by an individual, while the latter relates to the uncertainty of words used by a group of individuals [20–27]. In this paper, we argue that handling both uncertainties is important because different FMEA users express their opinions in different ways in accomplishing a team-based activity, *viz.* intra- and inter- uncertainties exist simultaneously, and they imply risks [22,23].

A relatively new line of study suggests that T1FSs are not suitable to handle both uncertainties owing to a number of reasons [22–26]: (i) an T1FS with all its parameters defined implies no uncertainty for the word used; (ii) different people may interpret the same word differently; therefore, uncertainties exist; and (iii) it is contradicting to use a "certain" (or precise) model to represent uncertainties. Even though the practicalities and contributions of type-1 fuzzy methods in FMEA [13–17] are known, it is not clear how intra- and inter- uncertainties of words should be handled with T1FSs [20–26]. These challenges can potentially be solved by using an extension of T1FSs, i.e., interval type-2 fuzzy sets (IT2FSs) [22–28]. While IT2FSs have received much attention, the use of IT2FSs in FMEA is relatively new [2,29]. Comparing with T1FSs, IT2FSs offer a more realistic means with the capability of modelling second-order uncertainties [30–33]. A number of theoretical investigations with respect to the properties of IT2FSs have been developed [22–25,27,30–34]. Many applications of IT2FSs have been reported too, e.g. [22–26,28,29].

Motivated by the usefulness and flexibility of IT2FSs, a new perceptual computing (Per-C)–based RPN (hereafter abbreviated as Per-C-RPN) model with IT2FSs is proposed. Per-C is adopted owing to its effectiveness in handling inherent uncertainties in words [23]. Specifically, Per-C is able to handle subjectivity, vagueness, imprecision, and uncertainty while achieving tractability and robustness in modelling human decision-making behaviours [22–26]. Although many fuzzy decision making problems have been successfully solved by using Per-C [22–26,28], its application to FMEA is new, and it provides a useful solution to address the limitations of FMEA. In this paper, the effectiveness of the Per-C-RPN model in FMEA is evaluated using an edible bird nest (EBN) farming task in Sarawak, Borneo Island.

In terms of contributions, a new Per-C-RPN model that preserves intra- and inter- uncertainties of linguistic words in group decision behaviours is introduced. A new FMEA procedure with the proposed Per-C-RPN model is devised. Besides that, the Per-C-RPN model produces RPN scores that can be expressed in both numerals and linguistic words. This advantage provides a better insight pertaining to the risk of a failure mode, in a way that humans can understand the underlying risk semantically in a straightforward manner.

The organisation of this paper is as follows. Preliminaries of the proposed Per-C-RPN model are presented in Section 2. The FMEA procedure with the proposed Per-C-RPN model is explained in Section 3. Simulations with benchmark information [10] are presented in Section 4. A real case study of EBN farming is reported in Section 5. Conclusions are presented in Section 6.

2. Preliminaries

In this section, the notations and definitions used are presented in Section 2.1, while the background of Per-C and FMEA are described in Sections 2.2 and 2.3, respectively. The proposed Per-C RPN model is presented in Section 2.4.

2.1. Notations and definitions

The related mathematical notations and their descriptions are listed in Table 1.

Definition 1 *([35])*. An T1FS, u, in the universe of discourse, U, is denoted as $u = \{(x, \mu_u(x) | x \in U)\}$, where $\mu_u(x)$ is the T1FS membership function of u. u is a normal T1FS iff $\exists x \in U$, such that $max_x \mu_u(x) = 1$. Otherwise, if $max_x \mu_u(x) < 1$, u is not normal, and is known as a sub-normal T1FS. In this paper, normalized T1FSs are considered because the maximum possible membership grade is assumed to be 1.

Definition 2 *([34,35])*. An T2FS, $\tilde{u}$, in the universe of discourse, U, can be represented by a type-2 membership function, $\mu_{\tilde{u}}$, as follows:

$$\tilde{u} = \{((x, u), \mu_{\tilde{u}}(x, u)) | \forall x \in U, \forall u \in J_x \subseteq [0, 1], 0 \le \mu_{\tilde{u}}(x, u) \le 1\} \tag{1}$$

where J_x is an interval in [0, 1]. ũ can also be represented as follows:

$$\tilde{u} = \int_{x \in U} \int_{u \in J_x} \mu_{\tilde{u}}(x, u) / (x, u) \tag{2}$$

where $J_x \subseteq [0, 1]$ and $\int\int$ is the union over all admissible x and u.

Definition 3 *([34,35])*. An IT2FS, $\tilde{u}$, in the universe of discourse, U, as illustrated in Fig. 1(a), can be viewed as a special case of an T2FS when all $\mu_{\tilde{u}}(x, u) = 1$, as follows.

$$\tilde{u} = \int_{x \in U} \int_{u \in J_x} 1 / (x, u) \tag{3}$$

where $J_x \subseteq [0, 1]$.

Definition 4 *([34,35])*. An IT2FS, $\tilde{u}$, is described by its FOU, i.e., $FOU(\tilde{u})$, where $FOU(\tilde{u})$ is described by its LMF and UMF of $\tilde{u}$, i.e., $\underline{\mu}_{\tilde{u}}$ and $\bar{\mu}_{\tilde{u}}$, respectively, as shown in Fig. 1. Both $\underline{\mu}_{\tilde{u}}$ and $\bar{\mu}_{\tilde{u}}$ are T1FSs, as follows.

$$FOU(\tilde{u}) = \bigcup_{\forall x \in X} \left[\underline{FOU(\tilde{u})}, \overline{FOU(\tilde{u})}\right] = \bigcup_{\forall x \in X} \left[\underline{\mu}_{\tilde{u}}(x), \bar{\mu}_{\tilde{u}}(x)\right] \tag{4}$$

where $\cup$ is a set-theoretic union.

Remark: The FOU of $\tilde{u}$ can be viewed as a collection of T1FSs [23–25]. Each T1FS captures the uncertainty of a person with respect to $\tilde{u}$. A group of T1FSs refer to the uncertainties of a group of people with respect to $\tilde{u}$ [23–25].

2.2. Background of perceptual computing

The general structure of Per-C is depicted in Fig. 2. It consists of three components [22–26], i.e., an encoder, a computing-with-words (CWW) engine, and a decoder. Linguistic grades or words from humans are converted into IT2FSs through the encoder. The CWW engine aggregates the outputs from the encoder. The decoder maps the outputs of the CWW engine into a recommendation, which can be in the form of a word, rank, or class.

2.3. Background of failure mode and effect analysis

A number of solutions to tackle the shortcomings of the conventional RPN model in FMEA have been proposed in the literature.

Table 1
A list of mathematical notations and their descriptions.

Notations	Descriptions
C	Set for risk factors, where $C = \left\{S, O, D\right\}$
$\hat{C}_{\tilde{Y}_{F_i},l}$	Left centroids of $\tilde{Y}_{F_{i\|i=1,2,\ldots,n}}$, $\forall \hat{C}_{\tilde{Y}_{F_i},l} \in D_Y$
$\hat{C}_{\tilde{Y}_{F_i},r}$	Right centroids of $\tilde{Y}_{F_{i\|i=1,2,\ldots,n}}$, $\forall \hat{C}_{\tilde{Y}_{F_i},r} \in D_Y$
$\hat{C}_{\tilde{Y}_{F_i}}$	Per-C-RPN scores in crisp values of $\tilde{Y}_{F_{i\|i=1,2,\ldots,n}}$, $\forall \hat{C}_{\tilde{Y}_{F_i},r} \in D_Y$
dX_C	Domain of $\tilde{X}_{iC}^k$. dX_C is a continuous scale [0, 10], where $\forall x_{ic}^k \in dX_C$
dW_C	Domain of $\tilde{W}_C^k$. dW_C is a continuous scale [0, 10], where $\forall w_C^k \in dW_C$
dw	Domain of $\tilde{w}^k$. dw is a continuous scale [0, 10], where $\forall w^k \in dw$
D_R	Domain of $\tilde{Y}_{Rg}$. D_R is a continuous scale [0, 10], where $\forall y_g \in D_R$
D_Y	Per-C–RPN space of $\tilde{Y}_{F_i}$. D_Y is a continuous scale [0, 10], where $\forall y_i \in D_Y$
F_i	Label of failure mode, where $i = 1, 2, \ldots, n$
$\mathrm{FOU}(\tilde{u})$	Footprint of uncertainty (FOU) of IT2FS $\tilde{u}$ in the universe of discourse U
$\underline{FOU(\tilde{u})}$	Lower bound of $\mathrm{FOU}(\tilde{u})$
$\overline{FOU(\tilde{u})}$	Upper bound of $\mathrm{FOU}(\tilde{u})$
L	Left switch point between $\underline{\mu}_{\tilde{Y}_{F_i}}(y_d)$ and $\bar{\mu}_{\tilde{Y}_{F_i}}(y_d)$.
R	Right switch point between $\underline{\mu}_{\tilde{Y}_{F_i}}(y_d)$ and $\bar{\mu}_{\tilde{Y}_{F_i}}(y_d)$
$\mu_{\tilde{X}_{iC}^{k*}}\left(x_{ic}^k\right)$	Interval type-2 membership function of $\tilde{X}_{iC}^{k*}$ where $\forall x_{ic}^k \in dX_C$
$\mu_{\tilde{X}_{iC}^k}\left(x_{ic}^k\right)$	Interval type-2 membership function of $\tilde{X}_{iC}^k$ where $\forall x_{ic}^k \in dX_C$
$\bar{\mu}_{\tilde{X}_{ic}^k}\left(x_{ic}^k\right)$	Upper membership function (UMF) of $\tilde{X}_{iC}^k$, where $\forall x_{ic}^k \in dX_C$
$\underline{\mu}_{\tilde{X}_{ic}^k}\left(x_{ic}^k\right)$	Lower membership function (LMF) of $\tilde{X}_{iC}^k$, where $\forall x_{ic}^k \in dX_C$
$\bar{\mu}_{\tilde{X}_{iC}^{k*}}\left(x_{ic}^k\right)$	UMF of $\tilde{X}_{iC}^{k*}$, where $\forall x_{ic}^k \in dX_C$
$\underline{\mu}_{\tilde{X}_{iC}^{k*}}\left(x_{ic}^k\right)$	LMF of $\tilde{X}_{iC}^{k*}$, where $\forall x_{ic}^k \in dX_C$
$\bar{\mu}_{\tilde{W}_C^k}\left(w_C^k\right)$	UMF of $\tilde{W}_C^k$, where$\forall w_C^k \in dW_C$
$\underline{\mu}_{\tilde{W}_C^k}\left(w_C^k\right)$	LMF of $\tilde{W}_C^k$, where $\forall w_C^k \in dW_C$
$\bar{\mu}_{\tilde{w}^k}\left(w^k\right)$	UMF of $\tilde{w}^k$, where$\forall w^k \in dw$
$\underline{\mu}_{\tilde{w}^k}\left(w^k\right)$	LMF of $\tilde{w}^k$, where $\forall w^k \in dw$
$\underline{\mu}_{\tilde{Y}_{F_i}}(y_d)$	LMF of $\tilde{Y}_{F_i}$,$\forall y_d \in D_Y$
$\bar{\mu}_{\tilde{Y}_{F_i}}(y_d)$	UMF of $\tilde{Y}_{F_i}$,$\forall y_d \in D_Y$
$\underline{\mu}_{\tilde{Y}_{Rg}}(y_g)$	LMF of $\tilde{Y}_{Rg}$,$\forall \tilde{Y}_{Rg} \in D_R$
$\bar{\mu}_{\tilde{Y}_{Rg}}(y_g)$	UMF of $\tilde{Y}_{Rg}$,$\forall \tilde{Y}_{Rg} \in D_R$
$SJ\left(\tilde{Y}_{F_i}, \tilde{Y}_{\mathrm{R}g}\right)$	Jaccard Similarity measure of $\tilde{Y}_{F_i}$ and $\tilde{Y}_{\mathrm{R}g}$
TM_k	An FMEA user, where $k = 1, 2, \ldots, K$
ũ	An IT2FS
U	Universe of discourse
$\tilde{W}_C^k$	Relative importance of S,O and D given by TM_k in words, on domain dW_c
$\tilde{w}^k$	Linguistic description of the expertise level for each TM_k on the domain,dw
$\tilde{W}_C$	Aggregated the $\tilde{W}_C^k$ from FMEA users
$\tilde{X}_{iC}^k$	Linguistic ratings of $F_{i\|i=1,2,\ldots,n}$ for $C = \left\{S, O, D\right\}$ by TM_k on the domain dX_C
$\tilde{X}_{iC}^{k*}$	Linguistic rating for $\tilde{X}_{iC}^k$ after negative connotation (if it is necessary)
$\tilde{X}_{iC}^*$	Aggregated the $\tilde{X}_{iC}^k$ from FMEA users pertaining to F_i
y_s	Equally discretized spaces in the support of $\tilde{Y}_{F_i} \cup \tilde{Y}_{\mathrm{R}g}$ where $s = 1, 2, \ldots, 101$
y_d	Discretized points between the left- and right-end points of $\tilde{Y}_{F_i}$(i.e., y_1 and y_N, respectively) where $d = 1, 2, \ldots, N$and $N = 101$
$\tilde{Y}_{F_i}$	Per-C –RPN score for $F_{i\|i=1,2,\ldots,n}$ on D_Y
$\tilde{Y}_{\mathrm{R}g}$	Risk words in the risk rating scale, where $\mathrm{R}_{g\|g=1,2,\ldots,G}$
$[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	Parameters of $\overline{FOU(\tilde{u})}$ where $\bar{a}, \bar{b}, \bar{c}, \bar{d} \in U$ and $\bar{h} \in [0, 1]$
$\left[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}\right]$	Parameters of $\underline{FOU(\tilde{u})}$ where $\underline{a}, \underline{b}, \underline{c}, \underline{d} \in U$ and $\underline{h} \in [0, 1]$

These solutions can be classified into five major categories: artificial intelligence methods, multi-criteria decision-making methods, mathematical programming methods, integrated methods, and other methods [2]. Artificial intelligence methods include rule-base systems, fuzzy rule-base systems [36,37], evolving tree [38], fuzzy adaptive resonance theory [39], and others. As an example, in a fuzzy rule-base system, fuzzy if-then rules have been used to map S, O, D to RPN by incorporating human reasoning [4,8,36]. This method is useful to counter the underlying risk implication in which different combinations of S, O and D can produce exactly the same RPN score.

Multi-criteria decision-making methods consider S, O and D as the evaluation criteria and failure modes as the decision alternatives to be prioritized [10,13–17]. These methods consider the relative importance of S, O and D; therefore FMEA users are allow to assign different weights to different risk factors. Comparing with the conventional RPN model (by merely multiplying S, O and D), these methods provide a reliable and flexible way to prioritize the failure modes.

Mathematical programming methods use mathematical formulations, e.g., linear programming [40] and fuzzy data envelopment analysis [41], to prioritize the failure modes. These methods also consider the relative importance of S, O and D. Besides that, the RPN scores are consistent as they are computed systematically by using mathematical principles.

Integrated methods attempt to combine more than one methods for risk evaluation, e.g., a hybrid model of fuzzy TOPSIS and fuzzy analytical hierarchical process (AHP) [42], and a hybrid model of

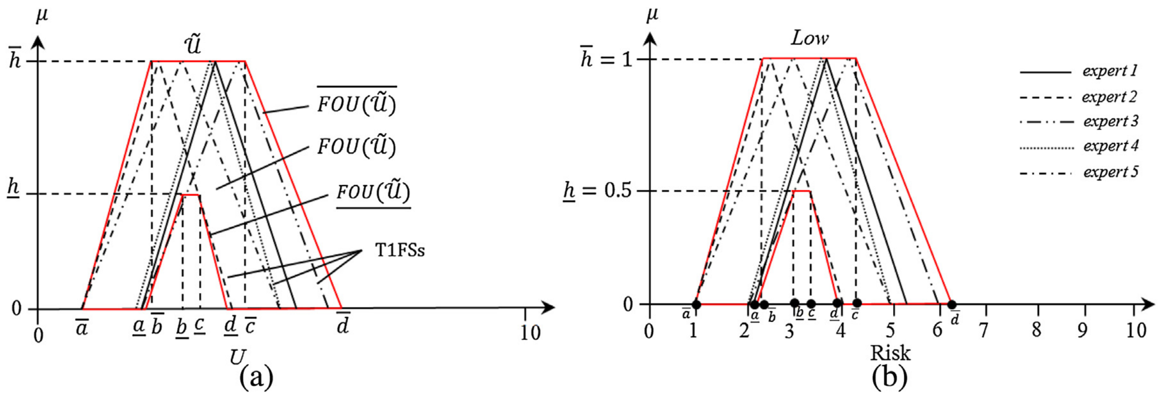

Fig. 1. (a) FOU of a generalized IT2FS $\tilde{u}$ and its parameters (b) an example of FOU "low risk" from five biological invasion experts [20].

Table 2
Scale tables for *S*, *O*, and *D*.

Risk factors	Words	General descriptions
Severity, *S*	Very Low Severity (*VLS*)	• Effect of the potential failure mode is not obvious and can be ignored • Excellent yield and product quality
	Low Severity (*LS*)	• Very minor impact to the production yield. • Failures cause a minor impact to EBN food production process control. The consequence will cause a minor effect to the products' cosmetic appearance and packaging.
	Moderate Severity (*MS*)	• Failures lead to the issue of minor security breaches of the farm, habitat of the swiftlets is affected by some of the pests and enemies of the swiftlets. The consequence will cause a reduction in the population of the swiftlets and the yield of the farm. • Failures cause a minor impact to the production yield.
	High Severity (*HS*)	• Failures lead to the issue of serious security breaches of the farm. Safety of the swiftlets will be threatened by its enemies, such as thieves and predators. • Failures cause a major impact to the production yield.
	Very High Severity (*VHS*)	• Failures lead to impacts to the product safety and quality • Compliance to law. • Major impact to the reputation of the company and the products. • Lead to failure to the yield management.
Occurrence, *O*	Extremely Low Occurrence (*ELO*)	• Failures happen at least once ever
	Very Low Occurrence (*VLO*)	• Failures happen at least once within 6–12 months
	Low Occurrence (*LO*)	• Failures happen at least once within 1–6 months
	Medium Occurrence (*MO*)	• Failures happen at least once times within 1–30 days
	High Occurrence (*HO*)	• Failures happen at least once within 1–8 working hours
	Very High Occurrence (*VHO*)	• Failures happen many times within 1 h
Detect, *D*	Very Weak Detection (*VWD*)	• No control action is available • No solution is available for solving the failure.
	Weak Detection (*WD*)	• Control actions may not detect the failure. • Appropriate actions may not be available and the failure cannot be solved
	Acceptable Detection (*AD*)	• Control actions can detect the failure within one to two process modules or steps. • In the farm management, control actions can detect the failure within one to three days • Appropriate actions are available. However the failure can be tricky and hard to solve.
	Good Detection (*GD*)	• Control actions can almost detect the failure on the spot within the same process module or steps • In the farm management, control actions can detect the failure within one day. • Appropriate actions are available to solve the failure and the weakness
	Excellent Detection (*ED*)	• Control actions can almost detect the failure on the spot and appropriate actions are taken to solve the failure and the weakness • Prevent the excursion from occurring.

Fig. 2. The structure of Per-C [22–26].

fuzzy evidential reasoning and grey theory [43]. These methods are more complicated as information is aggregated and prioritized with different models. As an example, fuzzy AHP is used to aggregate information while fuzzy TOPSIS is used to sort and prioritize the failure modes in [42]. Integrated methods are useful to introduce the use of imprecise assessment grades for risk analysis in FMEA.

Recently, a number of fuzzy methods with imprecise assessment grades and/or group decision behaviours that utilise T1FSs have been proposed, e.g., fuzzy VIKOR [13], fuzzy TOPSIS [14,15], fuzzy weighted geometric mean [16], and fuzzy weighted least square [17] methods. Liu et al. [13] proposed a fuzzy VIKOR model to find a compromise of priority ranking of failure modes by using imprecise assessment grades expressed in trapezoidal and triangular T1FSs. Liu et al. [14] integrated intuitionistic fuzzy sets into fuzzy TOPSIS. As such, FMEA users are able to assess *S*, *O* and *D* as well as their relative weights in imprecise assessment grades expressed in intuitionistic fuzzy sets [14]. Furthermore, Wang and Elhag [15] proposed a fuzzy TOPSIS model based on alpha level sets and fuzzy extension principles, while Wang et al., [16] proposed a method of fuzzy weighted geometric mean. Both methods [15,16] used trapezoidal and triangular T1FSs as imprecise assessment grades. Zhang and Chu [17] proposed a fuzzy weighted least square method. Different from [13–16], Zhang and Chu [17] argued that the same word from different FMEA users could mean differently owing to different backgrounds and preferences.

While the use of imprecise assessment grades has been widely discussed [13–17], the linguistic uncertainties inherent among FMEA users need further investigations. This is because the definition of fuzzy sets for a linguistic grade can be different for different users. Such issue has been mentioned in problems related to risk analysis [20]. As an example, in a biological invasion problem [20], five experts provided different definitions of fuzzy sets for the linguistic term "low risk" (see Fig. 1(b)), which could be represented by an IT2FS. This poses an interesting and important topic in FMEA, which is further analysed with our proposed Per-C-RPN model.

2.4. The proposed Per-C-RPN model

The proposed Per-C-RPN model is depicted in Fig. 3. The FMEA team consists of *K* team members (FMEA users), i.e., $TM_{k|k=1,\ldots,K}$, including a team leader, i.e., *FL*, where $FL \in TM_k$. The Per-C-RPN model considers the assessment grades in words provided by each $TM_{k|k=1,\ldots,K}$. The encoder converts each word into an IT2FS. These words with their IT2FSs are used for describing the expertise level of each $TM_{k|k=1,\ldots,K}$, i.e., $\tilde{w}^k$, the importance of *S*, *O* and *D*, i.e., $\tilde{W}_C^k$, as well as the *S*, *O*, and *D* scores for each F_i, i.e., $\tilde{X}_{iC}^k$. Note that $\tilde{w}^k$ is provided by *FL*, while $\tilde{W}_C^k$ and $\tilde{X}_{iC}^k$ are provided by each. These scores are then aggregated using the CWW engine (see Section 3 for details). The Per-C-RPN score, i.e., $\tilde{Y}_{F_i}$, is obtained for each F_i. Then, $\tilde{Y}_{F_i}$ is converted into an appropriate recommendation(s) consisting of the risk description and risk score.

3. The FMEA procedure incorporating the proposed Per-C-RPN model

In this section, the FMEA procedure incorporating the proposed Per-C-RPN model is presented, as summarized in Steps (1)–(19), in Fig. 4.

Each step is explained in detail, as follows. To ease the explanation, the EBN case study is used as an example.

Step 1. *Develop the scale tables of S, O, and D*. In this step, the total number of words used (usually from five to nine [23,44]) for the scale tables of *S*, *O*, and *D* is determined, respectively. The words used for each *S*, *O*, and *D* are further defined. A general description is assigned to each word with respect to each *S*, *O*, and *D*. Finally, the FOU of every word is developed using the Enhanced Interval Approach (EIA) [27] in two stages: data pre-processing and fuzzy set (FS) processing. The data pre-processing stage has four procedures: (1) bad data processing, (2) outlier processing, (3) tolerance limit processing, and (4) reasonable interval processing. After the data pre-processing stage, the remaining data are further analysed in the FS processing stage. The FS processing stage has five procedures: (1) mapping the pre-processed data into T1FS membership function; (2) establishing the FS uncertainty measures; (3) computing the uncertainty measures; (4) generating the general formulae; (5) establishing the nature of the FOU. EIA is a systematic and comprehensive approach with solid mathematical foundation. The details of EIA can be found in [27]. The *S*, *O*, and *D* scale tables used in this study are summarized in Table 2, with their FOUs presented in Table 3. Columns "$[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$" and "$[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$" are the parameters of each word. The details of the parameters are illustrated in Fig. 1b. As an example, in the *S* scale table, the expression (in words) pertaining to "Very Low Severity (VLS)" is used to describe that the consequence of a failure is unclear, which can be neglected. The consequence does not affect the yield and product quality. The parameters associated with the FOU of VLS are [0, 0, 0.14, 1.97, 1] and [0, 0, 0.07, 1.05, 1] for $\overline{FOU}(VLS)$ and $\underline{FOU}(VLS)$, respectively.

Step 2. *Develop the RPN scale table*. In this step, the number of risk words used to describe the risk level (denoted as *G*) is determined. The FOU of each risk word is also developed using the EIA method [27]. The RPN scale table (where *G*=5) is summarized in Table 4, along with their FOUs. As an example, the expression (i.e., risk word) of "Negligible Risk Level (NRL)" is parameterized as [0, 0, 0.27, 3.82, 1] and [0, 0, 0.22, 3.16, 1] for $\overline{FOU}(NRL)$ and $\underline{FOU}(NRL)$, respectively.

Step 3. *Develop the words for grading the expertise level of FMEA users and S, O, and D*. The number of words used to describe the expertise level of FMEA users and *S*, *O*, and *D* is determined. A general description is then assigned to each word. The FOU of each word is also developed using the EIA method [27]. To simplify the FMEA procedure, the same set of words is used for grading both the expertise level of FMEA users and *S*, *O*, and *D* in this study. The words with their FOUs are summarized in Table 5. As an example, the expression (i.e., word) of "Very Low (VL)" is parameterized as [0.00, 0.00, 1.50, 3.50, 1] and [0.00, 0.00, 0.50, 2.50, 1.00] for $\overline{FOU}(VL)$ and $\underline{FOU}(VL)$, respectively.

Step 4. *State the roles of all FMEA users, and grade the expertise level of each FMEA user*. The words in Table 5 are used for grading the expertise level of each FMEA user.

Steps 5–10. *Identify and examine the possible failure modes, effects, and causes. Determine the control and/or prevention method pertaining to each root cause.*

Steps 11–13. *Assess the failure modes by using the words in S, O and D scale tables.*

Step 14. *Process the risk factors with negative connotation*. Negative connotation is applied to the *D* scores because a failure mode

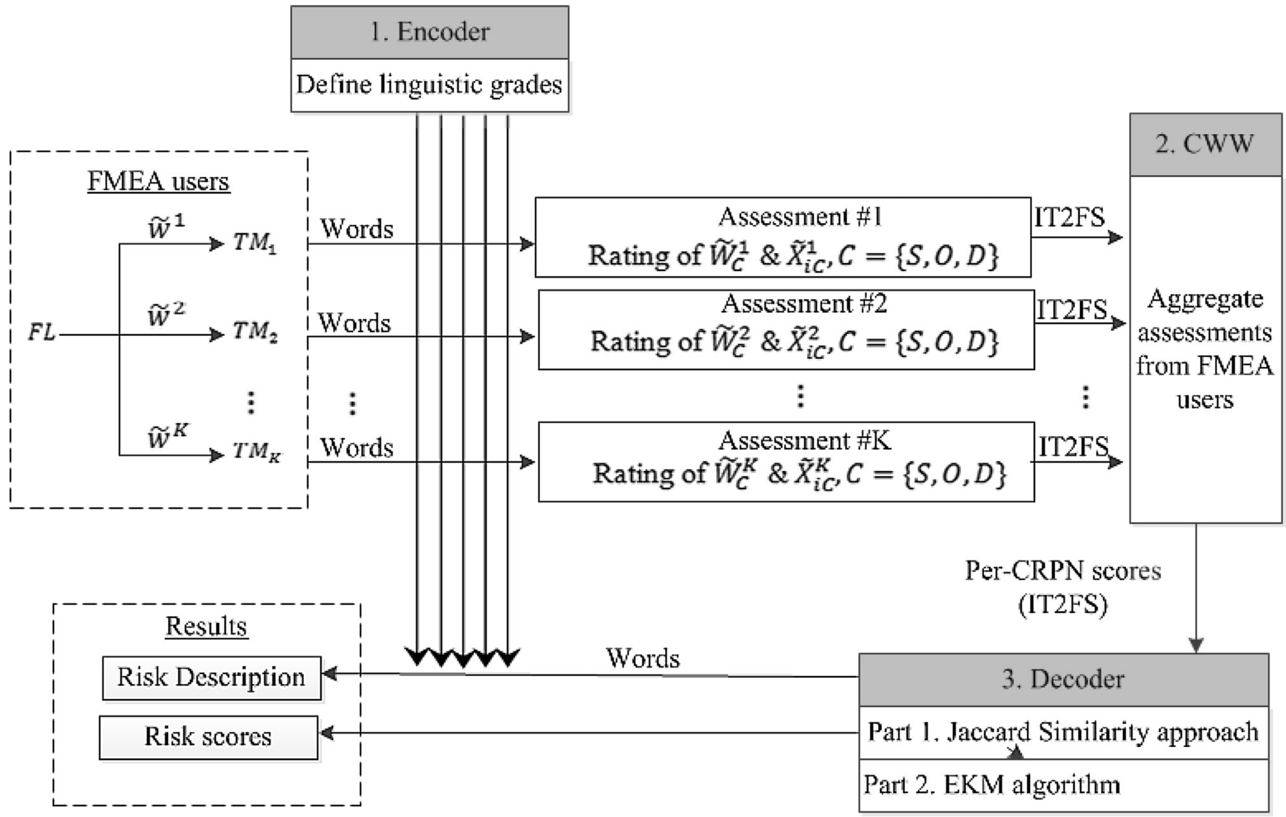

Fig. 3. The proposed Per-C-RPN model.

Table 3
FOUs of words for S, O, and D scale tables.

Risk factors	Words, $\tilde{u}$	$\overline{FOU}(\tilde{U})$ $[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$\underline{FOU}(\tilde{U})$ $[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$
Severity, S	*VLS*	[0, 0, 0.14, 1.97, 1]	[0, 0, 0.07, 1.05, 1]
	LS	[0.32, 1.95, 2.65, 4.28, 1]	[1.02, 2.3, 2.3, 3.58, 0.78]
	MS	[2.46, 4.65, 5.75, 8.51, 1]	[3.16, 5.14, 5.14, 6.84, 0.78]
	HS	[5.72, 7.35, 8.45, 9.76, 1]	[7.39, 8.02, 8.02, 8.98, 0.59]
	VHS	[8.03, 9.86, 10, 10, 1]	[9.08, 9.94, 10, 10, 1]
Occurrence, O	*ELO*	[0, 0, 0.16, 2.24, 1]	[0, 0, 0.06, 0.79, 1]
	VLO	[0.14, 1.70, 2.50, 3.63, 1]	[1.37, 2.16, 2.16, 3.26, 0.7]
	LO	[2.34, 3.90, 4.15, 5.46, 1]	[2.95, 4.04, 4.04, 5.35, 0.91]
	MO	[4.63, 5.85, 5.90, 7.17, 1]	[4.65, 5.87, 5.87, 7.05, 0.98]
	HO	[6.37, 7.50, 8.30, 9.86, 1]	[6.74, 7.84, 7.84, 8.63, 0.7]
	VHO	[7.76, 9.84, 10, 10, 1]	[9.21, 9.94, 10, 10, 1]
Detect, D	*VWD*	[0, 0, 0.06, 0.92, 1]	[0, 0, 0.05, 0.66, 1]
	WD	[0.27, 1.05, 1.35, 2.27, 1]	[0.43, 1.19, 1.19, 1.83, 0.82]
	AD	[1.17, 2.65, 3.45, 4.79, 1]	[2.11, 3.07, 3.07, 4.13, 0.72]
	GD	[3.16, 5.00, 5.65, 7.42, 1]	[3.88, 5.33, 5.33, 6.83, 0.82]
	ED	[5.13, 9.66, 10.0, 10.0, 1]	[5.92, 9.72, 10.0, 10.0, 1]

Table 4
Risk words of the FOUs for the RPN scale table.

Risk words, $\tilde{u}$	$\overline{FOU}(\tilde{u})$ $[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$\underline{FOU}(\tilde{u})$ $[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$
Negligible Risk Level (*NRL*)	[0, 0, 0.27, 3.82, 1]	[0, 0, 0.22, 3.16, 1]
Low Risk Level (*LRL*)	[1.92, 3.55, 4.00, 5.84, 1]	[2.47, 3.76, 3.76, 5.18, 0.87]
Medium Risk Level (*MRL*)	[4.33, 5.60, 5.85, 7.05, 1]	[4.65, 5.73, 5.73, 6.87, 0.90]
Serious Risk Level (*SRL*)	[6.15, 7.35, 8.30, 9.71, 1]	[7.35, 7.85, 7.85, 8.55, 0.59]
Very Serious Risk Level (*VSRL*)	[7.63, 9.83, 10.0, 10.0, 1]	[9.08, 9.94, 10.0, 10.0, 1]

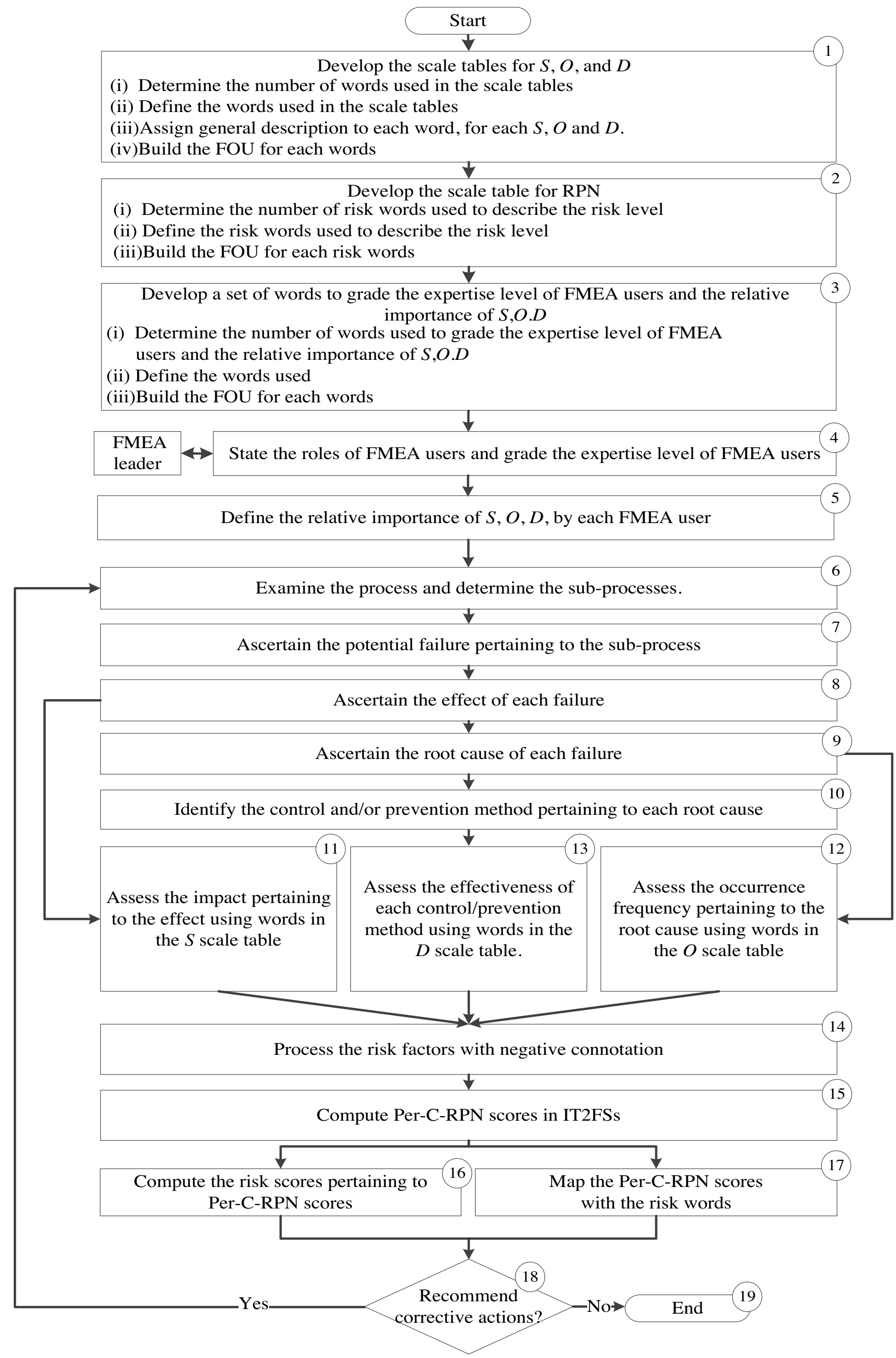

Fig. 4. The FMEA methodology incorporating the proposed Per-C –based RPN model.

with weak detection capability means it still lack of control action or solution which needs immediate attention. In this step, the LMF and UMF of $\tilde{X}^k_{iC}$ are processed, and the resulting new LMF and UMF after negative connotation are obtained using Eq. (5).

$$\mu_{\tilde{X}^{k*}_{iC}}\left(x^k_{ic}\right) = \begin{cases} \mu_{\tilde{X}^k_{iC}}\left(10 - x^k_{ic}\right), & IfC = \{D\} \\ \mu_{\tilde{X}^k_{iC}}\left(x^k_{ic}\right), & IfC = \{S, O\} \end{cases}, \forall x^k_{iC} \tag{5}$$

The UMF and LMF of $\mu_{\tilde{X}^{k*}_{iC}}\left(x^k_{ic}\right)$ can be written as Eqs. (6) and (7), respectively

$$\bar{\mu}_{\tilde{X}^{k*}_{iC}} = \begin{cases} \bar{\mu}_{\tilde{X}^k_{iC}}\left(10 - x^k_{iC}\right), & IfC = \{D\} \\ \bar{\mu}_{\tilde{X}^k_{iC}}\left(x^k_{iC}\right), & IfC = \{S, O\} \end{cases}, \forall x^k_{iC} \tag{6}$$

$$\underline{\mu}_{\tilde{X}^{k*}_{iC}} = \begin{cases} \underline{\mu}_{\tilde{X}^k_{iC}}\left(10 - x^k_{iC}\right), & IfC = \{D\} \\ \underline{\mu}_{\tilde{X}^*_{iC}}\left(x^k_{iC}\right), & IfC = \{S, O\} \end{cases}, \forall x^k_{iC} \tag{7}$$

Step 15. *Compute the Per-C-RPN scores of IT2FSs*. Aggregate the subjective judgement of FMEA users by using Eqs. (8)–(9). Based on the Linguistic Weighted Average (LWA) method [23,25], we obtain

$$\tilde{X}^*_{iC} = \frac{\sum_{k=1}^{K} \tilde{X}^{k*}_{iC} \tilde{w}^k}{\sum_{k=1}^{K} \tilde{w}^k}, \quad \mathrm{i} = 1, \ldots, \mathrm{n}, \quad \mathrm{C} = \left\{S, O, D\right\}, \tag{8}$$

$$\tilde{W}_C = \frac{\sum_{k=1}^{K} \tilde{W}^k_C \tilde{w}^k}{\sum_{k=1}^{K} \tilde{w}^k}, \quad \mathrm{C} = \left\{S, O, D\right\}, \tag{9}$$

and $\tilde{Y}_{F_i}$ is obtained using Eq (10).

$$\tilde{Y}_{F_i} = \frac{\tilde{X}^*_{iS}\tilde{W}_S + \tilde{X}^*_{iO}\tilde{W}_O + \tilde{X}^*_{iD}\tilde{W}_D}{\tilde{W}_S + \tilde{W}_O + \tilde{W}_D} \qquad i = 1, \ldots, n, \tag{10}$$

Step 16. *Convert the Per-C-RPN scores of IT2FSs into crisp values*. The left- and right-end points of $\tilde{Y}_{F_i}$ (i.e., y_1 and y_N, respectively) are discretized into N points. The discretized points (i.e., y_d where $d = 1, 2, 3, \ldots, N$,) are computed using Eq. (11).

$$y_d = y_1 + (d-1)\frac{y_{101} - y_1}{N-1} \tag{11}$$

Then, the left and right centroids of $\tilde{Y}_{F_i}$, i.e., $\hat{C}_{\tilde{Y}_{F_i},l}$ and $\hat{C}_{\tilde{Y}_{F_i},r}$, are obtained using Eq. (12) and (13), respectively, where $\underline{\mu}_{\tilde{Y}_{F_i}}(y_d)$ and $\bar{\mu}_{\tilde{Y}_{F_i}}(y_d)$ are the lower and upper membership degrees of $\tilde{Y}_{F_i}$ pertaining to y_d, respectively. Note that L and R in Eqs. (12) and (13) denote the left and right switch points, respectively. L and R are determined using the Enhanced Karnik-Mendel (EKM) algorithm [23,45].

$$\begin{aligned}\hat{C}_{\tilde{Y}_{F_i},l} &= \min_{\forall \theta_d \in \left[\underline{\mu}_{\tilde{Y}_{F_i}}(y_d), \bar{\mu}_{\tilde{Y}_{F_i}}(y_d)\right]} \left(\frac{\sum_{d=1}^{N} y_d \theta_d}{\sum_{d=1}^{N} \theta_d}\right) \\ &= \frac{\sum_{d=1}^{L} y_d \bar{\mu}_{\tilde{Y}_{F_i}}(y_d) + \sum_{d=L+1}^{N} y_d \underline{\mu}_{\tilde{Y}_{F_i}}(y_d)}{\sum_{d=1}^{L} \bar{\mu}_{\tilde{Y}_{F_i}}(y_d) + \sum_{d=L+1}^{N} \underline{\mu}_{\tilde{Y}_{F_i}}(y_d)}\end{aligned} \tag{12}$$

$$\begin{aligned}\hat{C}_{\tilde{Y}_{F_i},r} &= \max_{\forall \theta_d \in \left[\underline{\mu}_{\tilde{Y}_{F_i}}(y_d), \bar{\mu}_{\tilde{Y}_{F_i}}(y_d)\right]} \left(\frac{\sum_{d=1}^{N} y_d \theta_d}{\sum_{d=1}^{N} \theta_d}\right) \\ &= \frac{\sum_{d=1}^{R} y_d \underline{\mu}_{\tilde{Y}_{F_i}}(y_d) + \sum_{d=R+1}^{N} y_d \bar{\mu}_{\tilde{Y}_{F_i}}(y_d)}{\sum_{d=1}^{R} \underline{\mu}_{\tilde{Y}_{F_i}}(y_d) + \sum_{d=R+1}^{N} \bar{\mu}_{\tilde{Y}_{F_i}}(y_d)}\end{aligned} \tag{13}$$

Subsequently, the Per-C-RPN scores in crisp values of $\tilde{Y}_{F_i}$, i.e., $\hat{C}_{\tilde{Y}_{F_i}}$, is computed using Eq. (14).

$$\hat{C}_{\tilde{Y}_{F_i}} = \frac{\hat{C}_{\tilde{Y}_{F_i},r} + \hat{C}_{\tilde{Y}_{F_i},l}}{2} \tag{14}$$

Remark: The EKM algorithm is used owing to a number of reasons. Firstly, the proposed Per-C RPN model is inspired by the Per-C paradigm, and EKM is part of the conventional Per-C methodology [23]. Secondly, EKM in Per-C has been successfully used in various applications especially decision making related problems (e.g., [23–26]). Thirdly, which is the most important reason, each failure mode is associated with a crisp Per-C-RPN score in this study. The main purpose of using crisp Per-C-RPN scores is to order and prioritize the failure modes, i.e., failure modes with higher crisp Per-C-RPN scores have higher priorities. As a result, we only need an efficient and straightforward method to convert Per-C-RPN scores of IT2FSs into crisp values, such that the failure modes can be ordered and prioritized. In this study, EKM has shown to be efficient in ordering and prioritizing the failure modes, empirically, in Sections 4 and 5. In Section 4, the empirical results show that the risk ordering outcomes are robust against uncertainties by using the EKM algorithm. In Section 5, the domain experts are satisfied with the risk ordering outcome, again by using the EKM algorithm. In addition, we have conducted experiments to compare the ranking orders from the EKM algorithm and those from the Greenfield-Chiclana [31] and Nie-Tan [33] methods. While the risk scores from different methods are slightly different, the ranking orders are identical.

Table 5
Words and their respective FOUs [23].

Words, $\tilde{u}$	$\overline{FOU}(\tilde{u})$ $[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$\underline{FOU}(\tilde{u})$ $[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$
Very Low, *VL*	[0.00, 0.00, 1.50, 3.50, 1]	[0.00, 0.00, 0.50, 2.50, 1.00]
Low, *L*	[0.50, 2.50, 3.50, 5.50, 1]	[1.50, 3.00, 3.00, 4.50, 0.75]
Moderate, *M*	[2.50, 4.50, 5.50, 7.50, 1]	[3.50, 5.00, 5.00, 6.50, 0.75]
High, *H*	[4.50, 6.50, 7.50, 9.50, 1]	[5.50, 7.00, 7.00, 8.50, 0.75]
Very High, *VH*	[6.50, 8.50, 10.0, 10.0, 1]	[7.50, 9.50, 10.0, 10.0, 1.00]

Step 17. *Map the Per-C-RPN scores of IT2FSs to risk words*. $\tilde{Y}_{F_i}$ is mapped to risk words using the Jaccard Similarity approach [23], i.e., Eq. (15). The degree of similarity (in percentages) between $\tilde{Y}_{F_i}$ and $\tilde{Y}_{R_g}$ is denoted as $SJ\left(\tilde{Y}_{F_i}, \tilde{Y}_{R_g}\right)$, and $\tilde{Y}_{F_i}$ is mapped to two risk words with the highest two percentages of similarity.

$$SJ\left(\tilde{Y}_{F_i}, \tilde{Y}_{R_g}\right) = \frac{\sum_{s=1}^{N} \min\left(\bar{\mu}_{\tilde{Y}_{F_i}}(y_s), \bar{\mu}_{\tilde{Y}_{R_g}}(y_s)\right) + \sum_{s=1}^{N} \min\left(\underline{\mu}_{\tilde{Y}_{F_i}}(y_s), \underline{\mu}_{\tilde{Y}_{R_g}}(y_s)\right)}{\sum_{s=1}^{N} \max\left(\bar{\mu}_{\tilde{Y}_{F_i}}(y_s), \bar{\mu}_{\tilde{Y}_{R_g}}(y_s)\right) + \sum_{s=1}^{N} \max\left(\underline{\mu}_{\tilde{Y}_{F_i}}(y_s), \underline{\mu}_{\tilde{Y}_{R_g}}(y_s)\right)} \times 100\% \tag{15}$$

where y_s $(s = 1, \ldots, N)$ are equally spaced in the support of $\tilde{Y}_{F_i} \cup \tilde{Y}_{R_g}$. Note that $SJ\left(\tilde{Y}_{F_i}, \tilde{Y}_{R_g}\right) \approx 100$ indicates that $\tilde{Y}_{F_i}$ is almost mapped to $\tilde{Y}_{R_g}$, while $SJ\left(\tilde{Y}_{F_i}, \tilde{Y}_{R_g}\right) \approx 0$ indicates $\tilde{Y}_{F_i}$ is not likely to be mapped to $\tilde{Y}_{R_g}$.

Step 18. *Determine the corrective action*. If any corrective action is needed, go back to Step 6.

Step 19. End.

4. Simulation study with a benchmark problem

The background of a benchmark problem [10] is presented in Section 4.1. The simulation results are presented and discussed in Section 4.2. A comparative study between the proposed model and other existing methods is presented in Section 4.3.

4.1. Background

A simulation study using benchmark FMEA information in [10] is used, but uncertainties are added to the available information [10], in order to allow our proposed method to be analysed and compared critically. In accordance with [10], four experts are involved in an FMEA activity with eight failure modes, i.e., valve closing time is too long or no action (F_1), valve cannot be closed tightly (F_2), large leak of valve shaft (F_3), valve fluctuations (F_4), valve jams when opening and closing (F_5), valve shaft fracture (F_6), malfunction of valve shaft support bearing (F_7), and excessive noise or abnormal noise of the valve system (F_8). Linguistic terms in Tables 6 and 7 are used to rate these failure modes and the importance of each criterion, respectively. Column "words" indicates the linguistic terms, while Column "T1FSs" indicates the parameters of the associated linguistic terms in T1FSs. As an example,

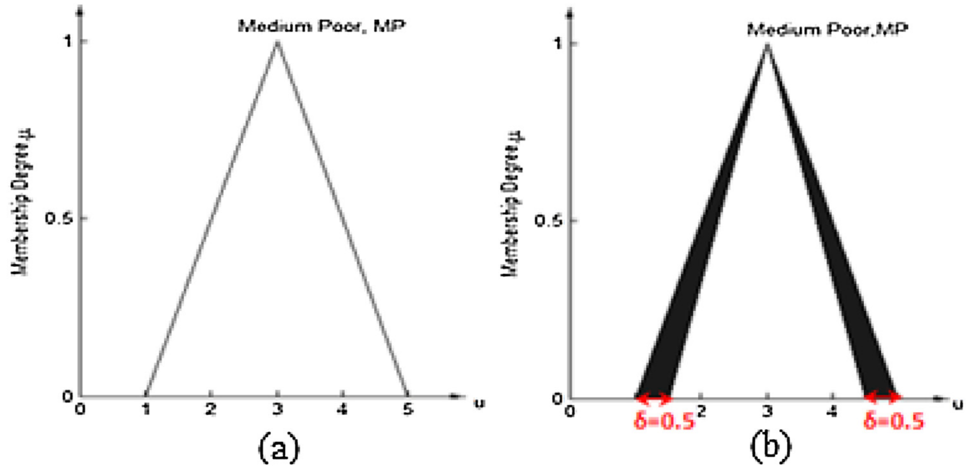

Fig. 5. Fuzzy set representations of "Medium Poor" (a) without uncertainty and (b) with uncertainty δ=0.5.

Table 6
Linguistic grades for the ratings of failure modes [10].

Words	T1FSs	T1FSs with uncertainties $\delta = 0.5$	
	$[a, b, c, d, h]$	$[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$
Very Poor (*VP*)	[0, 0, 0, 1, 1]	[0, 0, 0, 1, 1]	[0, 0, 0, 0.5, 1]
Poor (*P*)	[0, 1, 1, 3, 1]	[0, 1, 1, 3, 1]	[0.5, 1, 1, 2.5, 1]
Medium Poor (*MP*)	[1, 3, 3, 5, 1]	[1, 3, 3, 5, 1]	[1.5, 3, 3, 4.5, 1]
Fair (*F*)	[3, 5, 5, 7, 1]	[3, 5, 5, 7, 1]	[3.5, 5, 5, 6.5, 1]
Medium Good (*MG*)	[5, 7, 7, 9, 1]	[5, 7, 7, 9, 1]	[5.5, 7, 7, 8.5, 1]
Good (*G*)	[7, 9, 9, 10, 1]	[7, 9, 9, 10, 1]	[7.5, 9, 9, 9.5, 1]
Very Good (*VG*)	[9, 10, 10, 10, 1]	[9, 10, 10, 10, 1]	[9.5, 10, 10, 10, 1]

Table 7
Linguistic grades for the importance of each criterion [10].

Words	T1FSs	T1FSs with uncertainties $\delta = 0.5$	
	$[a, b, c, d, h]$	$[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$
Very Low (*VL*)	[0, 0, 0, 1, 1]	[0, 0, 0, 1, 1]	[0, 0, 0, 0.5, 1]
Low (*L*)	[0, 1, 1, 3, 1]	[0, 1, 1, 3, 1]	[0.5, 1, 1, 2.5, 1]
Medium Low (*ML*)	[1, 3, 3, 5, 1]	[1, 3, 3, 5, 1]	[1.5, 3, 3, 4.5, 1]
Medium (*M*)	[3, 5, 5, 7, 1]	[3, 5, 5, 7, 1]	[3.5, 5, 5, 6.5, 1]
Medium High (*MH*)	[5, 7, 7, 9, 1]	[5, 7, 7, 9, 1]	[5.5, 7, 7, 8.5, 1]
High (*H*)	[7, 9, 9, 10, 1]	[7, 9, 9, 10, 1]	[7.5, 9, 9, 9.5, 1]
Very High (*VH*)	[9, 10, 10, 10, 1]	[9, 10, 10, 10, 1]	[9.5, 10, 10, 10, 1]

"Medium Poor" is represented by a triangular T1FS with parameters $[a, b, c, d, h] = [1, 3, 3, 5, 1]$, as illustrated in Fig. 5 (a). In this study, uncertainties are added to these T1FSs by introducing δ. As an example, "Medium Poor" in the T1FS of Fig. 5(a) is blurred by δ = 0.5, resulting in an IT2FS, as shown in Fig. 5(b). As shown in Tables 6 and 7, all linguistic terms in T1FSs are associated with uncertainties of δ=0.5 (described in columns "T1FSs with uncertainties of δ = 0.5") in this study.

A summary of the ratings provided by FMEA users is presented in Table 8. The importance of *S*, *O*, and *D* have been rated by each FMEA user, as tabulated in column "$\tilde{W}^k$". As an example, TM_1 and TM_4 have graded *S* as *M* and *H*, while TM_2 and TM_3 have graded *S* as *MH*, respectively. The ratings for the failure modes are summarized in columns "Failure Modes". As an example, TM_1 has rated the *S*, *O*, and *D* scores of F_1 as Very Good (*VG*), Medium Poor (*MP*), and Good (*G*), respectively. In this section, simulations are conducted with five δ settings, i.e., $\delta = 0.0, 0.25, 0.50, 0.75, 1$.

4.2. Simulation results and discussion

Table 9 summarizes the computed Per-C-RPN scores for the eight failure modes, with $\delta = 0.5$. Column "Failure Modes, F_i" indicates the failure modes. Columns "$\overline{FOU\left(\tilde{Y}_{F_i}\right)}$" and "$\underline{FOU\left(\tilde{Y}_{F_i}\right)}$" are the parameters of the Per-C-RPN scores of IT2FSs, i.e., the upper and lower membership functions, respectively. To ease the prioritization of the failure modes, the Per-C-RPN scores of IT2FSs (i.e., $\tilde{Y}_{F_i}$) are simplified to their respective crisp risk scores (Step 15), as tabulated in column "Risk scores". The failure modes are sorted according to their crisp risk scores, as summarized in column "Risk Ranking". Each failure mode is also associated with a risk description, as summarized in column "Risk Description". Therefore, F_1, F_2, F_3, F_4, F_5, F_6, F_7, and F_8 are associated with crisp risk scores of 6.901, 2.8884, 3.956, 4.073, 5.449, 5.145, 5.367, and 5.193 respectively. These eight failure modes are sorted using the risk scores. As a result, F_1 has the highest risk, which is followed by F_5, F_7, F_8, F_6, F_4, F_3, and F_2. Although the failure modes are sorted based on their risk scores, it can be observed that the risk scores for F_5 and F_7 are close to each other (i.e.,5.449 and 5.367, respectively). In such situation, it is more meaningful to describe the risk in words. As such, F_5 is described as 64.4% medium risk and 22.3% medium high risk, while F_7 is described as 69.8% medium risk and 21.1% medium high risk.

Fig. 6 shows the risk ranking outcomes obtained with different δ settings, i.e., $\delta = 0.0, 0.25, 0.50, 0.75, 1$. It is observed that F_1 is rated as the highest risk, which is followed by F_5, F_7, F_8, F_6, F_4, F_3, and F_2. The results of δ=0, 0.25, 0.5, 0.75, are consistent too. However, when a high degree of linguistic uncertainties (i.e., δ=1) is applied, the ranking order between F_8 and F_6 is reversed, i.e., the ranking order becomes F_1, F_5, F_7, F_6, F_8, F_4, F_3, and F_2. This observation implies uncertainties can influence the final evaluation result in an FMEA activity. The simulation results indicate that the proposed Per-C-RPN model is robust against uncertainties. In other words, uncertainties in linguistic terms with different δ settings do not affect the risk ordering outcomes of the proposed Per-C-RPN model significantly.

4.3. Comparison with other methods

In this section, four existing methods, i.e., the conventional RPN model [1], TOPSIS [46], fuzzy TOPSIS-fuzzy AHP [42], fuzzy TOPSIS [10] are compared with our proposed Per-C-RPN model. The simulation results of $\delta = 0.0$ are summarized in Table 10. Note that the results of the four compared methods are extracted from the rele-

Table 8
Assessment information on the eight failure modes by four FMEA users.

Risk Factors, C	TM_k	$\tilde{W}^k$	Failure Modes							
			F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8
Severity, S	TM_1	M	VG	P	MP	MG	VG	VG	MG	F
	TM_2	MH	VG	P	MP	MG	VG	VG	MG	F
	TM_3	MH	VG	VP	F	MG	MG	VG	G	MG
	TM_4	H	G	MP	MP	F	G	VG	G	MG
Occurrence, O	TM_1	ML	MP	MP	MG	P	MP	VP	F	F
	TM_2	M	MP	MP	MG	P	MP	P	F	MG
	TM_3	M	F	F	F	MP	F	P	MG	F
	TM_4	MH	P	MP	F	MP	F	MP	F	MG
Detect, D	TM_1	M	G	MP	MP	MP	MP	P	P	MP
	TM_2	M	G	F	MP	P	MP	P	P	F
	TM_3	M	MG	F	P	MP	P	MP	MP	MP
	TM_4	MH	F	MP	MP	MP	MP	F	MP	MP

Table 9
FOUs of the Per-C-RPN scores for the eight failure modes ($\delta = 0.5$).

Failure Modes, F_i	$\overline{FOU}(\tilde{Y}_{F_i})$ $[\bar{a}, \bar{b}, \bar{c}, \bar{d}, \bar{h}]$	$\underline{FOU}(\tilde{Y}_{F_i})$ $[\underline{a}, \underline{b}, \underline{c}, \underline{d}, \underline{h}]$	Risk Scores	Risk Ranking	Risk Descriptions
F_1	[5.30, 7.11, 7.11, 8.36, 1]	[4.55, 7.11, 7.11, 8.83, 1]	6.901	1	14.2%M, 92.0%MH
F_2	[1.41, 2.76, 2.76, 4.46, 1]	[0.90, 2.76, 2.76, 5.05, 1]	2.884	8	15.3%L, 85.9%ML
F_3	[2.19, 3.90, 3.90, 5.77, 1]	[1.60, 3.90, 3.90, 6.40, 1]	3.956	7	40.5%ML, 37.1%M
F_4	[0.25, 3.96, 3.96, 5.98, 1]	[1.62, 3.96, 3.96, 6.70, 1]	4.073	6	37.3%ML, 42.4%M
F_5	[3.63, 5.53, 5.53, 7.21, 1]	[2.93, 5.53, 5.53, 7.81, 1]	5.449	2	64.4%M, 22.3%MH
F_6	[3.52, 5.14, 5.14, 6.81, 1]	[2.78, 5.14, 5.14, 7.36, 1]	5.145	5	86.1%M, 14.7%MH
F_7	[3.55, 5.40, 5.40, 7.16, 1]	[2.85, 5.40, 5.40, 7.84, 1]	5.367	3	69.8%M, 21.1%MH
F_8	[3.41, 5.21, 5.21, 6.97, 1]	[2.79, 5.21, 5.21, 7.55, 1]	5.193	4	81.0%M, 16.7%MH

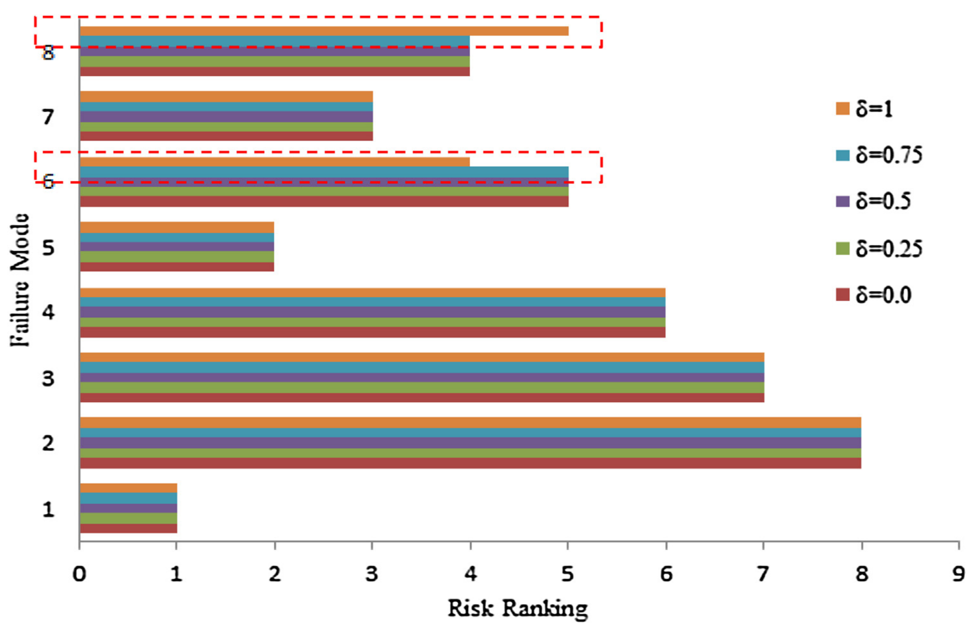

Fig. 6. Risk ranking outcomes with δ=0.0, 0.25, 0.50, 0.75, 1.

Table 10
Comparison of ranking outcomes of different methods.

F_i	Conventional RPN [1]		TOPSIS [46]		Fuzzy TOPSIS-Fuzzy AHP [42]		Fuzzy TOPSIS [10]		The proposed method	
	Risk Scores	Risk Ranking	Risk Scores	Risk Ranking	Risk Scores	Risk Ranking	Risk Scores	Risk Ranking	Risk Scores	Risk Ranking
F_1	252	1	0.794	1	0.253	1	0.240	1	6.827	1
F_2	48	7	0.210	8	0.124	8	0.132	8	2.902	8
F_3	96	6	0.300	7	0.159	6	0.172	6	3.967	7
F_4	96	6	0.438	6	0.155	7	0.147	7	4.092	6
F_5	144	3	0.650	2	0.202	2	0.194	3	5.422	2
F_6	120	4	0.623	3	0.194	4	0.177	5	5.095	5
F_7	112	5	0.534	5	0.197	3	0.196	2	5.366	3
F_8	180	2	0.544	4	0.189	5	0.191	4	5.183	4

vant papers, as indicated in Table 10. All methods rank F_1 with the highest risk, while F_2 with the lowest risk. The conventional RPN model is less effective as it cannot distinguish the risk ranking of F_3 and F_4. In general, TOPSIS [46], Fuzzy TOPSIS-Fuzzy AHP [42], Fuzzy TOPSIS [10] and our proposed model work well with $\delta = 0.0$, but with slightly different ranking outcomes. As an example, three existing methods (i.e., TOPSIS [46], Fuzzy TOPSIS-Fuzzy AHP [42] and the proposed method) rank F_5 with the second highest risk score, while Fuzzy TOPSIS [10] and the conventional RPN model [1] rank F_5 with the third highest risk score.

Note that while TOPSIS [46], Fuzzy TOPSIS-Fuzzy AHP [42], Fuzzy TOPSIS [10] methods work well with $\delta = 0.0$, it is not clear how these methods work with other δ settings. Comparatively, our proposed model can deal with different uncertainties i.e., $\delta = 0$, 0.02, 0.05, 0.75, 1.00, as reported in the previous section.

5. Case study on edible bird nest farming

The background of an EBN case study is introduced in Section 5.1. Linguistic grades for assessment are modelled in Section 5.2. Information and data collected are presented in Section 5.3. The outcomes of the proposed Per-C-RPN model are presented in Section 5.4. Finally, a comprehensive discussion is presented in Section 5.5.

5.1. Background of the case study

Two swiftlets farms in Sarawak are studied. Two independent control measures are needed in a swiftlet farm, i.e., environmental control (C1) and pest/enemy control (C2). The former provides a good environment for the existing swiftlets to live, as well as for attracting new swiftlets to migrate in. The important potential failure modes include failure to control the environmental settings of temperature ($F_{C1,1}$), humidity ($F_{C1,2}$), air quality ($F_{C1,3}$), and lighting intensity ($F_{C1,4}$). The latter indicates the threats faced by a swiftlets farm, primarily theft (by human) ($F_{C2,1}$), owls ($F_{C2,2}$), Asian glossy starling ($F_{C2,3}$), bats ($F_{C2,4}$), home lizards ($F_{C2,5}$), rats ($F_{C2,6}$), cockroaches ($F_{C2,7}$), and ants ($F_{C2,8}$). It is essential to install a good security system to prevent theft because of the high market value of EBN. It is also important to have a proper pest control system to ensure smooth operations of a swiftlets farm.

5.2. Modelling of the linguistic grades for assessment

In this case study, the proposed FMEA procedure has been evaluated by five FMEA users, i.e., farm owner (TM_1), farm manager 1 (TM_2), farm manager 2 (TM_3), farm supervisor 1 (TM_4), and farm supervisor 2 (TM_5). Table 2 depicts the S, O, D scale tables. Firstly, the FMEA users have been asked to choose between 0 and 10 for each word in Table 2. The interval end-points from five FMEA users have been processed using the EIA method [27]. As an example, Fig. 7 shows the FOU of "Medium Severity (MS)". The intra- uncertainty of each FMEA user pertaining to MS is presented as an T1FS, as shown in Fig. 7(a). It can be observed that the FMEA users have provided slightly different T1FSs for MS, indicating inter-uncertainty. On the other hand, FMEA users may possibly provide different opinions. As such, the users' opinions are pre-processed using the EIA [27] before the FOU of an IT2FS is obtained. The pre-processing procedure includes filtering of bad data and outliers as well as setting the tolerance limits and reasonable intervals. It is worth-mentioning that the EIA provides an effective means to pre-process experts' opinions. By using the pre-processing procedure, non-convexity of the FOU can be avoided. However, it leads to an increase in the uncertainty band of the FOU owing to uncertainties that a group of users may have about certain words, i.e., inter-uncertainty [23] is increased.

5.3. Information and data gathering

The role of each FMEA user has been assigned by the FMEA leader i.e., TM_1. The proficiency of each team member has been rated by TM_1 using the words in Table 5. As the founder cum owner of the swiftlets farm with 20 years of experience and with good knowledge in managing the farm, TM_1 has been self-rated as "high". Being the farm managers, TM_2 and TM_3 handle several key activities, i.e., determining preventive and corrective maintenances, planning strategies for enhancing yield, and organising associated businesses. With 15 years of experience, both TM_2 and TM_3 are graded to have the same expertise, i.e., "medium". Being the farm supervisors, TM_4 and TM_5 monitor the day-to-day farm activities, supervise general farm workers, assist in the development and implementation of farm safety, and conduct training for farm workers. Armed with 20 years and 4 years of experience, the expertise levels of TM_4 and TM_5 are graded as "medium" (owing to lack of comprehensive training despite having 20 years of experience) and "low", respectively.

A summary of the assessment grades provided by FMEA users is tabulated in Table 11. The expertise levels of these FMEA users are presented in column "$TM_k(\tilde{w}^k)$". All S, O, and D are rated by each FMEA user, as tabulated in column $\tilde{W}_C^k$. As an example, TM_1 and TM_5 have graded S as L. TM_2, TM_3, and TM_4 have graded S as M. The ratings for the failure modes associated with the environmental control (C1) and pest/enemy control (C2) are summarized in columns C1 and C2. As an example, TM_1 have rated the S, O, and D scores for $F_{C1,1}$ in C1 as low severity (LS), extremely low occurrence (ELO), and excellent detection (ED), respectively.

5.4. Risk prioritization outcomes

Information summarized in Table 11 is aggregated with our proposed method in Steps (14)-(15) using Eqs. (5)–(10). The FOUs of the Per-C-RPN scores are presented in Table 12. Column "Aspects of control" indicates both environmental and pest/enemy control measures. Column "Failure modes, $F_{\cdot,i}$" indicates the failure modes for C1 and C2. Columns "$\overline{FOU\left(\tilde{Y}_{F_{\cdot,i}}\right)}$" and "$\underline{FOU\left(\tilde{Y}_{F_{\cdot,i}}\right)}$" are the parameters of the Per-C-RPN scores of IT2FSs, i.e., the upper and lower membership functions, respectively. As an example, the FOU of the failure modes in C1 is presented in Fig. 8. To ease the prioritization of these failure modes, the Per-C-RPN scores of IT2FSs (i.e., $\tilde{Y}_{F_{\cdot,i}}$) are simplified to their respective crisp risk scores, as tabulated in column "Risk scores". The failure modes are sorted according to the crisp risk scores, as summarized in column "Risk ranking". Each failure mode is also associated with a risk description, as summarized in column "Risk description". The details are analysed and discussed, as follows.

5.5. Discussion

5.5.1. Environmental control (C1)

For C1, $F_{C1,1}$ (temperature), $F_{C1,2}$ (humidity), $F_{C1,3}$ (air quality), and $F_{C1,4}$(lighting intensity) are associated with crisp risk scores of 3.19, 2.90, 4.06, and 1.97, respectively. Based on the sorted risk scores, $F_{C1,3}$ has the highest risk, which is followed by $F_{C1,1}$, $F_{C1,2}$, and $F_{C1,4}$. From Table 11, two FMEA users with "high" and "medium" expertise levels (i.e., TM_1 and TM_2) have rated $F_{C1,3}$ with "Very High Severity" and "High Severity" for S, respectively. Therefore, $F_{C1,3}$ requires intensive attention. A discussion with all FMEA users suggest that $F_{C1,3}$ should be the main priority in C1, because poor air quality in the swiftlet farm occurs as a result of

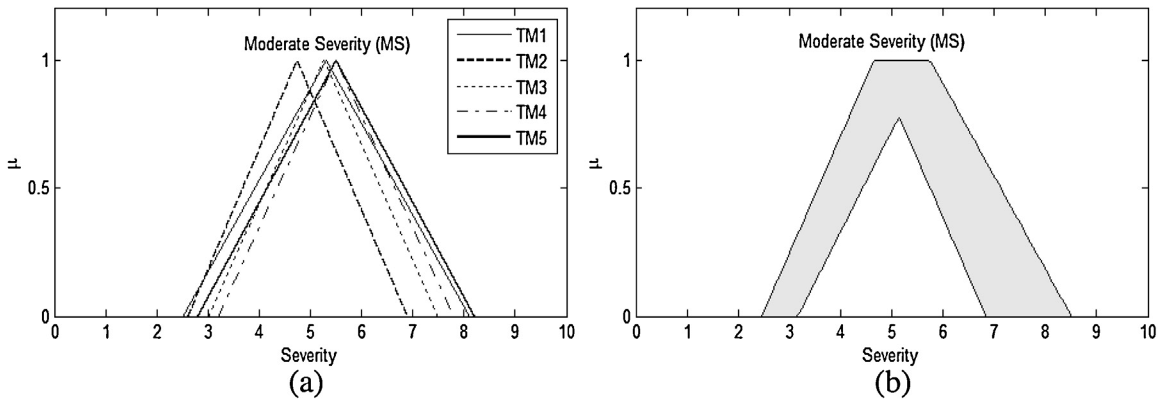

Fig. 7. Word "Medium Severity (*MS*)". (a) T1FSs for *MS* from different FMEA users. (b) IT2FS for *MS* obtained using the EIA method [27].

Table 11
Assessment of the failure modes for EBN farming, i.e., the environmental control (C1) and pest/enemy control (C2).

C	$TM_k(\tilde{w}^k)$	$\tilde{W}_C^k$	C1				C2							
			$F_{C1,1}$	$F_{C1,2}$	$F_{C1,3}$	$F_{C1,4}$	$F_{C2,1}$	$F_{C2,2}$	$F_{C2,3}$	$F_{C2,4}$	$F_{C2,5}$	$F_{C2,6}$	$F_{C2,7}$	$F_{C2,8}$
S	$TM_1\,(H)$	*L*	*LS*	*MS*	*VHS*	*VLS*	*HS*	*MS*	*MS*	*MS*	*VLS*	*LS*	*VLS*	*LS*
	$TM_2\,(M)$	*M*	*MS*	*MS*	*MS*	*VHS*	*HS*	*MS*	*MS*	*MS*	*VLS*	*LS*	*LS*	*LS*
	$TM_3\,(M)$	*M*	*MS*	*LS*	*HS*	*VLS*	*MS*	*LS*	*MS*	*LS*	*LS*	*VLS*	*VLS*	*LS*
	$TM_4\,(M)$	*M*	*MS*	*LS*	HS	*VLS*	*MS*	*LS*	*MS*	*LS*	*LS*	*VLS*	*LS*	*VLS*
	$TM_5\,(L)$	*L*	*MS*	*LS*	*HS*	*LS*	*VHS*	*LS*	*MS*	*LS*	*VLS*	*VLS*	*LS*	*VLS*
O	$TM_1\,(H)$	*H*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*
	$TM_2\,(M)$	*M*	*ELO*	*ELO*	*ELO*	*VLO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*
	$TM_3\,(M)$	*H*	*VLO*	*ELO*	*ELO*	*VLO*	*ELO*	*ELO*	*VLO*	*ELO*	*ELO*	*ELO*	*ELO*	*ELO*
	$TM_4\,(M)$	*VH*	*VLO*	*VLO*	*VLO*	*VLO*	*ELO*	*VLO*	*VLO*	*VLO*	*ELO*	*VLO*	*ELO*	*ELO*
	$TM_5\,(L)$	*M*	*VLO*	*VLO*	*VLO*	*VLO*	*VLO*	*ELO*	*VLO*	*VLO*	*VLO*	*ELO*	*VLO*	*VLO*
D	$TM_1\,(H)$	*VH*	*ED*	*ED*	*ED*	*ED*	*ED*	*ED*	*AD*	*ED*	*GD*	*ED*	*AD*	*ED*
	$TM_2\,(M)$	*VH*	*ED*	*ED*	*ED*	*ED*	*ED*	*ED*	*GD*	*ED*	*GD*	*ED*	*WD*	*ED*
	$TM_3\,(M)$	*H*	*GD*	*GD*	*ED*	*ED*	*ED*	*ED*	AD	*ED*	*AD*	*ED*	*WD*	*ED*
	$TM_4\,(M)$	*VH*	*GD*	*GD*	*ED*	*GD*	*ED*	*GD*	AD	*ED*	AD	*GD*	*WD*	*ED*
	$TM_5\,(L)$	*VH*	*GD*	*GD*	*GD*	*GD*	*GD*	*GD*	AD	*ED*	AD	*GD*	*WD*	*GD*

Table 12
FOUs of the Per-C-RPN scores pertaining to the environmental control (C1) and the pest and enemy control (C2) as well as the analysed risk outcomes.

Aspects of control	Failure modes, $F_{\cdot,i}$	$\overline{FOU(\tilde{Y}_{F_{\cdot,i}})}$, $[\bar{a},\bar{b},\bar{c},\bar{d},\bar{h}]$	$\underline{FOU(\tilde{Y}_{F_{\cdot,i}})}$, $[\underline{a},\underline{b},\underline{c},\underline{d},\underline{h}]$	Risk scores	Risk ranking	Risk descriptions
Environmental control (C1)	$F_{C1,1}$	[0.26, 2.07, 3.34, 7.16, 1]	[1.04, 2.48, 3.05, 5.26, 0.70]	3.19	2	20.86%*NRL*, 46.94%*LRL*
	$F_{C1,2}$	[0.20, 1.73, 2.93, 6.79, 1]	[0.79, 2.12, 2.70, 4.94, 0.70]	2.90	3	25.38%*NRL*, 40.89%*LRL*
	$F_{C1,3}$	[0.50, 2.62, 4.32, 8.54, 1]	[1.50, 2.94, 4.43, 6.79, 0.59]	4.06	1	46.38%*LRL*, 22.00%*MRL*
	$F_{C1,4}$	[0.05, 0.78, 1.59, 5.28, 1]	[0.34, 1.05, 1.63, 3.77, 0.70]	1.97	4	48.81%*NRL*, 19.09%*LRL*
Pest and enemy control (C2)	$F_{C2,1}$	[0.29, 1.95, 3.54, 8.23, 1]	[0.96, 2.22, 3.67, 6.07, 0.59]	3.52	3	19.17%*NRL*, 45.44%*LRL*
	$F_{C2,2}$	[0.15, 1.39, 2.54, 6.72, 1]	[0.61, 1.73, 2.39, 4.72, 0.70]	2.69	5	29.85%*NRL*, 35.77%*LRL*
	$F_{C2,3}$	[0.83, 3.53, 5.02, 8.19, 1]	[2.09, 4.09, 4.44, 6.45, 0.70]	4.36	1	51.19%, *LRL*, 25.64%*MRL*
	$F_{C2,4}$	[0.07, 1.02, 2.12, 6.61, 1]	[0.40, 1.34, 2.09, 4.48, 0.70]	2.46	6	36.23%*NRL*, 30.98%*LRL*
	$F_{C2,5}$	[0.27, 1.78, 3.06, 7.03, 1]	[0.83, 2.20, 2.64, 4.89, 0.70]	2.98	4	23.98%*NRL*, 41.39%*LRL*
	$F_{C2,6}$	[0.05, 0.73, 1.47, 5.33, 1]	[0.30, 0.94, 1.55, 3.74, 0.70]	1.94	7	50.68%*NRL*, 18.85%*LRL*
	$F_{C2,7}$	[0.52, 2.57, 4.04, 8.02, 1]	[1.39, 3.09, 3.55, 6.04, 0.70]	3.76	2	51.01%*LRL*, 17.92%*MRL*
	$F_{C2,8}$	[0.02, 0.54, 1.25, 4.96, 1]	[0.19, 0.73, 1.40, 3.50, 0.70]	1.75	8	59.01%*NRL*, 14.92%*LRL*

pollutants, e.g., Nitrite gas (i.e., NO_3) from the swiftlet's dropping. As such, raw EBN absorbs NO_3, and changes its colour from white to red [47]. This is a common challenge in EBN farming [47]. Indeed, the lack of a proper control of $F_{C1,3}$ can lead to food safety and quality issue. Although $F_{C1,3}$ has the highest risk score in C1, the risk score of $F_{C1,3}$ is between the low and medium risk levels, i.e., 46.38% "Low Risk Level" and 22.00% "Medium Risk Level". This is because $F_{C1,3}$ has good *O* and *D* ratings. Owing to the low occurrence rates, $F_{C1,3}$ is assigned with *O* ratings of "Extremely Low Occurrence" or "Very Low Occurrence". Besides that, $F_{C1,3}$ is assigned with *D* ratings of "Good Detection" or "Excellent Detection", as a result of two effective preventive methods: (1) the floor has been maintained at a dry state at all times, and the temperature has been maintained between 26 and 28°C; (2) the bird's droppings have been cleared at all times. This implies that the risk of $F_{C1,3}$ is acceptable, and the consequences due to $F_{C1,3}$ are manageable and are in good control. This analysis also suggests the importance of detecting and controlling $F_{C1,3}$ in EBN farming.

It is also important to provide a comfortable environment that attracts the migration of swiftlets into the farm, i.e., control of temperature ($F_{C1,1}$), humidity ($F_{C1,2}$), and lighting intensity ($F_{C1,4}$). Amongst these three factors, controlling the temperature in the

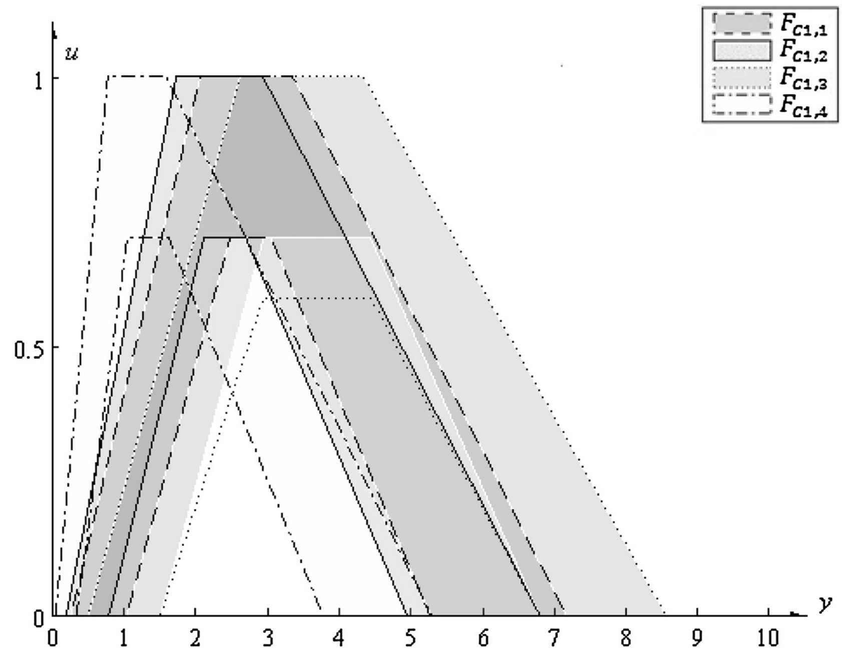

Fig. 8. Per-C-RPN scores for the failure modes of C1.

farm is the most difficult one, as Sarawak is in a tropical region with an equatorial climate. Therefore, $F_{C1,1}$ is rated the second most important risk factor. However, the risk of $F_{C1,1}$ is interpreted as 20.86% of "Negligible Risk Level" and 46.94% of "Low Risk Level", owing to the existing effective methods in maintaining the farm temperature. Nevertheless, a few suggested corrective actions for $F_{C1,1}$ are: (1) modifying the form design; (2) installing a humidifier; (3) painting the wall with heat reflective paint; (4) installing cavity wall insulation; (5) installing polystyrene board and sponge on the roof.

Being relatively easy to maintain, $F_{C1,2}$ and $F_{C1,4}$ are assigned with relatively good *S*, *O*, *D* grades. Their risk descriptions in words are 25.38% of "Negligible Risk Level", 40.89% of "Low Risk Level", and 48.81%of "Negligible Risk Level", 19.09%of "Low Risk Level", respectively.

5.5.2. Pest/enemy control (C2)

For C2, $F_{C2,1}$, $F_{C2,2}$, $F_{C2,3}$, $F_{C2,4}$, $F_{C2,5}$, $F_{C2,6}$, $F_{C2,7}$, and $F_{C2,8}$ are assigned with crisp risk scores of 3.52, 2.69, 4.36, 2.46, 2.98, 1.94, 3.76, and 1.75, respectively. The descending order of the failure modes is $F_{C2,3}$, $F_{C2,7}$,$F_{C2,1}$, $F_{C2,5}$, $F_{C2,2}$, $F_{C2,4}$,$F_{C2,6}$, and $F_{C2,8}$. The risk levels of $F_{C2,3}$ and $F_{C2,7}$ are in between "Low Risk Level" and "Medium Risk Level", i.e., 51.19%of "Low Risk Level", 25.64% of "Medium Risk Level", and 51.01% of "Low Risk Level", 17.92% of "Moderate Risk Level", respectively. A discussion with all FMEA users has indicated that the invasion of Asian glossy starling ($F_{C2,3}$) and cockroaches ($F_{C2,7}$) cannot be avoided. In regards to $F_{C2,3}$, and a consensus has been achieved from all FMEA users, i.e., "moderate severity" for *S*, as shown in Table 11. Indeed, the invasion of Asian glossy starling has a significant impact, with potential destruction to the bird nest. It is difficult to detect Asian glossy starling as its size is similar to that of the swiftlets. Therefore, most of the FMEA users have rated "acceptable detection" for *S* in regards to $F_{C2,3}$. Fortunately, the occurrence of $F_{C2,3}$ is rare. As such, the ratings of "extremely low occurrence" and "very low occurrence" are given for *O*. The invasion risk is followed by cockroaches, which is tagged with "weak detection". This analysis shows that an effective method to reduce or eliminate the invasion of Asian glossy starling and cockroaches is important for EBN farming.

The risk scores of $F_{C2,1}$, $F_{C2,5}$, $F_{C2,2}$, $F_{C2,4}$,$F_{C2,6}$, and $F_{C2,8}$ are between "Negligible Risk Level" and "Low Risk Level". This implies that the risks of $F_{C2,1}$, $F_{C2,5}$, $F_{C2,2}$, $F_{C2,4}$,$F_{C2,6}$, and $F_{C2,8}$ could be neglected. As an example, the risks of $F_{C2,1}$ (theft) are 19.17%of "Negligible Risk Level" and 45.44% of "Low Risk Level". One FMEA user has rated "Very High Severity" for *S* in regards to $F_{C2,1}$. Two of the FMEA users have given "High Severity", and the remaining "Medium Severity". The rational is that the invasion of theft usually results in damages to the structure of the swiftlets farm, and also affects the swiftlets' nest and living atmosphere. Besides that, this usually leads to a higher degree of loss, as compared with those caused by other pests. However, human invasion is preventable and detectable by installing a security alarm system, a surveillance camera, or employing security officers; therefore leading to good *O* and *D* ratings.

5.5.3. Remarks

It is observed that the proposed Per-C-RPN model provides a viable solution to encode the words adopted by FMEA users using IT2FSs. Besides that, the proposed model is beneficial because the inherent uncertainties in words are preserved throughout the prioritization procedure of FMEA. A Per-C-RPN score is generated for each failure mode, and is coded with an IT2FS. The Per-C-RPN score is subsequently decoded into a crisp risk score for ascertaining the risk priority of a particular failure mode, which is then mapped into a set of risk words for explaining the failure risk in terms of words. As such, the proposed model keeps all the original data/information as they are, therefore minimizing loss of information.

6. Conclusions

A new Per-C-RPN model pertaining to FMEA has been introduced in this study. The FMEA procedure incorporates the proposed Per-C-RPN model. The model adopts linguistic words as the assessment grades, which provide a natural and flexible assessment methodology for FMEA users. Besides that, the inherited uncertainties in the words used for group assessment are preserved in the FMEA procedure. Based on a benchmark problem and an EBN case study, the proposed model has been shown to be useful and effective. The Per-C-RPN model is able to generate rational risk scores, which can be further interpreted semantically in terms of linguistic words. The outcome shows that such feature is important for decision making, because it allows FMEA users to have a better understanding with respect to the associated risks. Besides that, the obtained results are in good agreement with the feedback from the domain experts (FMEA users).

For further work, it is interesting to study how the consensus achieved from group decision making [48–50] can be incorporated into the proposed Per-C-RPN model. As an example, the consensus measure can be used to determine the expertise level of each FMEA user. Besides that, the LWA algorithm [25] in the CWW engine can be replaced with other perceptual reasoning methods [51] for capturing experts' knowledge and allowing non-linear mapping of S, O, D to RPN scores. In addition, the use of other suitable techniques [30–33] to defuzzify the Per-C-RPN scores can be investigated.

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