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A novel efficient approach for DFMEA combining 2-tuple and the OWA operator

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ABSTRACT

Design Failure Mode and Effect Analysis (DFMEA) is the application of the Failure Mode and Effects Analysis (FMEA) method specifically to product design. DFMEA is not only an important risk assessment technique but also a major task for enterprises in implementing production management. The purpose is to ensure that the product can achieve its designed functions under specific operating conditions. Most current DFMEA methods use the Risk Priority Number (RPN) value to evaluate the risk of failure. However, conventional RPN methodology has the serious problem of measurement scales and loses some valued information, which experts have to provide. In order to improve the method of RPN evaluation, this paper proposes a novel technique, combining 2-tuple and the Ordered Weighted Averaging (OWA) operator for prioritization of failures in a product DFMEA. A case of the Color Super Twisted Nematic (CSTN) that has been drawn from a midsized manufacturing factory is presented to further illustrate the proposed approach. After comparing the result that was obtained from the proposed method with the other two listed approaches, it was found that the proposed approach can effectively solve the problem of measurement scales and has not lost any expert to provide the useful information. As a result, stability of the product and process can be assured.

1. Introduction

Risk assessment is a preventive analysis task of product design and the production planning process. It is utilized to find weaknesses of the product design and production process in early stages before going into mass production, to allow the product to have better quality and reliability, which in turn increases the market competitiveness. Then, risk assessment may help designers to minimize the possibilities or possible consequences of critical system failures to provide a safe and reliable product design. The greatest benefit is realized from risk assessment when it is done early in the design phase and tracks product changes as they evolve; design changes can then be made more economically than if the problems are discovered after the design is complete.

Design Failure Mode Effects Analysis (DFMEA) is a widely used risk assessment tool to identify the potential failure modes of a product. DFMEA is the application of the Failure Mode and Effects Analysis (FMEA) method specifically to product design. FMEA was first developed as a formal design methodology in the 1960s by the automotive and machine industries, with their obvious reliability and safety requirements. FMEA objectives included understanding criticalities and dependencies within any type of system. This knowledge facilitated the evaluation of design and process options for achieving the reliability and life cycle cost objectives. The American army began using FMEA in the 1970s and in 1974 produced the army standard, "MIL-STD-1629: procedures for performing a failure mode effects and criticality analysis." In 1980, there also was a second printing of MIL-STD-1629A. In 1990, the International Organization for Standardization (ISO) recommended the use of FMEA for design review in the ISO9000 series (Teoh & Case, 2005). Today, FMEA has been adopted in many places, such as the aerospace, military, automobile, electricity, mechanical, and semiconductor industries.

Among DFMEA's goals is to increase the robustness of a design by systematically listing its potential failure modes. It is used to ensure that all design failure modes have been considered and assessed with an aim of reduction and even elimination. Most current DFMEA methods use the Risk Priority Number (RPN) value to evaluate the risk of failure. In the conventional RPN method, three parameters – the severity of the failure (S), the probability of failure (O), and the probability of not detecting the failure (D) – are utilized to describe each failure mode by rating them on a numerical scale from 1 to 10. Three parameters, S, O, and D, are evaluated according ordinal scales of measure. The RPN value is obtained by finding the product of these three factors. Therefore, $\mathrm{RPN} = S \times O \times D$. Those failure modes and causes that have the highest scores should then be addressed through product redesign.

Many reports discuss RPN as a related subject, such as Sankar and Prabhu (2001), who proposed a modified approach for

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prioritization of failure modes in FMEA called risk priority rank. Their approach extended risk prioritization beyond the conventional RPN method. The ranks 1 through 1000 were used to represent the increasing risk of the 1000 possible *S-O-D* combinations. Bowles and Pelaez (1995) were the first to use fuzzy logic for directly working with linguistic terms in making criticality assessments. A great deal of works in the literature (Bowles & Pelaez, 1995; Pillay & Wang, 2003; Xu, Tang, Xie, Ho, & Zhu, 2002) have been carried out using fuzzy RPN methods. However, these studies and conventional RPN method lose some information which the experts provide the valued information, which may cause bias conclusion. In 2000, Herrera and Martinez proposed the 2-tuple fuzzy linguistic representation model, which allows one to make processes of computing with words without loss of information. This model is based on the concept of symbolic translation. It represents linguistic information by means of linguistic 2-tuples and defines a set of functions to facilitate computational processes over 2-tuples.

Another important shortcoming of conventional RPN methods is that the three parameters S, O, and D are evaluated according to discrete ordinal scales of measure. But, they are treated as if the numerical operations on them, most notably multiplication, are meaningful. The results are not only meaningless but in fact misleading (Evie, 2008). Therefore, this paper used the Ordered Weighted Average (OWA) operator to resolve the problem of measurement scale. The concept of OWA operators was proposed by Yager (1988). It is a technique to get optimal weights of attributes based on the rank of these weighting vectors after processing aggregation. O'Hagan (1988) developed a procedure to generate OWA weights for given degree of *orness* α, to maximize entropy. Many related studies have been published in recent years. For example, Fuller and Majlender (2001) used Lagrange multipliers to derive a polynomial equation and then determine the optimal weighting vector by solving a constrained optimization problem. Chang, Cheng, and Chang (2008) used intuitionistic fuzzy set and OWA operators to evaluate the system reliability of an aircraft propulsion system.

In order to effectively resolve the above mentioned RPN evaluation problem, this paper proposed a novel technique, combining 2-tuple and OWA operator for prioritization of failures in DFMEA. For verification of the proposed approach, a numerical example of a 1.8-in. Color Super Twisted Nematic (CSTN) DFMEA is adopted in this paper. The result of the proposed method is compared with the conventional RPN and linguistic ordered weighted averaging operator (LOWA) methods.

The rest of this article is organized as follows. Section 2 reviews some research related to this paper – DFMEA, OWA operators, LOWA method, and the 2-tuple fuzzy linguistic representation method. Section 3 presents the proposed approach, which combines the 2-tuple and the OWA operator method for DFMEA. A numerical example of a 1.8-in. CSTN is adopted, and some comparisons with the listed approaches are discussed in Section 4. The final section makes conclusions.

2. Related works

2.1. DFMEA

DFMEA, as a formal design methodology, was first proposed by NASA in 1963 for their obvious reliability requirements. In 1977, it was adopted and promoted by Ford Motor Company. The main objective of DFMEA is to discover and correct the potential failure problems during the stages of design and production. Each failure mode is assessed in three parameters, namely, severity, likelihood of occurrence, and difficulty of detection of the failure mode. A typical evaluation system gives a number between 1 and 10 (with 1 being the best and 10 being the worst) for each of the three parameters. By multiplying the values for severity (S), occurrence (O), and detectability (D), the team obtains a Risk Priority Number (RPN), which is $\text{RPN} = S \times O \times D$. These risk priority numbers help the team to identify the parts or processes that need priority actions for improvement. Tables 1–3 list the scales that are used to measure the three factors (Ford Motor Company, 1988). Failure modes with higher RPN values are assumed to be more important and are given higher priorities than those with lower RPN values.

The conventional RPN method has been widely adopted in safety analysis; however, it has three main shortcomings, as follows: (1) there is a problem of the measurement scale; (2) severity, occurrence, and detection are not considered to be weighted with respect to one another in terms of risk; (3) loses some information which the experts provide to have the valued information.

2.1.1. Problem of the measurement scale

Bowles's paper (2003) indicates that ordinal measurement scales frequently are used. But the operations of multiplication and division are not meaningful for ordinal numbers, and addition and subtraction, while sometimes meaningful, must be done care-

Table 2
Suggested evaluation criteria and ranking system for the occurrence of failure in a design FMEA (Ford Motor Company, 1988).

Probability of failure	Possible failure rates	Rank
Extremely high: Failure almost inevitable	≧ in 2	10
Very high	1 in 3	9
Repeated failures	1 in 8	8
High	1 in 20	7
Moderately high	1 in 80	6
Moderate	1 in 400	5
Relatively low	1 in 2000	4
Low	1 in 15,000	3
Remote	1 in 150,000	2
Nearly impossible	≦ 1 in 1,500,000	1

Table 1
Suggested evaluation criteria and ranking system for the severity of effects for a design FMEA (Ford Motor Company, 1988).

Effect	Criteria: severity of effect	Rank
Hazardous	Failure is hazardous, and occurs without warning. It suspends operation of the system and/or involves noncompliance with government regulations	10
Serious	Failure involves hazardous outcomes and/or noncompliance with government regulations or standards	9
Extreme	Product is inoperable with loss of primary function. The system is inoperable	8
Major	Product performance is severely affected but functions. The system may not operate	7
Significant	Product performance is degraded. Comfort or convince functions may not operate	6
Moderate	Moderate effect on product performance. The product requires repair	5
Low	Small effect on product performance. The product does not require repair	4
Minor	Minor effect on product or system performance	3
Very minor	Very minor effect on product or system performance	2
None	No effect	1

Table 3
Suggested evaluation criteria and ranking system for the detection of a cause of failure or failure mode in a design FMEA (Ford Motor Company, 1988).

Detection	Criteria: likelihood of detection by design control	Rank
Absolute uncertainty	Design control does not detect a potential cause of failure or subsequent failure mode; or there is no design control	10
Very remote	Very remote chance the design control will detect a potential cause of failure or subsequent failure mode	9
Remote	Remote chance the design control will detect a potential cause of failure or subsequent failure mode	8
Very low	Very low chance the design control will detect a potential cause of failure or subsequent failure mode	7
Low	Low chance the design control will detect a potential cause of failure or subsequent failure mode	6
Moderate	Moderate chance the design control will detect a potential cause of failure or subsequent failure mode	5
Moderately high	Moderately high chance the design control will detect a potential cause of failure or subsequent failure mode	4
High	High chance the design control will detect a potential cause of failure or subsequent failure mode	3
Very high	Very high chance the design control will detect a potential cause of failure or subsequent failure mode	2
Almost certain	Design control will almost certainty detect a potential cause of failure or subsequent failure mode	1

fully because they assume an equal interval between the category labels.

The fundamental problem of the conventional RPN method is that the three parameters S, O, and D are evaluated according to discrete ordinal scales of measure. But they are treated as if numerical operations on them, most notably multiplication, are meaningful. The results are not only meaningless but in fact misleading.

2.1.2. Severity, occurrence, and detection are not weighted with respect to one another in terms of risk

As a result, some (S, O, D) scenarios produce RPN values that are lower than other combinations but potentially dangerous. For example, the scenario (extreme severity, moderately high occurrence, very high detection) with an RPN of 96 ($8 \times 6 \times 2$) is lower than the scenario (extreme severity, moderate occurrence, high detection), with an RPN of 120 ($8 \times 5 \times 3$), even though it should have a higher priority for a corrective action.

2.1.3. Loses some information which the experts provide to have the valued information

In the conventional DFMEA method, for each failure mode, experts point out the severity of the failure (S), the probability of failure (O), and the probability of not detecting the failure (D) individually to establish the corresponding RPN value. However, it has a serious drawback: the "loss of information," which implies a lack of precision in the final results. For example, suppose that there are four experts to point out the s of the two failure modes. Failure mode 1 has an s value of 5 (each expert pointed out value are 5, 5, 4, and 4, respectively), and failure mode 2 has an s value of 5 (each expert pointed out value are 5, 6, 5, and 5, respectively); thus, they have the same s value of 5 for the 2 failure modes. However, in practice, failure mode 2 is more serious than failure mode 1. The result of the conventional RPN method is that it will loses some information, which the experts provide to have the valued information, which may cause biased conclusions.

2.2. OWA operators

2.2.1. Basic concept

The concept of OWA operators was first introduced by Yager in 1988. It is an important aggregation operator within the class of weighted aggregation methods. The OWA operator has the ability to get optimal weights of the attributes based on the rank of these weighting vectors after an aggregation process (see Definition 1).

Definition 1. An OWA operator of dimension n is a mapping $F: R^n \rightarrow R$, which has an associated n weighting vector $W = [w_1, w_2, \ldots, w_n]^T$ that has the properties

$$\sum_i w_i = 1, \quad \forall w_i \in [0,1], \quad i = 1, \ldots, n,$$

such that

$$f(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i b_i \tag{1}$$

where b_i is the ith largest element of the collection of the aggregated objects $a_1, a_2, \ldots, a_n$. The function value $f(a_1, a_2, \ldots, a_n)$ determines the aggregated value of arguments, $a_1, a_2, \ldots, a_n$.

A number of special cases of this operator are illustrated in the following instances. If the components in W are such that $w_1 = 1$ and $w_j = 0$ for all $j \neq 1$, we get $\text{OWA}(a_1, a_2, \ldots, a_n) = \text{Max}_j[a_j]$. This weighting vector is denoted as W^*. If the weights are $w_n = 1$ and $w_j = 0$ for $j \neq n$, one gets $\text{OWA}(a_1, a_2, \ldots, a_n) = \text{Min}_j[a_j]$. This weighting vector is denoted as W_*. If the weights are $w_j = \frac{1}{n}$ for all j, denoted as W_n, then $\text{OWA}(a_1, a_2, \ldots, a_n) = (\frac{1}{n})\sum_{j=1}^{n} a_j$.

Yager (1988) also introduced two important characterising measures with respect to the weighting vector W of an OWA operator. One of these two measures is *orness* of the aggregation, which is defined as follows.

Definition 2. Assume F is an OWA aggregation operator with weighting function $W = [w_1, w_2, \ldots, w_n]$. The degree of "*orness*" associated with this operator is defined as

$$orness(W) = \frac{1}{n-1} \sum_{i=1}^{n} (n-i) w_i \tag{2}$$

where $orness(W) = \alpha$ is a situation parameter.

It is clear that $orness(W) \in [0, 1]$ holds for any weighting vector.

The second characterising measure introduced by Yager (1988) is a measure of *dispersion* of the aggregation, which is defined in Definition 3.

Definition 3. Let W be a weighting vector with elements $w_1 \cdots w_n$. The measure of *dispersion* of W is defined as

$$dispersion(W) = -\sum_{i=1}^{n} w_i \ln w_i \tag{3}$$

The dispersion measure of W takes into account all of the information in the aggregation. It is really a measure of entropy, which implies the following properties:

(1) If $w_i = 1$ for some i, then the $dispersion(W) = 0$, a minimum value.
(2) If $w_i = \frac{1}{n}$ for all i, then the $dispersion(W) = \ln n$, a maximum value.

O'Hagan (1988) combined the principle of maximum entropy and OWA operators to propose a particular OWA weight that has maximum entropy with a given level of *orness*. This approach is based on the solution of the following mathematical programming problem:

$$\text{Maximize}: -\sum_{i=1}^{n} w_i \ln w_i$$
$$\text{Subject to}: \frac{1}{n-1}\sum_{i=1}^{n}(n-i)w_i = \alpha, \quad 0 \leqslant \alpha \leqslant 1, \qquad (4)$$
$$\sum_{i=1}^{n} w_i = 1, \quad 0 \leqslant w_i \leqslant 1, \quad i = 1,\ldots,n.$$

2.2.2. Determination of OWA weights

Fuller and Majlender (2001) used the method of Lagrange multipliers to transfer Yager's OWA equation to derive a polynomial equation, which can determine the optimal weighting vector under maximal entropy. By their method, the associated weighting vector is obtained by Eqs. (5)–(7).

$$\ln w_j = \frac{j-1}{n-1}\ln w_n + \frac{n-j}{n-1}\ln w_1 \quad \Rightarrow w_j = \sqrt[n-1]{w_1^{n-j} w_n^{j-1}} \qquad (5)$$

$$\text{and } w_n = \frac{((n-1)\alpha - n)w_1 + 1}{(n-1)\alpha + 1 - nw_1} \qquad (6)$$

then

$$w_1[(n-1)\alpha + 1 - nw_1]^n = ((n-1)\alpha)^{n-1}\cdot[((n-1)\alpha - n)w_1 + 1] \qquad (7)$$

where w is weight vector, n is the number of attributes, and α is the situation parameter.

The optimal value of w_1 should satisfy Eq. (7). Once w_1 is obtained, then w_n can be determined from Eq. (6), and the other weights are obtained from Eq. (5). In a special case, when $w_1 = w_2 = \cdots = w_n = \frac{1}{n}$, then $dispersion(W) = \ln n$, which is the optimal solution to Eq. (4) when $\alpha = 0.5$.

2.3. The LOWA method

The linguistic ordered weighted averaging operator (LOWA) is based on the ordered weighted averaging (OWA) operator defined by Yager (1988) and the convex combination of linguistic labels defined by Delgado et al. (2002).

Let $\{a_1, a_2, \ldots, a_m\}$ be a set of labels to aggregate; then the LOWA operator ϕ is defined as (Herrea, Herrera-Viedma, & Verdegay, 1996)

$$\phi(a_1, a_2, \ldots, a_m) = W\cdot B^T = C^m\{w_k, b_k, k = 1,\ldots,m\}$$
$$= w_1 \otimes b_1 \oplus \left((1-w_1)\otimes C^{m-1}\{\beta_h, b_h, h = 2,\ldots,m\right) \qquad (8)$$

where $W = [w_1, w_2, \ldots, w_m]$ is a weighting vector, such that $w_i \in [0,1]$ and $\sum_i w_i = 1$; $\beta_h = w_h/\sum_2^m w_k, h = 2,3,\ldots,m$, and B is the associated ordered label vector. Each element $b_i \in B$ is the ith largest label in the collection $a_1, a_2, \ldots, a_m$. $\otimes$ and $\oplus$ are the product of a number by a label and the addition of two labels, respectively. C^m is the convex combination operator of m labels, and if m = 2, then it is defined as

$$C^2\{w_i, b_i, i = 1,2\} = w_1 \otimes s_j \oplus (1-w_1)\otimes s_i = s_k,$$
$$s_j, s_i \in S, \quad (j \geqslant i) \qquad (9)$$

such that

$$k = \min\{T, i + \text{round}(w_1\cdot(j-i))\}, \qquad (10)$$

where round$(\cdot)$ is the usual round operation, and $b_1 = s_j, b_2 = s_i$.

If $w_j = 1$ and $w_i = 0$ with $i \neq j \quad \forall i$, then the convex combination is defined as:

$$C^m\{w_i, b_i, i = 1,2,\ldots,m\} = b_j.$$

2.4. The 2-tuple fuzzy linguistic representation method

The 2-tuple linguistic variable is formed by combining the 2-tuple linguistic variable (s_i, α) (Herrea & Martinez, 2000a, 2000b), where the semantic element s_i is assessed by the linguistic variable s defined in the linguistic term set $S = \{s_0, s_1, \ldots, s_g\}$ and $i \in [0, g]$.

Definition 4. (Delgado et al., 2002; Herrea & Martinez, 2000a, 2000b): Let β be the result of an aggregation of the indexes of a set of labels assessed in a linguistic term set s; i.e., the result of a symbolic aggregation operation. $\beta \in [0, g]$, and g+1 is the cardinality of s. Let $i = \text{round}\ (\beta)$ and $\alpha = \beta - i$ be 2 values such that $i \in [0, g]$ and $\alpha \in [(-0.5, 0.5)]$; then α is called a symbolic translation.

Definition 5. (Delgado et al., 2002; Herrea & Martinez, 2000a, 2000b): Let $S = \{s_0, s_1, \ldots, s_g\}$ be a linguistic term set and $\beta \in [0, g]$ be a value representing the result of a symbolic aggregation operation; then, the 2-tuple that expresses the equivalent information to β is obtained with the following function:

$$\Delta : [0, g] \to S \times [-0.5, 0.5) \qquad (11)$$

$$\Delta(\beta) = (s_i, \alpha), \text{with}\begin{cases} s_i, & i = \text{round}\ (\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases} \qquad (12)$$

where round $(\cdot)$ is the usual round operation, s_i has the closest index label to "β," and " α " is the value of the symbolic translation.

Definition 6. (Delgado et al., 2002; Herrea & Martinez, 2000a, 2000b): Let $x = \{(r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)\}$ be a set of 2-tuples; the 2-tuple arithmetic mean $\bar{x}^e$ is computed as,

$$\bar{x}^e = \Delta\left(\sum_{i=1}^{n}\frac{1}{n}\Delta^{-1}(r_i, \alpha_i)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right) \qquad (13)$$

The arithmetic mean for 2-tuples allows us to compute the mean of a set of linguistic values without any loss of information.

Definition 7. (Martinez, 2007): Let $A = \{(r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)\}$ be a set of 2-tuples and $W = (w_1, w_2, \ldots, w_n)$ be an associated weighting vector that satisfies (i) $w_i \in [0,1]$ and (ii) $\sum w_i = 1$. The 2-tuple OWA operator F^e for linguistic 2-tuples is computed as

$$F^e((r_1, \alpha_1), (r_2, \alpha_2), \ldots, (r_n, \alpha_n)) = \Delta\left(\sum_{j=1}^{n} w_j\cdot\beta_j^*\right), \qquad (14)$$

where β_j^* is the jth largest of the β_i values.

The comparison of linguistic information represented by 2-tuples is carried out according to an ordinary lexicographic order. Let (s_k, α_1) and (s_l, α_2) be 2 2-tuples, with each one representing a linguistic assessment:

- if $k < l$ then (s_k, α_1) is smaller than (s_l, α_2)
- if $k = l$ then

(1) if $\alpha_1 = \alpha_2$ then (s_k, α_1), (s_l, α_2) represents the same information,
(2) if $\alpha_1 < \alpha_2$ then (s_k, α_1) is smaller than (s_l, α_2),
(3) if $\alpha_1 > \alpha_2$ then (s_k, α_1) is bigger than (s_l, α_2).

3. Proposed combination of 2-tuple and the OWA operator approach

DFMEA is used in the manufacturing industry to improve product quality and productivity. Most current DFMEA methods use the RPN value to evaluate the risk of failure. However, the traditional approach has many shortcomings that affect its effectiveness and limit its usefulness, especially in the early stages of design. The conventional RPN method, as summarized in the Section 2.1, has three main shortcomings: (1) there is a problem with the measurement scale; (2) severity, occurrence, and detection are not weighted with respect to one another in terms of risk; and (3) it loses some information which the experts provide to have the valued information. Therefore, to overcome the above mentioned shortcomings, a novel approach using 2-tuple and the OWA operator method to evaluate the orderings of risk for failure problems is proposed in this section.

3.1. The reason for using 2-tuple and the OWA operator

The result of the conventional RPN method will loses some information which the experts provide to have the valued information, which may cause bias conclusion. For example, suppose that there are four experts to point out the severity of the failure (S) of the two failure modes. Failure mode 1 has an s value of 5 (each expert pointed out value are 5, 5, 4, and 4, respectively), and failure mode 2 has an s value of 5 (each expert pointed out value are 5, 6, 5, and 5, respectively). According to the conventional RPN method, they have the same s value of 5 in the two failure modes. However, in practice, failure mode 2 is more serious than failure mode 1. The 2-tuple method may effectively solve this problem. In the 2-tuple method, failure mode 1 has the s value $(5, -0.5)$, and failure mode 2 has the s value $(5, 0.25)$. In this way, the experts provide all information that can be considered so that they cannot lose any useful information.

Most of the literature that confers on RPN-related issues and the conventional RPN method does not consider the ordered weight, which may cause biased conclusions. The ordered weight is one of the most important factors in evaluating the risk of failure. For example, there are two failure modes: one (referred to as scenario 1) has an RPN value of 120 (S, O, and D are 5, 6, and 4, respectively), and the other one (referred to as scenario 2) has an RPN value of 105 (S, O, and D are 5, 7 and 3, respectively). In this example, it is found that s is 5 in both scenarios 1 and 2. In scenario 1, the value of D is higher than scenario 2's. In scenario 2, the value O is higher than scenario 1's. For any decision-maker, he should give higher allocation resources to defend the most dangerous scenario. He would choose the highest value of 7 in scenario 2 as a higher priority. According to the conventional RPN method, scenario 1 (RPN = 120) is assumed to be more important than scenario 2 (RPN = 105) and is given a higher priority. However, in practice, scenario 2 is more important than scenario 1.

3.2. The procedure of the proposed approach

This paper proposes seven steps in order to implement risk assessment on a 1.8-in. CSTN failure diagnosis. The following steps also are the basis of a model for combining the 2-tuple and the OWA operator approach for risk assessment.

Step 1. List potential failure modes.
Based on historical data and past experiences, list the potential failure modes of each risk assessment member of the whole system.

Step 2. List potential effects of failure modes.
Discover how systems fail and what causes each type of failure. Arrange failure mode contents in the DFMEA table. List the reasons of failure mode occurrence.

Table 4
The DFMEA of 1.8-in. CSTN.

No.	Process description	Potential failure mode	Potential failure effect	Potential failure cause	Existing process control
1	Dimension design	Incorrect mechanical design	Parts interfere each other when the module assembly	Incorrect parts design due to the dimensions	Design the module by using 3D software
2	Assembly the display	Incorrect mechanical design	Difficult to assembly the display	Lower yield rate for the assembly	Set up the design rule for different component parts
3	Flex	Low yield ratio	Supplier can not submit the quantity	It is small for the trace line and close to the edge for the pad.	Use the precision mold to cut the outline
4	Flex	It is short of Nonadhesive copper in the further	Supplier can not submit the quantity	The material is specifically	Used general material
5	Lightguide performance	Poor lightguide performance	Low or Uneven Luminance	Poor lightguide pattern design	Lightguide pattern simulation before tool-making
6	Lightguide performance	Poor Lightguide performance	Low or Uneven Luminance	Incorrect structure design OD the area for light through to lightguide	Confirm the performance again after having the lightguide sample
7	Flex Assembly	Performance of display no good	Poor brightness	Light Bar leaves Holder	Uses adhesive and bezel to fix the light bar
8	Interface design of module	Display mirror	LCD Display NG	IC pad design mirror	Doublecheck drawing
9	LCM Audible noise	LCM will have regular noise occur	Makes the user feel uncomfortable	Improper IC software setting	Using those ICs that have been qualified
10	LCM Audible noise	LCM will have regular noise occur	Makes the user feel uncomfortable	Mechanical design can not isolate from noise	Mechanical design must consider the "Echo" effect.
11	Cross talk	Poor performance	Black line and white line on the panel	ITO impedance too high	Removal and first inspection
12	Cross talk	Poor performance	Black line and white line on the panel	Vth can't meet IC Vop	Inspection of the electric station of LCD
13	Cross talk	Poor performance	Black line and white line on the panel	Bias label tolerance too large.	Control current of module for the IC
14	Contrast Ratio	Poor performance	Selected driving conditions not sufficient to drive LCD to optimal display conditions	LCD driving voltage too high	Product engineer calculates correct driving voltage based on the driving conditions provided by the customer.
15	Background color	Uneven background color	Uneven LCD background color (under lit up backlight conditions)	Uneven cell gap	Use bonding seal application for negative and STN products
16	Background color	Uneven background color	Uneven LCD background color (under lit up backlight conditions)	Uneven cell gap	Full electrical testing

Fig. 1. 1.8-in. CSTN.

Table 5
The S, O, and D of the possible range of failures.

No.	S				O				D			
	P1	P2	P3	P4	P1	P2	P3	P4	P1	P2	P3	P4
1	6	7	6	4	3	3	3	4	2	3	5	3
2	5	5	5	4	2	3	3	4	2	3	3	5
3	6	5	6	7	4	5	4	4	2	3	1	1
4	5	5	4	5	4	6	5	5	3	2	3	4
5	5	7	4	5	2	4	4	3	3	3	1	2
6	5	7	4	5	3	3	2	2	4	3	4	2
7	6	4	7	6	2	2	1	2	2	3	2	1
8	7	8	8	9	2	2	2	1	2	2	2	3
9	5	6	4	5	5	5	4	5	2	1	1	2
10	4	5	6	6	7	6	4	6	4	5	6	6
11	5	7	6	5	2	3	3	3	3	4	2	4
12	6	7	6	5	4	4	4	4	3	4	2	4
13	6	7	6	6	2	3	2	3	5	5	6	5
14	7	5	4	5	4	3	3	3	2	3	4	2
15	5	6	5	5	4	6	3	4	1	2	1	1
16	6	3	5	4	5	4	3	3	4	3	3	3

Step 3. Define the scales for S, O, and D, respectively.
For each failure mode, experts point out the severity of the failure (S), the probability of failure (O), and the probability of not detecting the failure (D) individually to establish the corresponding linguistic value.

Step 4. Calculate the OWA weights.
From Section 2.2.2, use Eqs. (5)–(7) to calculate the OWA weights.

Step 5. Calculate aggregated value by OWA weights.
In this step, the experts must decide prerequisite situation parameter (α). According the Step 3 and Step 4, use Eq. (1) to calculate the aggregated value by OWA weights.

Step 6. Rank the priority for assessing failure risk.
According to the aggregated values by OWA weights from the largest to the smallest, which takes cause of failure out of the risk prioritization ranking.

Step 7. Analyze the results and provide suggestions.
From Step 6, the results can be further analyzed to provide the decision-maker with feasible solutions.

4. Case study: 1.8-in. CSTN

In recent years, the market for the new portable electronic products has grown explosively. In these applications – e.g., mobile phones, PDAs, MP3 players, and other consumer electronics – liquid crystal display (LCD) technologies have played an important role owing to the requirements of light weight, small size, low power, and durable reliability. Basically, there are two main streams in LCD technologies. They are Color Super Twisted Nematic (CSTN) LCD and Thin Film Transistor (TFT) LCD. TFT LCD provides more vivid colors and sharper images. However, they are expensive, due to low fabrication yield due to the large panel size. On the counterpart, CSTN LCDs are more cost-attractive due to the much simpler process in manufacturing. Thus, for the cost concern, CSTN LCD has been more favored.

In this section, this research uses a real case of a 1.8-in. CSTN in order to demonstrate the procedure proposed in this paper. The CSTN has a lower cost than TFT LCD. It has major applications in mobile phones and MP3/MP4. The DFMEA of this CSTN is shown in Table 4 and case data from a midsized manufacturing factory located in Gueishan Industrial Park in Taiwan. The figure of the 1.8-in. CSTN product is shown in Fig. 1. This DFMEA team has four experts; the S, O, and D of the possible range of the failures are defined and organized in Table 5.

4.1. Solution based on the conventional RPN method (Ford Motor Company, 1988)

The conventional RPN method is a risk assessment based on the severity, frequency of occurrence, and detection of an item failure on a numerical scale from 1 to 10. These rankings are then multiplied to give the RPN. Failure modes having a high RPN are assumed to be more important and given a higher priority than

Table 6
The RPN of the 1.8-in. CSTN.

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
S	6	5	6	5	5	5	6	8	5	5	6	6	6	5	5	5
O	3	3	4	5	3	3	2	2	5	6	3	4	3	3	4	4
D	3	3	2	3	2	3	2	2	2	5	3	3	5	3	1	3
RPN	54	45	48	75	30	45	24	32	50	150	54	72	90	45	20	60

Table 7
The collective values of the 1.8-in. CSTN by the LOWA method.

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
S	s_6	s_5	s_6	s_5	s_5	s_5	s_6	s_8	s_5	s_5	s_6	s_6	s_6	s_5	s_5	s_5
O	s_3	s_3	s_4	s_5	s_3	s_3	s_2	s_2	s_5	s_6	s_3	s_4	s_3	s_3	s_4	s_4
D	s_3	s_3	s_2	s_3	s_2	s_3	s_2	s_2	s_2	s_5	s_3	s_3	s_5	s_3	s_1	s_3
LOWA	s_5	s_4	s_5	s_5	s_4	s_4	s_5	s_6	s_5	s_6	s_5	s_5	s_5	s_4	s_4	s_5

those having a lower RPN. The RPN of the 1.8-in. CSTN is shown in Table 6.

4.2. Solution based on the LOWA method (Delgado et al., 2002; Yager, 1988)

The linguistic ordered weighted averaging operator (LOWA) is based on the OWA operator defined by Yager (1988) and on the convex combination of linguistic labels defined by Delgado et al. (2002). The method offers a computationally feasible method for aggregating linguistic information of the corresponding linguistic labels. The collective values of the 1.8-in. CSTN by the LOWA method is shown in Table 7.

This part uses No. 1, whose severity rank is s 6 in this example; the calculation flow is as follows:

$$C^4\{w_k, b_k, k = 1, \ldots, 4\} = C^4\{(w_1, b_1), (w_2, b_2), (w_3, b_3), (w_4, b_4)\}$$
$$= (0.25 \otimes s_7) \oplus (1 - 0.25) \otimes C^3\left\{\left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_4\right)\right\}$$
$$C^3\left\{\left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_4\right)\right\}$$
$$= \left(\frac{1}{3} \otimes s_6\right) \oplus \left(1 - \frac{1}{3}\right) \otimes C^2\left\{\left(\frac{1}{2}, s_6\right), \left(\frac{1}{2}, s_4\right)\right\}$$
$$C^2\left\{\left(\frac{1}{2}, s_6\right), \left(\frac{1}{2}, s_4\right)\right\}$$
$$= \left(\frac{1}{2} \otimes s_6\right) \oplus \left(1 - \frac{1}{2}\right) \otimes (s_4) = s_k$$
$$k = \min\{10, 4 + \mathrm{round}(0.25 \cdot (6 - 4))\}$$
$$= 5 \Rightarrow C^2\left\{\left(\frac{1}{2}, s_6\right), \left(\frac{1}{2}, s_4\right)\right\} = s_5$$
$$C^3\left\{\left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_4\right)\right\} = \left(\frac{1}{3} \otimes s_6\right) \oplus \left(\frac{2}{3} \otimes s_5\right)$$
$$k = \min\left\{10, 5 + \mathrm{round}\left(\frac{1}{3} \cdot (6 - 5)\right)\right\}$$
$$= 5 \Rightarrow C^3\left\{\left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_6\right), \left(\frac{1}{3}, s_4\right)\right\} = s_5$$
$$C^4\left\{\left(\frac{1}{4}, s_7\right), \left(\frac{1}{4}, s_6\right), \left(\frac{1}{4}, s_6\right), \left(\frac{1}{4}, s_4\right)\right\}$$
$$= (0.25 \otimes s_7) \oplus (0.75 \otimes s_5)$$
$$k = \min\left\{10, 5 + \mathrm{round}\left(\frac{1}{4} \cdot (7 - 5)\right)\right\}$$
$$= 6 \Rightarrow C^4\left\{\left(\frac{1}{4}, s_7\right), \left(\frac{1}{4}, s_6\right), \left(\frac{1}{4}, s_6\right), \left(\frac{1}{4}, s_4\right)\right\} = s_6$$

This part uses No., whose collective value rank is s 5 by the LOWA method in this example; the calculation flow is as follows:

In this example, the initial weighting vector is $[0.682, 0.236, 0.082](\alpha = 0.8)$.

$$F_Q(s_6, s_3, s_3) = W^* \cdot B^T = [0.682, 0.236, 0.082] \cdot [s_6, s_3, s_3]^T$$
$$= C^3\{(0.682, s_6), (0.236, s_3), (0.082, s_3)\}$$
$$= (0.682 \otimes s_6) \oplus (1 - 0.682) \otimes C^2\{(0.742, s_3), (0.258, s_3)\}$$
$$C^2\{(0.742, s_3), (0.258, s_3)\} = (0.742 \otimes s_3) \oplus (1 - 0.742) \otimes s_3 = s_k$$
$$k = \min\{10, 3 + \mathrm{round}(0.742 \cdot (3 - 3))\}$$
$$= 3 \Rightarrow C^2\{(0.742, s_3), (0.258, s_3)\} = s_3$$
$$C^3\{(0.682, s_6), (0.236, s_3), (0.082, s_3)\}$$
$$= (0.682 \otimes s_6) \oplus (1 - 0.682) \otimes s_3 = s_k$$
$$k = \min\{10, 3 + \mathrm{round}(0.682 \cdot (6 - 3))\}$$
$$= 5 \Rightarrow C^3\{(0.682, s_6), (0.236, s_3), (0.082, s_3)\} = s_5$$

4.3. Solution based on the proposed method

Fuzzy logic provides a tool for directly working with the linguistic terms used in making the risk assessment. The analysis uses linguistic variables to describe the severity, frequency of occurrence, and detection of the failure. The proposed method is applied to the 1.8-in. CSTN in this section. The results of the first 3 steps of the proposed method are shown in Table 4 (Steps 1 and 2) and in Table 5 (Step 3). The following procedure describes the rest of steps.

Step 4. *Calculate the OWA weights*
Sensitivity analysis enables the identification of different α values to evaluate their impact on the risk ranking. According to Eqs. (5)–(7), the optimal weighting vector under the maximal entropy for $n = 3$ is calculated and organized in Table 8.

Step 5. *Calculate aggregated value by OWA weights*
In this step, the experts must decide prerequisite situation parameter (α). According to integrated experts' knowledge and experience, the α value of the 1.8-in. CSTN is 0.8. Based on Table 5, Eqs. (8),(9),(10) and (13), the aggregate of the OWA value ($\alpha = 0.8$) of the 1.8-in. CSTN is calculated and shown in Table 9. The following example is made to further explain the calculating process.This part uses No. 1, whose collective value rank is ($s5, -0.045$), by the proposed method in this example; the calculation flow is as follows:In this example, the initial weighting vector is $[0.682, 0.236, 0.082](\alpha = 0.8)$.

$$\bar{x}^e = \Delta\left(\sum_{i=1}^{n} \frac{1}{n} \Delta^{-1}(r_i, \alpha_i)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n} \beta_i\right)$$
$$\bar{S}_1 = \frac{6+7+6+4}{4} = 5.75 \quad \Rightarrow \bar{x}^e_{S_1} = (s_6, -0.25)$$
$$F_Q(\Delta(5.75), \Delta(3.25), \Delta(3.25))$$
$$= W^* \cdot B^T = [0.682, 0.236, 0.082] \cdot [\Delta(5.75), \Delta(3.25), \Delta(3.25)]^T$$
$$= C^3\{(0.682, \Delta(5.75)), (0.236, \Delta(3.25)), (0.082, \Delta(3.25))\}$$
$$= (0.682 \otimes \Delta(5.75)) \oplus (1 - 0.682) \otimes C^2\{(0.742, \Delta(3.25)), (0.258, \Delta(3.25))\} C^2\{(0.742, \Delta(3.25)), (0.258, \Delta(3.25))\}$$
$$= (0.742 \otimes \Delta(3.25)) \oplus (1 - 0.742) \otimes \Delta(3.25) = \Delta(\theta)$$
$$\theta = \min\{10, 3.25 + \mathrm{round}(0.742 \cdot (3.25 - 3.25))\}$$
$$= 3.25 \Rightarrow C^2\{(0.742, \Delta(3.25)), (0.258, \Delta(3.25))\} = \Delta(3.25)$$
$$C^3\{(0.682, \Delta(5.75)), (0.236, \Delta(3.25)), (0.082, \Delta(3.25))\}$$
$$= (0.682 \otimes \Delta(5.75)) \oplus (1 - 0.682) \otimes \Delta(3.25) = \Delta(\theta)$$
$$\theta = \min\{10, 3.25 + \mathrm{round}(0.682 \cdot (5.75 - 3.25))\}$$
$$= 4.955 \Rightarrow C^3\{(0.682, \Delta(5.75)), (0.236, \Delta(3.25)), (0.082, \Delta(3.25))\} = \Delta(4.955)$$

Step 6. *Rank the priority for assessing failure risk*
From Table 9, the prioritization of the failure modes for the 1.8-in. CSTN by the proposed method is shown in Table 10.

Table 8
The optimal weighting vector under the maximal entropy ($n = 3$).

Alpha	w_1	w_2	w_3
0.5	0.333333	0.333333	0.333333
0.6	0.438355	0.323242	0.238392
0.7	0.553955	0.291992	0.153999
0.8	0.681854	0.235840	0.081892
0.9	0.826294	0.146973	0.026306
1	1	0	0

Table 9
The aggregate of the OWA value ($\alpha = 0.8$) of the 1.8-in. CSTN.

No.	*s*	*O*	*D*	Using 2-tuple and OWA
1	(s 6,−0.25)	(s 3,0.25)	(s 3,0.25)	(s 5,−0.045)
2	(s 5,−0.25)	(s 3,0)	(s 3,0.25)	(s 4,0.252)
3	(s 6,0)	(s 4,0.25)	(s 2,−0.25)	(s 5,0.238)
4	(s 5,−0.25)	(s 5,0)	(s 3,0)	(s 5,−0.223)
5	(s 5,0.25)	(s 3,0.25)	(s 2,0.25)	(s 5,−0.468)
6	(s 5,0.25)	(s 3,−0.5)	(s 3,0.25)	(s 5,−0.448)
7	(s 6,−0.25)	(s 2,−0.25)	(s 2,0)	(s 5,−0.463)
8	(s 8,0)	(s 2,−0.25)	(s 2,0.25)	(s 6,0.130)
9	(s 5,0)	(s 5,−0.25)	(s 2,−0.5)	(s 5,−0.346)
10	(s 5,0.25)	(s 6,−0.25)	(s 5,0.25)	(s 6,−0.409)
11	(s 6,−0.25)	(s 3,−0.25)	(s 3,0.25)	(s 5,−0.086)
12	(s 6,0)	(s 4,0)	(s 3,0.25)	(s 5,0.302)
13	(s 6, 0.25)	(s 3,−0.5)	(s 5,0.25)	(s 6,−0.294)
14	(s 5,0.25)	(s 3,0.25)	(s 3,−0.25)	(s 5,−0.427)
15	(s 5,0.25)	(s 4,0.25)	(s 1,0.25)	(s 5,−0.314)
16	(s 5,−0.5)	(s 4,−0.25)	(s 3,0.25)	(s 4,0.220)

4.4. Comparisons and discussion

In order to evaluate the proposed method, a case study verification is performed in Section 4, which compares the proposed approach (combining 2-tuple and the OWA operator method) with the conventional RPN method and LOWA method. The input data are shown in Tables 4 and 5. The results of the three methods are presented in Table 10. These three methods have their special attributes, respectively, and the main differences are shown in Table 11.

This paper has discovered the following findings. First, the problem of the measurement scale: The fundamental problem of the conventional RPN method is that the three parameters S, O, and D are evaluated according to discrete ordinal scales of measure. But they are treated as if the numerical operations performed on them, most notably multiplication, are meaningful. The results are not only meaningless but in fact misleading. The other two methods, LOWA and the proposed method, do not have the problem of measurement scale.

Second, the proposed approach achieves a more accurate risk ranking. Tables 6 and 10 clearly show that No. 1 has an RPN value of 54 (S, O, and D are 6, 3, and 3, respectively). No. 3 has an RPN value of 48 (S, O, and D are 6, 4, and 2, respectively). In this example, it is found that s is 6 for both No. 1 and No. 3. In No.1, the value of D is higher than No. 3. In No. 3, the value of O is higher than No. 1. For any decision-maker, he should give high allocation resources to defend the most dangerous scenario. He would choose the highest value of 4 in No. 3 as a higher priority. According to the conventional RPN method, No. 1 (RPN = 54) is assumed to be more important than No. 3 (RPN = 48) and is given a higher priority. That is because the conventional RPN method does not consider the ordered weight and obtains biased conclusions. In practice, No. 3 is more important than No. 1. The results of our proposed method show that No. 3 has a higher priority compared with No. 1. This shows that a more accurate ranking can be achieved by using the 2-tuple and the OWA operator method to evaluate the orders of risk for failure problems.

Table 11
The three methods' special attributes and main differences.

Method selection	Measurement scale	Complete information consideration	Order weight
Conventional RPN method	No	Partial	No
LOWA method	Yes	Partial	Yes
Proposed method	Yes	Yes	Yes

Third, loses some information which the experts provide to have the valued information. The conventional RPN method and LOWA method have the same serious drawback, the "loss of information," which implies a lack of precision in the final results. In this CSTN case, we can find that the severity of the failure (S) value of No. 4 and No. 5 have the same s value, 5 (based on the conventional RPN method), and the same collective value, s 5 (based on the LOWA method); thus, they have the same priority based on these 2 approaches. However, in practice, No. 5 is more serious than No. 4. In the proposed method, use the 2-tuple linguistic variable (s_i, α) to represent the collective value of s. The No. 4 collective value is $(5, -0.25)$ and the No. 5 collective value is $(5, 0.25)$ for s. The results show that the proposed method is without loss of information, which the experts provide to have valued information.

Fourth: verify performance of the proposed method. In order to verify the performance of the proposed method, this research has gathered domain experts to check the results of the ranking orders of risk for failure. According to the domain experts, they indicate that this proposed method, which ranks the orders of risk for failure in the 1.8-in. CSTN, is reasonable in real-world situations. As a result, the stability of the product and process can be assured.

5. Conclusion

This paper proposed a novel technique to assess the risk of the CSTN. It is useful when conducting DFMEA using 2-tuple and the OWA operator approach to assess the risk of potential failure

Table 10
The ranking comparison of the conventional RPN method, LOWA method, and the proposed method.

No.	RPN	LOWA	Using 2-tuple and OWA	Ranking RPN	Ranking LOWA	Ranking using 2-tupe and OWA
1	54	s 5	(s 5,−0.045)	6	3	6
2	45	s 4	(s 4,0.252)	10	12	15
3	48	s 5	(s 5,0.238)	9	3	5
4	75	s 5	(s 5,−0.223)	3	3	8
5	30	s 4	(s 5,−0.468)	14	12	14
6	45	s 4	(s 5,−0.448)	10	12	12
7	24	s 5	(s 5,−0.463)	15	3	13
8	32	s 6	(s 6,0.130)	13	1	1
9	50	s 5	(s 5,−0.346)	8	3	10
10	150	s 6	(s 6,−0.409)	1	1	3
11	54	s 5	(s 5,−0.086)	6	3	7
12	72	s 5	(s 5,0.302)	4	3	4
13	90	s 5	(s 6,−0.294)	2	3	2
14	45	s 4	(s 5,−0.427)	10	12	11
15	20	s 4	(s 5,−0.314)	16	12	9
16	60	s 5	(s 4,0.220)	5	3	16

modes. This approach provides a more flexible structure for combining severity, occurrence, and detection parameters. In order to further illustrate the proposed method and compare it with the listing techniques of RPN methods, a CSTN example is adopted. This study also compared the results with the conventional RPN (Ford Motor Company, 1988) and LOWA (Delgado et al., 2002; Yager, 1988) methods. The results showed that the proposed approach can effectively solve conventional RPN method shortcomings. It is without loss of information, which the experts provide to have valued information. Moreover, the results obtained by the proposed method provide a more accurate and reasonable risk ranking for helping decision-makers find the most critical causes of failure and assign limited resources to the most serious risk items. Furthermore, the presented approach can be helpful for solving risk assessment problems in the product design phase.

The advantages of the proposed approach are summarized as follows.

(1) The proposed method can solve the problem of the measurement scale of conventional RPN methodology.
(2) The proposed method considers the ordered weight of severity, occurrence, and detection parameters.
(3) The proposed method without loses some information which the experts provide to have the valued information.
(4) The proposed method provides more accurate and effective information to assist the decision-making process.

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