Chapter 10

On the Use of Fuzzy Inference Systems for Assessment and Decision Making Problems

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Abstract. The Fuzzy Inference System (FIS) is a popular paradigm for undertaking assessment/measurement and decision problems. In practical applications, it is important to ensure the monotonicity property between the attributes (inputs) and the measuring index (output) of an FIS-based assessment/measurement model. In this chapter, the sufficient conditions for an FIS-based model to satisfy the monotonicity property are first investigated. Then, an FIS-based Risk Priority Number (RPN) model for Failure Mode and Effect Analysis (FMEA) is examined. Specifically, an FMEA framework with a monotonicity-preserving FIS-based RPN model that fulfils the sufficient conditions is proposed. A case study pertaining to the use of the proposed FMEA framework in the semiconductor industry is presented. The results obtained are discussed and analyzed.

Keywords: Fuzzy inference system, monotonicity property, sufficient conditions, failure mode and effect analysis, risk priority number.

1 Introduction

In a Fuzzy Inference System (FIS)-based assessment/measurement model, an attribute(s) is the input(s) of the FIS, and a measuring index is the output of the FIS. The relationship between the attribute(s) and the measuring index is described by a set of fuzzy If-Then rules. The use of the FIS model in assessment/measurement applications is popular in the literature. Examples include an FIS-based Risk Priority Number (RPN) model [1] for Failure Mode and Effect Analysis (FMEA), an FIS-based Occurrence model [2] for FMEA, an FIS-based education assessment model [3], an FIS-based groundwater vulnerability assessment model [4], and various FIS-based risk assessment models [5-7]. There are several reasons why an FIS-based model, instead of the conventional assessment models, is preferred. These include (i) the FIS model allows the modeling of the nonlinear relationship between the measure index and the attributes [1, 4]; (ii) the FIS model is robust against uncertainty and vagueness [5-8]; (iii) the attributes can assume a qualitative, instead of quantitative, scale [1,3,5]. Various methods to improve the

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FIS-based assessment/measurement paradigm, either in general or specific applications, have been proposed. Some recent advances include the hierarchical or multi-layer FIS-based assessment models [9, 10], the FIS model with the grey relation theory [11], the monotonicity-relating properties of the FIS model [2, 9], the FIS-based assessment model with a learning procedure [8].

In this chapter, the monotonicity property of the FIS-based RPN model for FMEA is investigated. The monotonicity property of the FIS-based assessment/measurement paradigm has been explained in various cases. The importance of the monotonicity property in assessment and decision making problems, e.g., the assessment of sustainable development and measurement of material recyclability, has been described as the *natural requirement* in [9]. It is also possible to explain the importance of the monotonicity property from the theoretical aspect of the *length function* in the field of measure theory [12]. A valid comparison and/or ranking (which eventually leads to decision making) scheme among different objects/ situations based on the predicted measuring index is important [2, 13]. When tackling an assessment problem with an FIS-based model, the monotonicity property has to be satisfied so that meaningful results are obtained for decision making. For example, in the fuzzy RPN model, the monotonicity property ensures that the risks among different failure modes to be compared and ranked in a logical manner using the fuzzy RPN scores [2, 13, 14]. In [3], the significance of monotonicity in education assessment models is stressed, and the failure to fulfil monotonicity is considered as an anomaly.

The main aim of this work is to develop a simple (which can be easily understood by domain users), easy-to-use, and yet reliable procedure to preserve the monotonicity property of an FIS-based assessment and decision making model. In particular, the *sufficient conditions* for an FIS-based model to be monotone [2, 9, 13, 15] are examined. In the derivation, an FIS is treated as a function, and the *sufficient conditions* are the mathematical conditions such that the first derivative is always *greater than or equal to* or *less than or equal to* zero for a monotonic-increasing or decreasing FIS, respectively. From the derivation, two results are produced. First, at the antecedent part, a method to tune the membership function is obtained; second, at the consequence part, a monotonic rule base is required. In this work, these two conditions are applied directly to an FIS-based assessment and decision making model as a solution to preserve the monotonicity property.

FMEA is an effective problem prevention methodology that can be interfaced with many engineering and reliability approaches [16]. It is a systemized group of activities intended to recognize and to evaluate the potential failures of a product/process and the associated effects [17]. FMEA identifies actions which can reduce or eliminate the chances of the potential failures from recurring. It also helps users to identify the key design or process characteristics that require special controls for manufacturing, and to highlight areas for improvement [17]. Conventional FMEA uses an RPN to evaluate the risk associated with each failure mode. An RPN is a product of three risk factors, i.e., Severity (S), Occurrence (O), and Detect (D). FMEA assumes that multiple failure modes exist, and each failure mode has a different risk level that has to be evaluated, and ranked. In general, each S, O, or D value is an integer between 1 and 10, and is defined based on a scale table. The conventional RPN model can be replaced by an FIS-based assessment model [1, 2, 8, 13, 14]. The FIS-based RPN model allows the relationship between the RPN score and the three risk factors (S, O, and D) to be non-linear, which is too complicated to be modeled by the simple conventional RPN model. The FIS-based RPN model has been successfully applied to a number of FMEA problems. Examples include an auxiliary feed water system and a chemical volume control system in a nuclear power plant [18, 19], an engine system [20], a semiconductor manufacturing line [21], and a fishing vessel [22].

The objective of this work is to propose an FMEA framework with a monotonicity-preserving FIS-based RPN model. The idea is to incorporate the *sufficient conditions* into the FMEA framework that contains an FIS-based RPN model. The first condition comprises a method to fine-tune the membership functions of the FIS-based RPN model. The second condition highlights the importance of having a monotonic rule base for the FIS-based RPN model. These conditions can be viewed as a practical, easy, and reliable solution to preserve the monotonicity property of an FIS-based assessment and decision making model. It is possible to apply the same approach to other FIS-based models too. To further evaluate the proposed FMEA with an FIS-based RPN model, a case study using real data collected from a semiconductor manufacturing plant is presented.

This chapter is organized as follow. In section 2, the FIS model and the *sufficient conditions* are reviewed. In section 3, an FIS-based RPN model is explained. The proposed FMEA framework with an FIS-based assessment model and its applicability to the manufacturing process in a semiconductor plant are presented in sections 4 and 5, respectively. Concluding remarks are then presented in section 6.

2 A Review on Fuzzy Inference Systems and the *Sufficient Conditions*

An FIS can be viewed as a computing framework that is based on the concepts of fuzzy set theory, fuzzy production rule (If-Then rule), and fuzzy reasoning [24]. In an FIS, expert knowledge is represented by a rule base comprising a set of Fuzzy Production Rules (FPRs). Each FPR has two parts: an antecedent which is the input(s); a consequent which is the output. Generally, an FPR has the form:

$$\begin{aligned}&\textbf{IF}\left(x_1 \textbf{ is } \mathbf{A}_1^{j_1}\right)\textbf{AND}\left(x_2 \textbf{ is } \mathbf{A}_2^{j_2}\right)\ldots\textbf{ AND }\left(x_n \textbf{ is } \mathbf{A}_n^{j_n}\right)\\&\textbf{THEN } y \textbf{ is } B^{j_1 j_2 \cdots j_n}\end{aligned} \tag{1}$$

where x_i and y are the inputs and output of the FIS, respectively; A and B are the linguistic variables of the inputs and output, respectively. A is represented by the fuzzy membership function, labeled as $\mu(x)$. The output is obtained using a zero-order FIS as:

$$y = f\left(\bar{x}\right) = \frac{\sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=2}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_1^{j_1}(x_1) \times \mu_2^{j_2}(x_2) \times \ldots \times \mu_n^{j_n}(x_n) \times b^{j_1 j_2 \cdots j_n}}{\sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=2}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_1^{j_1}(x_1) \times \mu_2^{j_2}(x_2) \times \ldots \times \mu_n^{j_n}(x_n)} \quad (2)$$

where b is the *representative value* of fuzzy membership function B .

If for all x^a and x^b such that $x^a < x^b$, then for a function f to be monotonically increasing or decreasing, the condition $f(x^a) \le f(x^b)$ or $f(x^a) \ge f(x^b)$ must be satisfied, respectively. It is possible to investigate the monotonicity property of an FIS by differentiating y with respect to x_i . For a monotonically increasing model, $dy/dx_i \ge 0$. With the use of the *quotient rule*, let φ denote $\prod_{s=1,s\ne i}^{n} \mu_s^{j_s}(x_s)$. Then,

$$u(\bar{x}) = \sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=1}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_1^{j_1}(x_1) \times \mu_2^{j_2}(x_2) \times \ldots \times \mu_n^{j_n}(x_n) \times b^{j_1 j_2 \cdots j_n} = \sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=1}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_i^{j_i}(x_i) \times b^{j_1 j_2 \cdots j_n} \times \varphi$$

$$v(\bar{x}) = \sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=1}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_1^{j_1}(x_1) \times \mu_2^{j_2}(x_2) \times \ldots \times \mu_n^{j_n}(x_n) = \sum_{j_n=1}^{j_n=M_n} \cdots \sum_{j_2=1}^{j_2=M_2} \sum_{j_1=1}^{j_1=M_1} \mu_i^{j_i}(x_i) \times \varphi \,,$$

and $\partial = \left(v(x)\right)^2$

Using the quotient rule, assume $\pi^k = \prod_{s=1,s\ne i}^{n} \mu_s^{k}(x_s)$ and $\pi^l = \prod_{s=1,s\ne i}^{n} \mu_s^{l}(x_s)$,

$$f_{x_i}(\bar{x})' = \frac{1}{\partial}\left[\sum_{k=1}^{M'}\sum_{l=1}^{M'} \pi^k \pi^l \left[\sum_{p=1}^{p=M_i}\sum_{q=1}^{q=M_i}\left(\mu_i^p{}'(x_i) \times \mu_i^q(x_i) \times b^{j_1 j_2 \ldots j_i = p \ldots j_n}\right) - \sum_{p=1}^{p=M_i}\sum_{q=1}^{q=M_i}\left(\mu_i^p(x_i) \times \mu_i^q{}'(x_i) \times b^{j_1 j_2 \ldots j_i = p \ldots j_n}\right)\right]\right]$$

$$f_{x_i}(\bar{x})' = \frac{1}{\partial}\left[\sum_{k=1}^{M'}\sum_{l=1}^{M'} \pi^k \pi^l \left[\sum_{p=1}^{p=M_i}\sum_{q=1}^{q=M_i}\left(\left(b^{j_1 j_2 \ldots j_i = p \ldots j_n} - b^{j_1 j_2 \ldots j_i = q \ldots j_n}\right)\left(\mu_i^p{}'(x) \times \mu_i^q(x)\right)\right)\right]\right]$$

$$f_{x_i}(\bar{x})' = \frac{1}{\partial}\left[\sum_{k=1}^{M'}\sum_{l=1}^{M'} \pi^k \pi^l \left[\sum_{p=1}^{p=M_i-1}\sum_{q=p+1}^{q=M_i}\left(\left(b^{j_1 j_2 \ldots j_i = p \ldots j_n} - b^{j_1 j_2 \ldots j_i = q \ldots j_n}\right)\left(\mu_i^p{}'(x) \times \mu_i^q(x) - \mu_i^p(x) \times \mu_i^q{}'(x)\right)\right)\right]\right]$$

$$f_{x_i}(\bar{x})' = \frac{1}{\partial}\left[\sum_{k=1}^{M'}\sum_{l=1}^{M'} \pi^k \pi^l \left[\sum_{p=1}^{p=M_i-1}\sum_{q=p+1}^{q=M_i}\left(\left(b^{j_1 j_2 \ldots j_i = p \ldots j_n} - b^{j_1 j_2 \ldots j_i = q \ldots j_n}\right) \times \mu_i^p(x) \times \mu_i^q(x) \times \left(\frac{\mu_i^p{}'(x)}{\mu_i^p(x)} - \frac{\mu_i^q{}'(x)}{\mu_i^q(x)}\right)\right)\right]\right]$$

(3)

From Equation (3), to fulfill $dy/dx_i \geq 0$, two mathematical conditions (namely the *sufficient conditions*) are required, as follow;

Condition (1): $b^{j_1 j_2 \cdots j_i = p \cdots j_n} - b^{j_1 j_2 \cdots j_i = q \cdots j_n} \geq 0$ at the rule consequent. This requires that the fuzzy sets at the rule consequent to be of a monotonic order.

Condition (2): $\mu_i^p{}'(x)/\mu_i^p(x) - \mu_i^q{}'(x)/\mu_i^q(x) \geq 0$. This can be viewed as a method to fine-tune the membership function.

Note that $\mu'(x)/\mu(x)$ is the ratio between the rate of change in the membership degree and the membership degree itself. This ratio is similar to the principle of elasticity in mathematics and economy [25]. Assume that $\mu(x)$ is a Gaussian membership function, $G(x) = e^{-[x-c]^2/2\sigma^2}$. The derivative of $G(x)$ is $G'(x) = -((x-c))/\sigma^2)G(x)$. The ratio $G'(x)/G(x)$ of the Gaussian membership function returns a linear function, i.e.,

$$E(x) = G'(x)/G(x) = -(1/\sigma^2)x + (c/\sigma^2) \tag{4}$$

It can be viewed as a projection of Gaussian membership functions that allows the *sufficient conditions* to be visualized.

3 The Fuzzy Inference System-Based Risk Priority Number Model

An FIS-based RPN model takes three factors, i.e., S, O, and D, and produces an RPN scores via a fuzzy inference technique. In general, these three factors are estimated by experts in accordance with a scale from “1” to “10” based on a set of commonly agreed evaluation criteria. Tables 1, 2, and 3 summarize the evaluation criteria, which are used in a semiconductor manufacturing plant, for S, O, and D ratings, respectively.

Table 1. The scale table for Severity

Rank	**Linguistic Terms**	Criteria
10	**Very High** (Liability)	Failure will affect safety or compliance to law.
9~8	**High** (Reliability / reputation)	Customer impact. Major reliability excursions.
7~6	**Moderate** (Quality / Convenience)	Impacts customer yield. Wrong package/par/marking.
5~2	**Low** (Special Handling)	Yield hit, Cosmetic.
1	**None** (Unnoticed)	Unnoticed.

Table 2. The scale table for Occurrence

Rank	**Linguistic Terms**	Criteria
10~9	**Very High**	Many/shift, Many/day
8~7	**High**	Many/week, Few/week
6~4	**Moderate**	Once/week, Several/month
3	**Low**	Once/month
2	**Very Low**	Once/quarter
1	**Remote**	Once ever

Table 3. The scale table for Detect

Rank	**Linguistic Terms**	Criteria
10	**Extremely Low**	No Control available.
9	**Very Low**	Controls probably will not Detect
8~7	**Low**	Controls may not Detect excursion until reach next functional area.
6~5	**Moderate**	Controls are able to Detect within the same functional area
4~3	**High**	Controls are able to Detect within the same machine/module.
2~1	**Very High**	Prevent excursion from occurring

The membership functions of S, O, and D can be generated based on the criteria in Tables 1, 2, and 3 respectively. Figures 1, 2, and 3 depict the fuzzy membership function for S(μ_s), O(μ_o), and D(μ_d), respectively. As an example, referring to Figure 1, the second membership function of S, i.e., μ_s^2, with linguistic label of "*Low*" represents S ratings from 2 to 5, which corresponds to "*Yield hit, Cosmetic*" as in Table 1. The same scenario applies to Figure 2, e.g. the "*Moderate*" membership, i.e. μ_o^4, represents O ratings from 4 to 6, which corresponds to "*Once/week, Several/month*" as in Table 2. In Figure 3, the "*High*" membership function, i.e., μ_d^2, represents D ratings from 3 and 4, which corresponds to "*Controls are able to Detect within the same machine/module*" as in Table 3.

The output of the FIS-based RPN model, i.e., the RPN score, varies from 1 to 1000. In this study, it is divided into five equal partitions, with the fuzzy membership functions of B being "*Low*", "*Low Medium*", "*Medium*", "*High Medium*", and "*High*", respectively. The corresponding scores of b (the *representative value* of output membership function) are assumed to the point whereby the membership value of B is 1. Hence, b is 1, 250.75, 500.5, 750.25, and 1000, respectively.

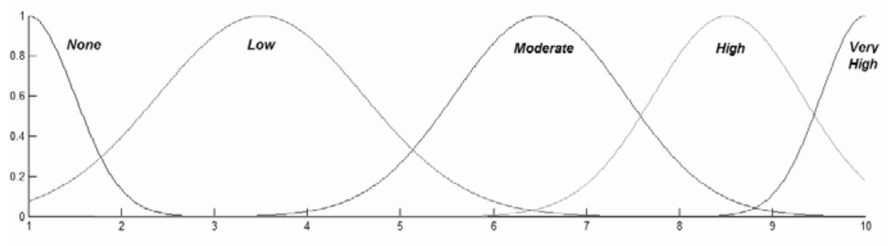

Fig. 1. The membership function of Severity

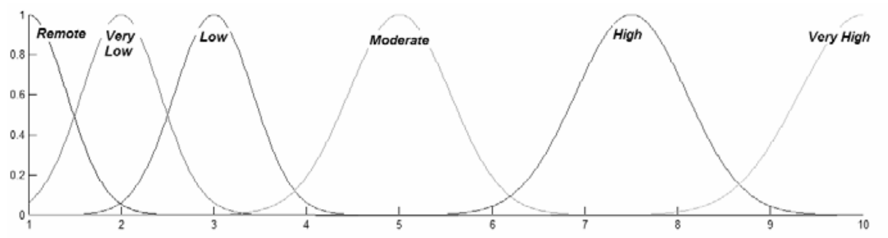

Fig. 2. The membership function of Occurrence

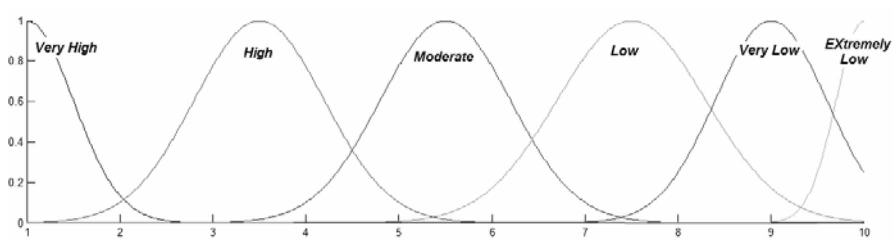

Fig. 3. The membership function of Detect

As explained earlier, a fuzzy rule base is a collection of knowledge from experts in the If-Then format. Considering S, O, and D, and their linguistic terms, the fuzzy rule base has 180 (5 (S) x 6 (O) x 6 (D)) rules in total using the grid partition approach. As an example, Figure 4 shows two rules that describe a small portion of the fuzzy rules collected from the domain expert (e.g. maintenance engineer).

Rule 1
If Severity is **Very High** and Occurrence is **Very High** and Detect is **Extremely Low** then RPN is **High**.
Rule 2
If Severity is **Very High** and Occurrence is **Very High** and Detect is **Very Low** then RPN is **High.**

Fig. 4. An example of two fuzzy production rules

In this work, a simplified zero-order Sugeno FIS is used to evaluate the RPN:

$$Fuzzy\_RPN\ score = \frac{\sum_{a=1}^{M_s}\sum_{b=1}^{M_o}\sum_{c=1}^{M_d}\mu_s^a(S)\times\mu_o^b(O)\times\mu_d^c(D)\times b^{a,b,c}}{\sum_{a=1}^{M_s}\sum_{b=1}^{M_o}\sum_{c=1}^{M_d}\mu_s^a(S)\times\mu_o^b(O)\times\mu_d^c(D)} \quad (5)$$

4 The Proposed FMEA Framework with a Monotonicity-Preserving FIS-Based RPN Model

In this chapter, it is argued that the FIS-based RPN model needs to satisfy the monotonicity property. The attributes of the FIS-based RPN model (i.e., S, O, and D ratings) are defined in such a way that the higher the inputs, the more critical the situation is. The output of the FIS-based RPN model (i.e., the RPN score) is a measure of the failure risk. The monotonicity property is important for the input-output relationship in practice, which allows a valid comparison among failure modes [2,13]. For example, for two failure modes with input sets $[5,5,6]$ (representing [S, O, and D]) and $[5,5,7]$, the RPN score for the second failure mode should be higher than or equal to that of the first. The prediction is deemed illogical if the RPN model yields a contradictory result. This can be explained by referring to Tables 1, 2, and 3. Let the two failure modes have the same S and O scores of 5, but with the D scores of 6 and 7 respectively. The failure mode with D of 6 ("*Controls are able to Detect within the same functional area*") represents a better control mechanism than that of D of 7 ("*Controls may not Detect excursion until reach next functional area.*"). Thus, the RPN score for $[5,5,6]$ should be lower than that of $[5,5,7]$. The monotonicity property states that as long as the D score increases, the RPN score should not decrease.

Figure 5 depicts a flow chart for the proposed FMEA framework with a monotone-preserving FIS-based RPN model. Note that an FMEA framework with an FIS-based RPN model has been proposed in [22]. Our proposed framework here can be viewed as an extension of that in [22]. In our proposed framework, the *sufficient conditions* are systematically incorporated into the FIS-based RPN model.

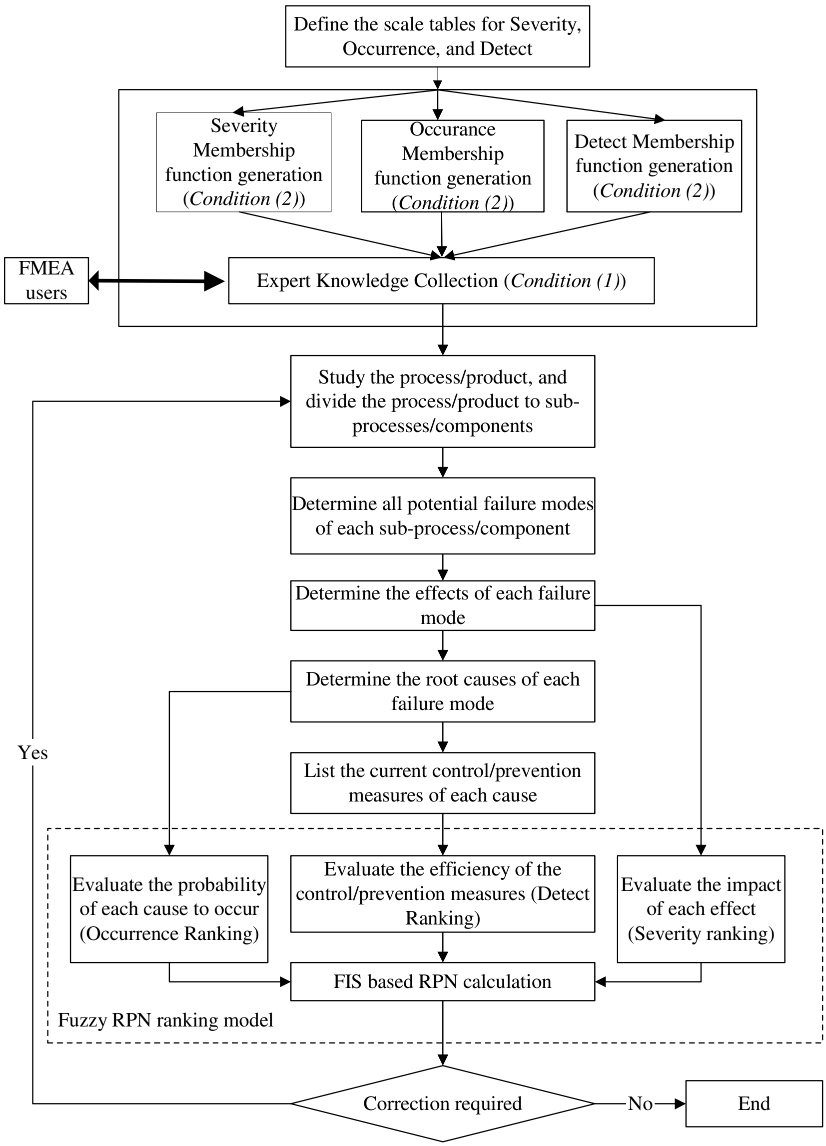

Fig. 5. The proposed FMEA procedure with the monotone-preserving FIS-based RPN model

The membership functions of S, O, and D are set in accordance with *Condition (1)*. *Condition (1)* can be viewed as the criteria for a set of valid rule base. It is used to check the validity of the collected rule base. It can also be used as a feedback mechanism to inform the FMEA users whenever an invalid rule is provided.

Condition (2) can be used as a criterion to fine-tune the fuzzy membership function. Figures 1, 2, and 3 illustrate the membership functions for S, O, and D respectively, which satisfy *Condition (2)*. Equation (4) allows this mathematical condition to be visualized. As an example, using Equation (4), the membership functions of S in Figure 1 can be projected as a set of linear lines as in Figure 6. One can see that the transformed linear lines of "*None*", "*Low*", "*Moderate*", "*High*", and "*Very High*" are in an ascending order. The linear line of "*Low*" is always greater than that of "*None*" over the universe of discourse (S from 1 to 10). The same applies to the membership functions of O and D, as in Figures 2 and 3 respectively. They can be projected as a set of linear lines, as in Figures 7 and 8, respectively.

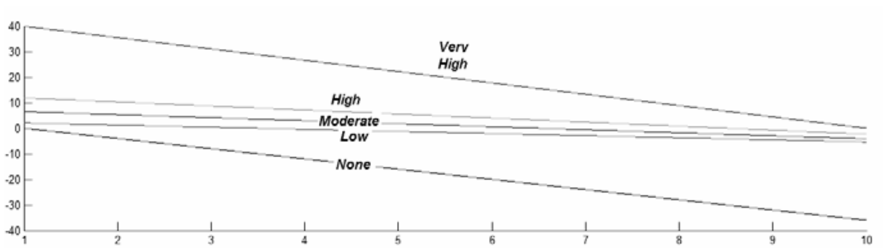

Fig. 6. Projection of the membership functions of Severity

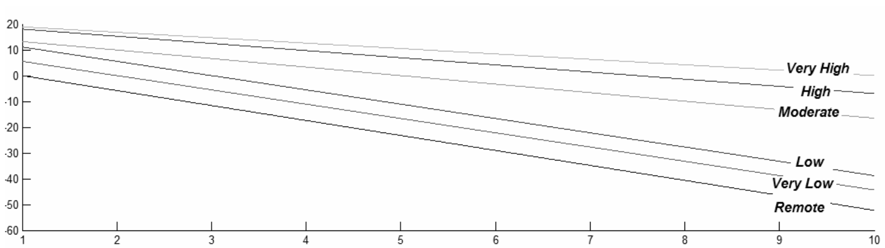

Fig. 7. Projection of membership functions of Occurrence

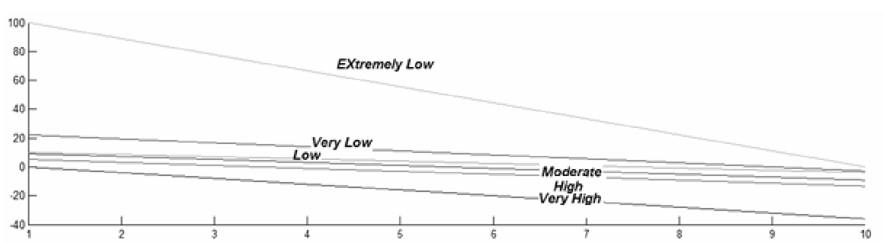

Fig. 8. Projection of the membership functions of Detect

5 A Case Study

To validate the proposed FMEA framework, an experiment with data/information collected from the Flip Chip Ball Grid Array (FCBGA) [23] process in a semiconductor manufacturing plant is conducted. FCBGA is a low cost semiconductor packaging solution which utilizes the Controlled Collapse Chip Connect technology, or known as Flip Chip (FC) for its die to substrate interconnection. FC was initiated at the early 1960s to eliminate the expanse, unreliability, and low productivity of the manual wire-bonding process [23]. A case study on one of the FCBGA manufacturing processes, i.e., wafer mounting process, is conducted.

Wafer mounting is a process of providing support to wafer and to facilitate the processing of the wafer from the sawing process through die attach while keeping dies from scattering when the wafer is cut. It consists of several steps, i.e., 1) frame loading; 2) wafer loading; 3) application of tape to the wafer and the wafer frame; 4) cutting of the excess tape; and 5) unloading of the mounted wafer. A number of potential failure modes to be prevented during this process are: wafer cracking or breakage, bubble trapping on the adhesive side of the tape, scratches on the active side of the wafer, and non-uniform tape tension which can result in tape wrinkles. With the FMEA methodology, these failure modes, their root causes, and their consequences (effects) are identified. The S, O and D ratings of each failure modes are further provided. An FIS-based RPN model is also constructed with the proposed procedure in Figure 5.

Table 4 summarizes the FMEA results using the traditional and the monotone-preserving FIS-based RPN model. Columns "*Sev*" (S), "*Occ*" (O), and "*Det*" (D) show the three attribute ratings describing each failure. The failure risk evaluation and prioritization outcomes based on the traditional RPN model are shown in columns "*RPN*" and "*RPN rank*", respectively. For example, in Table 4, failure mode "1" represents "*broken wafer*", which leads to yield loss, and is given a S score of 3 (refer to Table 1). This failure happens because of "*drawing out arm failure*", and because it rarely happens, it is assigned an O score of 1 (refer to Table 2). In order to eliminate the cause, software enhancement has been done as the action taken. Owing to the action taken is very effective, which can eliminate the root cause; a D score of 1 is given (refer to Table 3). Using the traditional RPN model ($RPN = S \times O \times D$), an RPN of 3 is obtained, with the lowest RPN ranking (*RPN rank*=1).

Column "*Fuzzy RPN*" shows the failures risk evaluation results using the proposed FMEA procedure. Sub-columns "*FRPN*" and "*FRPN Rank*" show the fuzzy failure risk evaluation and prioritization outcomes, respectively. Referring to the above example (failure mode=1), *FRPN*=2 (using Equation (5)) and *FRPN Rank*=1. Column "*Expert's Knowledge*" shows the linguistic term assigned by the maintenance engineers, *Low*, (*Low* is a fuzzy membership function with representative value, *b* of 1.00 (as in column *b*)).

Using the traditional RPN model that with a simple multiplication ($RPN = S \times O \times D$) scheme, the monotonicity relationship between the RPN score and S, O, and D can be guaranteed. However, it assumes the relationship between the RPN score and S, O, and D is of linearity, and ignores the qualitative information in the scale tables (S, O, and D). Hence, from Table 4, the predicted *RPN* scores are not in line with *experts' knowledge*.

Table 4. Failure risk evaluation, ranking and prioritization results using the traditional RPN model, as well as the fuzzy RPN and its enhanced models of the wafer mounting process

Failures Mode	Inputs ranking			RPN	RPN Rank	Fuzzy RPN model			
						Fuzzy RPN		Expert's Know ledge	
	Sev	Occ	Det			FRPN	FRPN Rank	Linguistic term	*b*
1	3	1	1	3	1	2	1	Low	1.00
2	3	2	1	6	2	2	1	Low	1.00
3	2	3	2	12	3	80	2	Low	1.00
4	3	1	2	6	2	108	3	Low	1.00
5	3	2	2	12	3	108	3	Low	1.00
6	3	3	2	18	5	108	3	Low Medium	250.75
7	2	4	2	16	4	161	4	Low Medium	250.75
8	2	2	3	12	3	187	5	Low Medium	250.75
9	2	3	3	18	5	187	5	Low Medium	250.75
10	3	4	1	12	3	190	6	Low Medium	250.75
11	3	4	2	24	6	216	7	Low Medium	250.75
12	3	2	3	18	5	251	8	Low Medium	250.75
13	3	3	3	27	7	251	8	Low Medium	250.75
14	3	2	4	24	6	280	9	Low Medium	250.75
15	4	3	4	48	11	285	10	Low Medium	250.75
16	2	2	10	40	9	437	11	Medium	500.50
17	3	2	5	30	8	472	12	Medium	500.50
18	3	3	5	45	10	472	12	Medium	500.50

With the FIS-based RPN model, the predicted *FRPN* scores are in agreement with *experts' knowledge*. For example, failure modes 1 to 5 are assigned with a linguistic term of *Low*. This is followed by failure modes 6 to 15, and 16 to 18, which are assigned with linguistic terms of *Low Medium* and *Medium*, respectively. Besides, from the observation in Table 4, the FIS-based RPN model (constructed with procedure as in Figure 5) is able to satisfy the monotonicity property for all failure modes, with no illogical predictions.

One of the effective methods to observe the monotonicity property is via the surface plot. Figure 9 depicts a surface plot of the fuzzy RPN scores versus O and D when S is set to 10. A monotonic surface is observed.

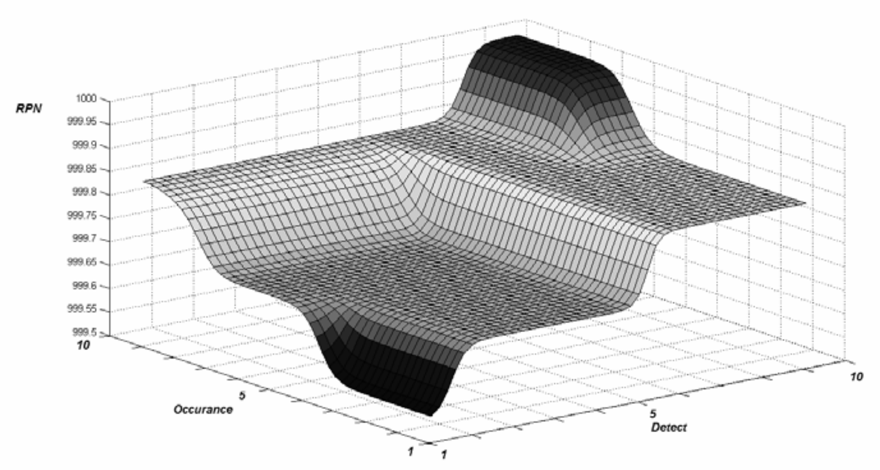

Fig. 9. The surface plot of the *FRPN* scores of Occurrence and Detect with Severity set to 10

6 Summary

In this chapter, the importance of an FIS-based assessment and decision making model to fulfill the monotonicity property is investigated. An FMEA framework with the monotonicity-preserving FIS-based RPN model has been examined. The monotonicity property is essential to ensure the validity of the fuzzy RPN scores such that a logical comparison among different failure modes in FMEA can be made. The *sufficient conditions* have been incorporated into the FMEA framework. This is a simple, easy, and reliable solution to preserve monotonicity in the FIS-based RPN model. A case study on the applicability of the FMEA framework with an FIS-based RPN model to a semiconductor process has been presented. The results have indicated the importance of the monotonicity property of the FIS-based RPN model.

It is possible to use a similar approach (by applying the *sufficient conditions*) in other FIS-based assessment models. In addition, it is worthwhile to investigate other properties of the *length function*, e.g., sub-additivity [12], for FIS-based assessment and decision making models in future work.

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