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On the use of fuzzy inference techniques in assessment models: part II: industrial applications

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Abstract In this paper, we study the applicability of the monotone output property and the output resolution property in fuzzy assessment models to two industrial Failure Mode and Effect Analysis (FMEA) problems. First, the effectiveness of the monotone output property in a single-input fuzzy assessment model is demonstrated with a proposed fuzzy occurrence model. Then, the usefulness of the two properties to a multi-input fuzzy assessment model, i.e., the Bowles fuzzy Risk Priority Number (RPN) model, is assessed. The experimental results indicate that both the fuzzy occurrence model and Bowles fuzzy RPN model are able to fulfill the monotone output property, with the derived conditions (in Part I) satisfied. In addition, the proposed rule refinement technique is able to improve the output resolution property of the Bowles fuzzy RPN model.

Keywords Assessment models · Monotone output property · Output resolution property · Failure mode and effect analysis · Risk priority number

1 Introduction

An assessment model is a mathematical model, which quantifies a situation/object and produces a measuring index, either in a numerical score of a continuous scale or a category to a situation/object, taking into consideration its attribute(s) (Dubois and Prade 1997; Cunningham 1986; Chatterji 2003). The estimated score or category

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represents the level of criticality or wellness, which will result in certain actions or decisions to be taken. From the literature review, fuzzy set methods have been widely used in assessment models (Dubois and Prade 1997; Figueira et al. 2005; Triantaphyllao 2000; Kaliszewski 2006). In Part I of this work, definitions of two common theoretical properties of assessment models, i.e., the monotone output property and the output resolution property, and the conditions how a Fuzzy Inference System (FIS)-based assessment models to fulfill the properties are presented. In this sequel paper, we focus on the fuzzy inference system (FIS)-based assessment models, with application to Failure Mode and Effect Analysis (FMEA) methodology (Ireson et al. 1995; Chrysler Corporation et al. 1995). Specifically, we examine the applicability of the two properties and the derived conditions to a proposed fuzzy occurrence model (a single-input fuzzy assessment model) and the Bowles fuzzy Risk Priority Number (RPN) model (Bowles and Peláez 1995) (a multi-input fuzzy assessment model). Both models are constructed with real information collected from a semiconductor manufacturing plant for Flip Chip Ball Grid Array (FCBGA) (Tummala 2000) products.

With regard to FMEA, a number of soft computing techniques have been researched to enhance its methodology. For example, in Lee (2001), a Bayesian belief network for FMEA modeling and analysis was examined. Application of expert systems to FMEA was suggested in Russomanno et al. (1992). In Bell et al. (1992), use of causal reasoning for automating FMEA was presented, while in Peláez and Bowles (1996), application of the fuzzy Cognitive Map to FMEA was explored. In this paper, we first examine the findings as presented in Part I with a proposed FIS-based occurrence model (a single-input fuzzy assessment model). The fuzzy occurrence model is proposed to automate the conventional occurrence score rating procedure. It produces a fuzzy occurrence score as a measure of occurrence of failures.

To further ascertain the effectiveness of the proposed monotone output and output resolution properties, an enhanced Bowles fuzzy RPN model is applied to FMEA problems. The Bowles fuzzy RPN model is a popular method, and has been successfully applied to a number of FMEA problems. For example, it was applied to FMEA of an auxiliary feed water system and a chemical volume control system in a nuclear power plant (Guimarães and Lapa 2004a,b). It was also used in FMEA of an engine system (Xu et al. 2002), a semiconductor manufacturing line (Tay and Lim 2006), and a fishing vessel (Pillay and Wang 2003). Over the years, several enhancements have also been proposed to the Bowles fuzzy RPN model. Development of a Bowles fuzzy RPN model using the grey relation theory is presented in Pillay and Wang (2003). In Xu et al. (2002), a Bowles fuzzy RPN model which allows interdependencies among all failures to be considered is proposed. In Tay and Lim (2006), a method to reduce the number of fuzzy rules in the Bowles fuzzy RPN model is reported. However, to the best of our knowledge, little attention is paid on the validity and the efficiency of the estimated numerical scores, as available in the literature. Therefore, in this paper, we investigate the efficiency of the estimated numerical scores, for both fuzzy occurrence model and Bowles fuzzy RPN model, in order to allow valid and meaningful comparisons among different failure modes in FMEA to be made.

This paper is organized as follows. Section 2 presents a review of FMEA methodology. In Sect. 3, the fuzzy occurrence model is presented. Besides, the applicability of the proposed property and derived conditions are examined. In Sect. 4, the Bowles fuzzy RPN model is presented. Again, the applicability of the proposed two properties and the derived conditions are examined, with two sets of real data/information collected from a semiconductor manufacturing process. Section 5 presents some concluding remarks and suggestions for further work.

2 The FMEA methodology

FMEA is an effective quality improvement and risk assessment tool, which can be interfaced with many engineering and reliability methods (Ireson et al. 1995; Chrysler Corporation et al. 1995). It is a systemized group of activities intended to recognize and to evaluate the potential failures of a product/process and its effects. Besides, FMEA identifies actions which can eliminate or reduce the chances of 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 in characteristic control or performance.

The RPN model is used to evaluate the risk associated with each failure mode in FMEA. Generally, the traditional RPN model takes three factors, i.e., severity, occurrence, and detect, and the RPN scores is determined by the multiplication of these three inputs scores, as shown in Eq. 1.

$$\text{RPN} = \text{Severity} \times \text{Occurrence} \times \text{Detect} \tag{1}$$

Severity is an assessment of the effect of potential failure mode. Occurrence is defined as the likelihood that a cause will occur. Detect is an assessment of the ability of current design control to detect a potential cause (Ireson et al. 1995; Chrysler Corporation et al. 1995). In general, these three factors are estimated by experts in accordance with a scale from "1" to "10" based on commonly agreed evaluation criteria. The higher the input scores, the more critical the situation is. Tables 1–3 summarize the evaluation criteria for severity, occurrence and detect ratings, respectively, which is used practically in a semiconductor manufacturing plant.

In summary, the conventional procedure of FMEA, as depicted in Fig. 1, is as follows.

(1) Define the scale table of severity, occurrence, and detect.

Table 1 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 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 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

(2) Study the intent, purpose, goal, objective of a product/process, which is generally identified by interaction among components/process flow diagram followed by task analysis.
(3) Identify potential failures of the product/process; which include problems, concerns, and opportunity of improvement.
(4) Identify consequence of failures to other components/next processes, operation, customers, and government regulations.
(5) Identify the potential root cause of potential failures.
(6) Conduct the first level method/procedure to detect/prevent failures of the product/process.
(7) Perform severity score rating: rank the seriousness of the effect of the potential failures.
(8) Perform occurrence score rating: estimation of the frequency for a potential cause of failures.
(9) Perform detect score rating: likelihood of the process control to detect a specific root cause of a failure.
(10) Compute the RPN: product of the three inputs (severity, occurrence, detect).
(11) Back to 2 if there is any correction.
(12) End.

3 Case study I: a single-input fuzzy assessment model

In the conventional FMEA methodology, the occurrence score is rated and updated manually from time to time by users (based on their experience/knowledge, and with reference to the latest data) in accordance with an occurrence scale table (Table 2), as depicted in Fig. 2.

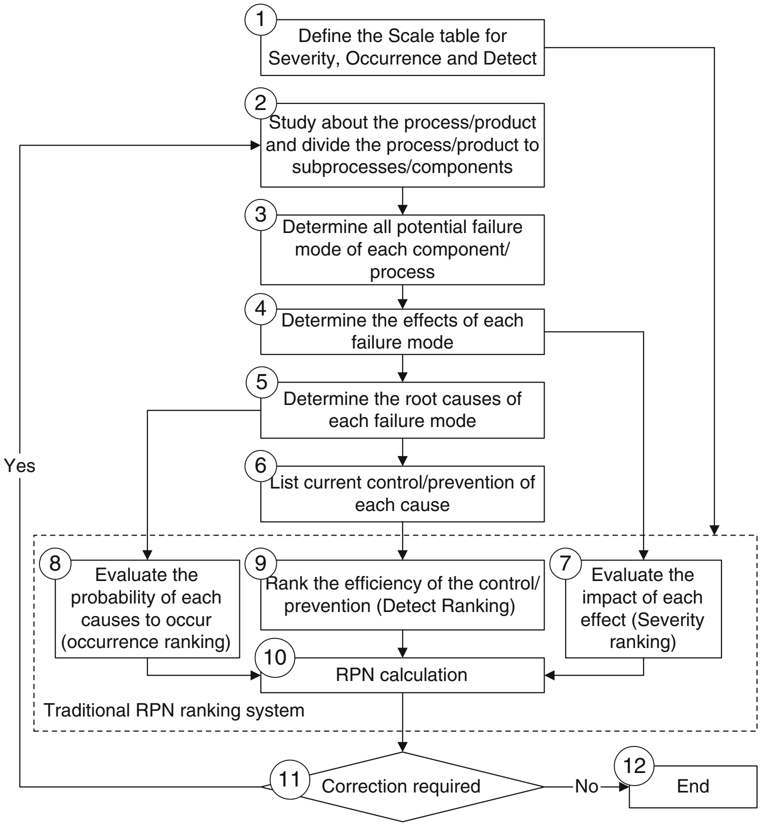


Fig. 1 The operation of FMEA

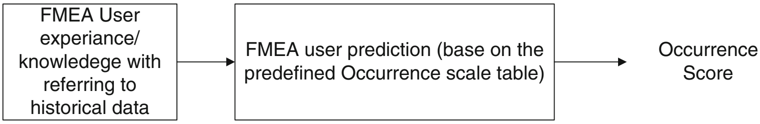


Fig. 2 The traditional way of predicting and updating occurrence score

In essence, from Eq. 1, getting a more accurate occurrence score rating will definitely contribute to a more meaningful RPN prediction. However, it is a tedious and time consuming process to update the scores manually from time to time. In addition, the method for updating the scores is often subjective, and is influenced by the user's mind states. Owing to these reasons, we suggest a generic framework that is equipped with a fuzzy occurrence model to predict and update the occurrence scores. This method can also be viewed as an automated procedure for occurrence score prediction.

In case study I, the proposed fuzzy occurrence model, which is an example of a single input fuzzy assessment model, is presented. We further discuss the applicability of the monotone output property and output resolution property to the proposed

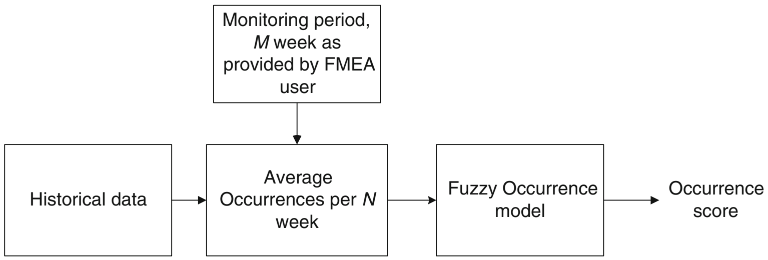


Fig. 3 The proposed frameworks for predicting and updating the occurrence score

fuzzy occurrence model. In addition, we demonstrate the usefulness of the derived conditions in Part I in this study.

3.1 The proposed fuzzy occurrence model

We view the occurrence score as a result of human perception towards the failure rate of a specific cause to occur, which can be substituted and performed by an intelligent inference system, for example, an FIS. Figure 3 shows the proposed framework to predict the occurrence score based on historical data.

The monitoring period, M week(s), which can be viewed as a sampling period, is first pre-determined by FMEA users. The rule-of-thumb is to choose a period which is sufficiently long enough to record a number of occurrences and the root cause of a failure. The frequency of a failure within M weeks is extracted from a historical database. This process can be accomplished either manually by the FMEA users, or automatically by a simple computer script. The frequency of the failure occurrence is then averaged per N weeks, using Eq. 2. The proposed fuzzy occurrence model converts an *Average Occurrence per N week* value to an *occurrence score*. In other words, the model takes *Average Occurrence per N week* as the attribute and produces a meaningful measuring score, i.e., the *occurrence score*.

$$Average\_Occurrences\_per\_N\_week = \frac{Count\_of\_particular\_failure}{M} \times N \tag{2}$$

As shown in Table 4, the proposed occurrence scale table is an enhanced version from the conventional occurrence scale table (Table 2). Table 4 also shows the extended classification/criteria describing each linguistic term for the occurrence scores (with $N = 52$, as used in this study). The attribute of the fuzzy occurrence model and its partitions, which range from 1 to 1,000, are shown in "Average number of failure occurred/52 weeks". The detailed description of each input partition is in "Criteria". We use the Gaussian membership function, $\mu^j(x)$, to represent each attribute's partition. For example, the fourth partition (from 13 to 52), $\mu^4(x)$, is called "Once/week" or "Several/month". The output, ranged from 1 to 10, is shown in "Occurrence Score".

Table 4 An extended scale table for the occurrence score

Occurrence scale table				
Occurrence score	Linguistic variable	Criteria	Average number of failures occurred/52 weeks	
			Lower limit estimation	Upper limit estimation
10	Very high	Many/shift	301	1,000
9		Many/day		
8	High	Many/week	53	300
7		Few/week		
6	*Moderate*	*Once/week*	*13*	*52*
5		*Several/month*		
4				
3	Low	Once/month	5	12
2	Very low	Once/quarter	3	4
1	Remote	Once ever	1	2

Again, every output partition is assigned a linguistic variable, B^j as shown in "Linguistic variable". For example, the forth output (from 4 to 6), B^4, is assigned the linguistic variable of "Moderate".

The Gaussian membership function is chosen because the Gaussian kernel function exhibits properties that are mathematically and computationally tractable (Masters 1993, 1995). The Gaussian kernel function is also a continuously differentiable function, and has the advantage of being smooth and nonzero at all points. Because of its smoothness and concise notation, the Gaussian membership function is a popular method for specifying fuzzy sets (Masters 1993, 1995). Besides, past experiences (Masters 1993, 1995) have indicated that it is a suitable choice in many applications, and has been a reliable performer.

The Gaussian membership function is defined by Eq. 3,

$$Gaussian(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{3}$$

where c and σ are center and width of the membership function respectively. Figure 4 illustrates an example of fuzzy membership function for *Average number of failure occur /52 week*. As an example, $\mu^4(x)$, as the italised row in Table 4, can be represented by membership function *mf4* as in Fig. 4. The logarithm scale is used for the input membership function because the input domain often is large, and the size of each partition often increases exponentially over the domain.

The occurrence scale table can be treated as a mapping from "Average number of failures occurred/52 weeks" to "Occurrence score", and can be explained by using fuzzy production rules. For example, referring to Table 4, Ranks 4–6 (as italised) can be expressed as follows.

IF *Average number of failures occurred /52 weeks* is "about log (13) to log (52)"**, THEN** *Occurrence Score* is "about 4 to 6".

A simplified Mamdani FIS (Yam 1999; Hisao et al. 2006; Hisao 1991), as shown in Eq. 4, is used to evaluate the occurrence score.

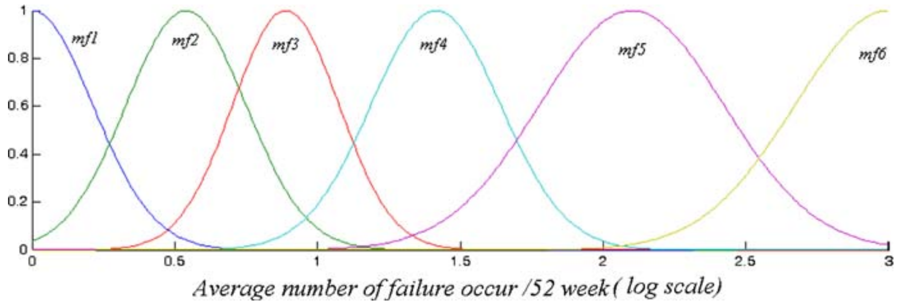


Fig. 4 Fuzzy Membership function for *Average number of failure occur/52 week*

$$\text{Occurrence score} = \frac{\sum_{j=1}^{j=M} \mu^j(x) \times b^j}{\sum_{j=1}^{j=M} \mu^j(x)} \tag{4}$$

where b^j is a representative value of B^j, as in Eq. 5.

$$b^j = rep(B^j) \tag{5}$$

We determine the value of b^j by the point where the membership value of B^j is 1. Hence, $b$is 1, 2, 3, 5, 7.5, and 10 for linguistic term *Remote, Very Low, Low, Moderate, High*, and *Very High* respectively.

3.2 Analysis of the monotone output property

The occurrence scale table is defined in such a way that the higher the "Average occurrences per N week", the higher the "occurrence score". For example, given two failures with "Average occurrences per N week" of 4 and 5, respectively, the predicted occurrence score for the second failure should be higher than that of the first. The prediction is deemed illogical if the fuzzy occurrence model yields a contradictory result. In other word, the monotone output property is applied.

From Part I, two conditions need to be fulfilled. It can be observed that Condition (1) is satisfied, as $rep(VeryHigh) > \cdots > rep(VeryLow) > rep(Remote)$. Condition (2) is used as a guideline to tune the membership function of "Average number of failure occur /52 week". Figure 4 shows an example that satisfies Condition (2). In this case, the number of output membership functions is equal to the number of fuzzy rules; therefore the rules refinement approach is not applicable.

Table 5 shows some of the predicted attribute and estimate pairs of the proposed fuzzy occurrence model. As can be seen, the monotone output property is satisfied. Columns "Average number of failures occurred/52 weeks" and "Occurrence score" are the input and output of the fuzzy occurrence model, respectively. Column "Expert's

Table 5 Some examples of the input and output pairs of the fuzzy occurrence model

Average number of failure occur/ 52 weeks	Occurrence score	Expert's knowledge		Average number of failure occur/ 52 weeks	Occurrence score	Expert's knowledge	
		Linguistic term	*b*			Linguistic term	*B*
1	1.0	Remote	1	52	6.3	Moderate	5
2	1.6	Remote	1	53	6.4	High	7.5
3	2.0	Very low	2	100	7.4	High	7.5
4	2.2	Very low	2	150	7.6	High	7.5
5	2.5	Low	3	200	7.8	High	7.5
6	2.6	Low	3	250	8.0	High	7.5
8	3.0	Low	3	300	8.4	High	7.5
10	3.3	Low	3	301	8.4	Very high	10
12	3.7	Low	3	400	9.0	Very high	10
13	3.9	Moderate	5	450	9.3	Very high	10
20	4.9	Moderate	5	500	9.5	Very high	10
25	5.2	Moderate	5	600	9.7	Very high	10
30	5.3	Moderate	5	700	9.8	Very high	10
35	5.5	Moderate	5	800	9.9	Very high	10
40	5.7	Moderate	5	900	9.9	Very high	10
45	6.0	Moderate	5	1,000	10.0	Very high	10

Knowledge" states the nearest linguistic term, and b is assigned with a particular "Average Occurrence per 52 week". For example, a failure with "Average Occurrence/52 week" of 2 is predicted to have an occurrence score of 1.6, which is assigned "Expert's Knowledge" of "*remote*" (where $b = 1$).

From Table 5, "Average number of failure occurred/52 weeks" from 1 to 2 is predicted to have occurrence scores of 1–1.6. This is close to the occurrence scale table, which gives an occurrence rating of 1. The same scenario is observed from the range from 3 to 4, which gives predicted occurrence scores of 2.0–2.2. Again, this is close to the predefined occurrence scale table, with an occurrence rating of 2. The same situation can be observed for other ranges. As a summary, the predicted occurrence scores are in accordance with the scale table.

Figure 5 shows "Occurrence Score" versus "Average Occurrences per N week" of the fuzzy occurrence model. Notice that the occurrence score increases monotonically

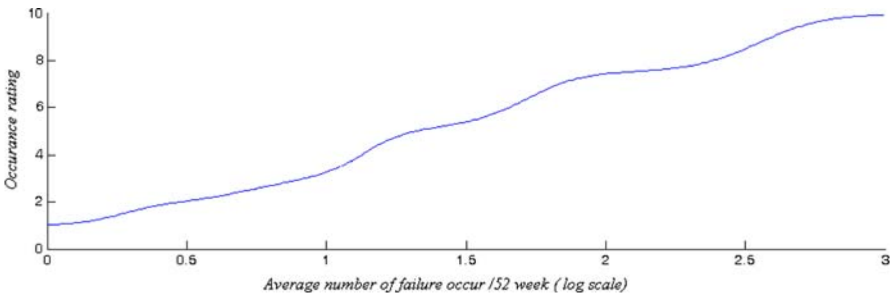


Fig. 5 "Occurrence score" versus "Average number of failures occurred/52 weeks"

over "Average number of failures occurred/52weeks"; therefore the monotone output property is fulfilled.

In short, the fuzzy occurrence model is able to produce monotonous outputs, hence giving logical estimate to failures. In other words, the monotone output property is fulfilled, and the proposed two conditions are satisfied.

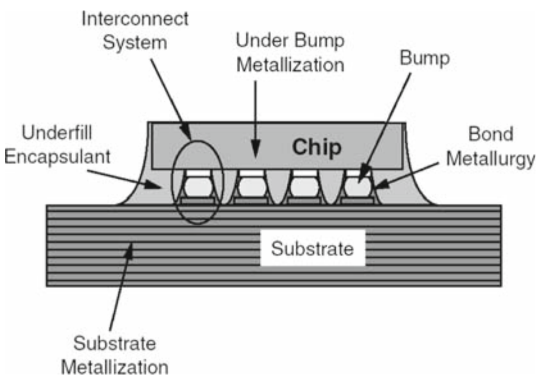
4 Case study II: a multi-input fuzzy assessment model

In this case study, the effectiveness of the Bowles fuzzy RPN model in fulfilling the monotone output property and the output resolution property is investigated. To validate the proposed derivations and suggestions, a series of experiments using data collected from a semiconductor manufacturing processes of Flip Chip Ball Grid Array (FCBGA) products is conducted. FCBGA is a low cost semiconductor packaging solution which utilizes the Controlled Collapse Chip Connect technology, or which is 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 manual wire bonding process (Tummala 2000). It utilizes solder bump interconnection, as shown in Fig. 6.

The manufacturing operation of FCPGA products is divided into nine processes, i.e., wafer fabrication, wafer reflow, wafer mounting, wafer sawing, chip attach (which can be subdivided to fluxing, chip place, reflow and deflux), underfill dispensing (which can be subdivided to prebake, dispensing, and cure), testing, FCBGA ball attach, final inspection, and packaging. Two processes i.e., wafer mounting and wafer dispensing, are used in this case study.

Wafer mounting is a process that facilitates the processing of the wafer from the sawing process through die attach while keeping dies from scattering when the wafer is cut. The process consists of several steps, i.e., (1) frame loading; (2) wafer loading; (3) application of tape to the wafer and wafer frame; (4) cutting of the excess tape; and (5) unloading of the mounted wafer. A number of potential failures 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.

Fig. 6 Schematic of the Flip Chip Interconnection system (adapted from Tummala 2000)



On the other hand, during the wafer underfill dispensing process, the bottom side of a silicon die of a flip chip is encapsulated. The main purpose of this process is to couple the chip and substrate over the entire area of the chip and to lower the effective thermo-mechanical stress on the flip chip interconnections. Besides, it intends to protect flip chip interconnections from environment effects and to absorb harmful alpha particle emissions from the lead in solders which can cause errors in logic circuits (Tummala 2000). This process consists of three steps: (1) pre-bake: to remove residual moisture from the die and the package before the underfill operation; (2) underfill material dispensing: to dispense liquid underfill material between the die and substrate; and (3) underfill material curing: to heat-treat the underfill material that has been dispensed between the die and substrate during underfill.

4.1 The Bowles fuzzy RPN model

Even through the traditional RPN model is simple and has been well accepted for safety analysis, it suffers from several weaknesses. In Bowles (1998), it is pointed out that the same RPN score can be obtained from a number of different score combinations of severity, occurrence, and detect. Although the same RPN is obtained, the risk can be different. In other words, the relative significance of the three factors is neglected in the traditional way of calculating the RPN, and the three factors are assumed to be of equal importance. However, this may not be the case in practice. In fact, it is argued that special attention should be given to failures with high ratings in severity regardless of the RPN (Chrysler Corporation et al. 1995). For example, for two failures with $RPN_1 = 10$ (severity) $\times$ 1 (occurrence) $\times$ 1 (detect) $= 10$, and $RPN_2 = 2$ (severity) $\times$ 5 (occurrence) $\times$ 1 (detect) $= 10$, the former should be given a higher priority as it has a higher score of severity.

On the other hand, there is a suggestion in Ben-Daya and Raouf (1993) to give the occurrence factor the most weight in the RPN calculation because it affects the likelihood of a fault reaching the customer. In Pillay and Wang (2003), it is stated that the FMEA scales for severity and detect are only qualitative. For example, a severity score of 8 does not necessarily twice as severe as that of 4. It is further stated that when the severity, occurrence, and detect ratings are multiplied together to get the RPN, the ratings are treated as if they represent numeric quantities. Indeed, the relative significance of the three factors varies based on the nature of a process or a product.

As an alternative to the traditional RPN model, Bowles proposed a fuzzy RPN model, which allows failure risk evaluation and prioritization to be conducted based on experts' knowledge (Bowles and Peláez 1995). The Bowles fuzzy RPN model considers severity, occurrence, and detect as the input attributes, and it produces the RPN as a measure of failures risk. Figure 7 summarizes the procedure of the Bowles fuzzy RPN model.

4.2 Development of the Bowles fuzzy RPN model

Attributes' membership functions of the Bowles fuzzy RPN model can be generated with reference to Tables 1–3, respectively. Instead of the triangle membership function as used in Bowles and Peláez (1995), the Gaussian membership function is used (with

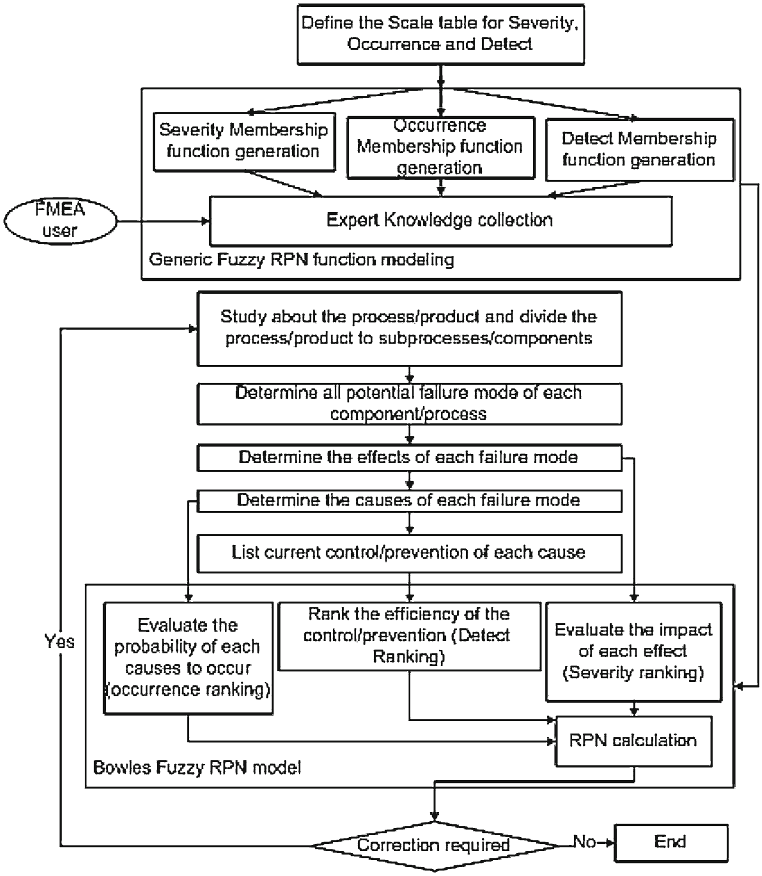


Fig. 7 FMEA with Bowles fuzzy RPN model

the reasons in Sect. 3.1). Figures 8–10 depict the fuzzy membership function for severity (μ_s), occurrence (μ_o), and detect (μ_d), respectively. As an example, referring to Fig. 8, the second membership function of severity, μ_s^2, with linguistic label of "Low", represents severity ratings from 2 to 5, which correspond to "yield hit, cosmetic impact, special internal handling, effort or annoyance" as in Table 1. The same scenario applies to Fig. 9, where the "Moderate" membership, μ_o^4, represents occurrence ratings from 4 to 6, which correspond to "Once/week, Several/month, Few/quarter" as in Table 2. In Fig. 10, the "High" membership function, μ_d^2, represents detect ratings from 3 and 4, which correspond to "Controls are able to Detect within the same machine/module" as in Table 3.

Similar to the traditional RPN model, the output of the Bowles fuzzy RPN model varies from 1 to 1,000. In this case study, it is divided into five equal partitions, with fuzzy membership functions, B, "Low", "Low Medium", "Medium", "High Medium", and "High", respectively. The corresponding b scores are assumed to the point where membership value of B is 1. Hence, b is 1, 250.75, 500.5, 750.25, and 1,000, respectively.

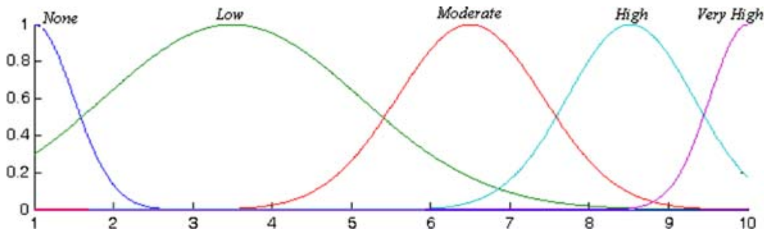


Fig. 8 The membership function of severity

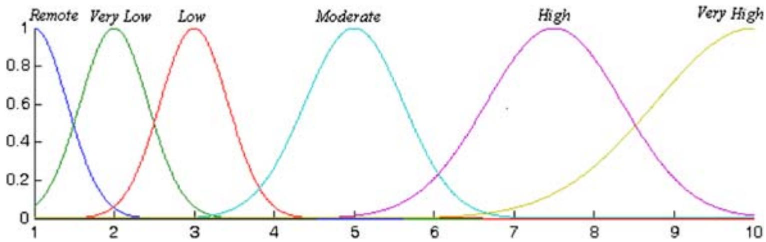


Fig. 9 The membership function of occurrence

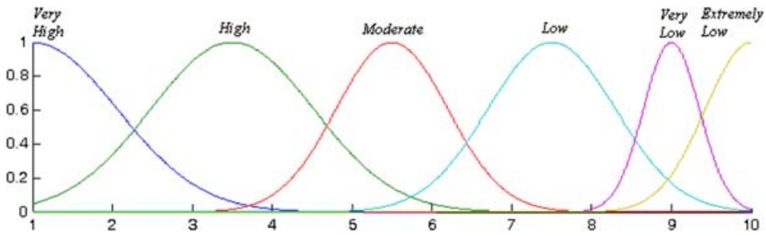


Fig. 10 The membership function of detect

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. 11 An example of two fuzzy production rules

A fuzzy rule base is a collection of knowledge from experts in the If-Then format. Considering the attributes and the linguistic terms describing each attribute, the fuzzy rule base has 180 (5 (severity) $\times$ 6 (occurrence) $\times$ 6 (detect)) rules in total using the grid partition approach (Jang et al. 1997; Lin and Lee 1995). Here, two sets of fuzzy rule base are collected from process engineers of the wafer mounting process and the wafer dispensing process, respectively. As an example, Fig. 11 shows two rules that describe a small portion of the fuzzy rules collected from wafer mounting process engineers.

In this paper, we use a simplified Mamdani FIS (Yam 1999; Hisao et al. 2006; Hisao 1991), is used to evaluate the RPN, as in Eq. 6.

$$\text{RPN score} = \frac{\sum_{a=1}^{M_s} \sum_{b=1}^{M_o} \sum_{c=1}^{M_d} \mu_s^a \times \mu_o^b \times \mu_d^c \times b^{a,b,c}}{\sum_{a=1}^{M_s} \sum_{b=1}^{M_o} \sum_{c=1}^{M_d} \mu_s^a \times \mu_o^b \times \mu_d^c} \tag{6}$$

4.3 Analysis of the bowles fuzzy RPN model

4.3.1 The monotone output property

Similar to the traditional RPN function, the three attributes of Bowles fuzzy RPN are defined in such a way that the higher the input scores, the more critical the situation. The output RPN is a measure of the failure risk. From the inputs–output relationship, the monotone output property can be applied to all these three attributes. For example, for two failures with input sets of 5 5 5 and 5 5 6 (severity, occurrence, and detect), the fuzzy RPN for the second failure should be higher than that of the first. Prediction is deemed illogical if a contradictory result is produced.

We argue that Condition (1) and Condition (2) (as in Part I) need to be satisfied for all attributes (severity, occurrence, and detect). Condition (1) suggests that a logical fuzzy rule base is needed. Again, Condition (2) gives a guideline on how the fuzzy membership functions of severity, occurrence, and detect should be tuned. Figures 8–10 depict an example of attribute membership functions that fulfill Condition (2).

4.3.2 The output resolution property

To allow valid and effective comparison among failures, the output resolution property is applied. In this case study, we set $\alpha = 1$. As in the previous example (Sect. 4.3.1), obtaining the same fuzzy RPN for both the failures is not representative enough for risk comparison between the two failures. Ideally, the Bowles fuzzy RPN model should be able to give a higher fuzzy RPN to the second failure as compared with that of the first, i.e., the second failure has a higher risk and has a higher priority.

To increase the output resolution of the Bowles fuzzy RPN model, we suggest to refine the original rule base with weighted fuzzy production rules. For the example in Fig. 11, with the rule refinement approach, Rule 2 is mapped 95% to *High* (b = 1,000) and 5% *to High Medium* (b = 750.25). Figure 12 shows the refined rules. This indicates that Rule 2 has a lower risk level as compared than that of Rule 1. The new b score for Rule 2 is 987.5125 ($0.95 \times 1{,}000 + 0.05 \times 750.25 = 987.5125$), and is equal to a new membership function between *High* and *High Medium*.

4.4 Results and discussion

Tables 6 and 7 summarize the failure risk evaluation, ranking, and prioritization results using the traditional and Bowles fuzzy RPN models for the wafer mounting and under-

Rule 1

If Severity is **Very High** and Occurrence is **Very High** and Detect is **Extremely Low** then RPN is **High**. --1.00

Rule 2

If Severity is **Very high** and Occurrence is **Very High** and Detect is **Very Low** then RPN is **High** --0.95

If Severity is **Very high** and Occurrence is **Very High** and Detect is **Very Low** then RPN is **High Medium**--0.05

Fig. 12 An example of two weighted fuzzy production rules

fill dispensing processes, respectively. Columns "Sev" (severity), "Occ" (occurrence), and "Det" (detect) show the three attribute ratings describing each failure. 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 6, failure mode "1" represents "broken wafer", which leads to yield loss, and is given a severity 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 occurrence score of 1 (refer to Table 2). In order to eliminate the cause, software enhancement has been done as action taken. Owing to the action taken is very effective, and can almost eliminate the root cause; a detect score of 1 is given (refer to Table 3). Using the traditional RPN model, an RPN of 3 is obtained, with the lowest RPN ranking (RPN rank = 1).

Column "Fuzzy RPN (FPR)" shows the failures risk evaluation results using the Bowles fuzzy RPN model, while sub-columns "FRPN" and "FRPN Rank" show its failure risk evaluation and prioritization outcomes, respectively. Referring to above example, FRPN = 10 and FRPN Rank = 1. Column "Expert's Knowledge (FPR)" shows the linguistic term assigned by process engineers, *Low* with $b = 1.00$. The evaluation result after rule refinement (column "Fuzzy RPN model after refinement") is FRPN = 10, with rank of 1, and is assigned a linguistic term of *Low* with $b = 1.00$.

From the observation, the Bowles fuzzy RPN model is able to fulfill the monotone output property for all failures. There are no illogical predictions found in both problems. However, it is not able to fulfill the output resolution property. For example, in Table 6, failures 2 and 3 are predicted to have the same FRPN of 19. Based on the severity, occurrence, and detect ratings, failure 3 should have a higher FRPN than that of failure 2. The same situations can be observed in failures 13 and 14 as well as 17 and 18. In Table 7, failures 1 and 2 as well as 4 and 5 are is predicted to have the same score (FRPN = 1 and FRPN = 15, respectively). Similar situation occurs in failures 17 to 23 (FRPN = 750) as well as 25 and 26 (FRPN = 925).

The output resolution problem is resolved after rule refinement, as shown in "Fuzzy RPN with rule refinement". After rule refinement, the Bowles fuzzy RPN model is able to evaluate failures in accordance with expert's knowledge, with different estimated scores. The monotone output property is still fulfilled. For example, in Table 6, failures 2 (FRPN = 19) and 3 (FRPN = 24) are predicted to have different FRPN scores after rule refinement. The same can be observed in failures 13 and 14 as well as 17 and 18. From Table 7, the same finding is obtained. After rule refinement, failures 1 (FRPN = 79) and 2 (FRPN = 86) as well as 4 (FRPN = 105) and 5 (FRPN = 114) are predicted to have different FRPN scores. Different FRPN scores are also estimated for failures 17–23, and this allows valid and useful comparisons to be made among them.

Table 6 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 model after refinement			
	Sev	Occ	Det			Fuzzy RPN (FPR)		Expert's knowledge (FPR)		Fuzzy RPN (WFPR)		Expert's knowledge (WFPR)	
						FRPN	FRPN rank	Linguistic term	*b*	FRPN	FRPN rank	Linguistic term	*b*
1	3	1	1	3	1	10	1	Low	1.00	10	1	Low	1.00
2	2	2	1	4	2	19	2	Low	1.00	19	2	Low	1.00
3	3	2	1	6	3	19	2	Low	1.00	24	3	Low	1.00
4	3	1	2	6	3	85	3	Low	1.00	85	4	Low	1.00
5	3	2	2	12	4	94	4	Low	1.00	94	5	Low	1.00
6	2	2	3	12	4	175	5	Low medium	250.75	175	6	Low medium	250.75
7	2	3	2	12	4	198	6	Low medium	250.75	198	7	Low medium	250.75
8	2	3	3	18	6	204	7	Low medium	250.75	204	8	Low medium	250.75
9	2	4	2	16	5	206	8	Low medium	250.75	235	10	Low medium	250.75
10	3	2	3	18	6	212	9	Low medium	250.75	211	9	Low medium	250.75
11	3	3	2	18	6	239	10	Low medium	250.75	239	11	Low medium	250.75
12	3	3	3	27	8	247	11	Low medium	250.75	247	12	Low medium	250.75
13	3	4	1	12	4	249	12	Low medium	250.75	254	13	Low medium	250.75
14	3	4	2	24	7	249	12	Low medium	250.75	284	14	Low medium	250.75
15	3	2	4	24	7	270	13	Low medium	250.75	262	15	Low medium	250.75
16	4	3	4	48	12	279	14	Low medium	250.75	277	16	Low medium	250.75
17	3	2	5	30	9	423	15	Medium	500.50	372	17	30% Low medium 70% Medium	425.58
18	3	3	5	45	11	423	15	Medium	500.50	404	18	10% Low medium 90% Medium	475.53
19	2	2	10	40	10	456	16	Medium	500.50	456	19	Medium	500.50

Table 7 Failure risk evaluation, ranking and prioritization results using the traditional RPN, as well as the fuzzy RPN and its enhanced models of the underfill dispensing process

Failures no	Inputs ranking			RPN	RPN rank	Fuzzy RPN model				Fuzzy RPN model after refinement			
	Sev	Occ	Det			Fuzzy RPN (FPR)		Expert's knowledge (FPR)		Fuzzy RPN (WFPR)		Expert's knowledge (FPR)	
						FRPN	FRPN rank	Linguistic term	*b*	FRPN	FRPN rank	Linguistic term	*b*
1	3	1	1	3	1	1	1	Low	1.00	79	1	70% Low 30% Low medium	75.925
2	3	1	2	6	2	1	1	Low	1.00	86	2	70% Low 30% Low medium	75.925
3	3	1	3	9	4	2	2	Low	1.00	99	3	60% Low 40% Low medium	100.9
4	3	2	1	6	2	15	3	Low	1.00	105	4	60% Low 40% Low medium	100.9
5	3	2	2	12	6	15	3	Low	1.00	114	6	60% Low 40% Low medium	100.9
6	4	2	1	8	3	22	4	Low	1.00	110	5	60% Low 40% Low medium	100.9
7	5	2	2	20	9	111	6	Low	1.00	184	7	60% Low 40% Low medium	100.9
8	3	3	2	18	8	239	7	Low medium	250.75	199	9	30% Low 70% Low medium	175.825
9	4	3	1	12	6	245	8	Low medium	250.75	190	8	30% Low 70% Low medium	175.825
10	5	1	5	25	11	270	9	Low medium	250.75	303	10	Low medium	250.75
11	8	1	1	8	3	453	10	Medium	500.50	454	11	Medium	500.5
12	3	3	10	90	18	502	11	Medium	500.50	502	12	Medium	500.5
13	8	1	2	16	7	523	12	Medium	500.50	524	13	Medium	500.5
14	8	2	1	16	7	624	13	High medium	750.25	624	14	High medium	750.25
15	8	2	2	32	12	643	14	High medium	750.25	645	15	High medium	750.25

Table 7 continued

Failures no	Inputs ranking			RPN	RPN rank	Fuzzy RPN model				Fuzzy RPN model after refinement			
	Sev	Occ	Det			Fuzzy RPN (FPR)		Expert's knowledge (FPR)		Fuzzy RPN (WFPR)		Expert's knowledge (FPR)	
						FRPN	FRPN rank	Linguistic term	*b*	FRPN	FRPN rank	Linguistic term	*b*
16	4	4	2	32	12	657	15	High medium	750.25	661	16	High medium	750.25
17	3	6	1	18	8	750	16	High medium	750.25	774	19	High medium	750.25
18	3	6	2	36	13	750	16	High medium	750.25	782	20	High medium	750.25
19	3	7	1	21	10	750	16	High medium	750.25	798	23	80% High medium 20%High	800.2
20	3	7	2	42	15	750	16	High medium	750.25	800	24	80% High medium 20%High	800.2
21	4	5	1	20	9	750	16	High medium	750.25	751	17	High medium	750.25
22	4	5	2	40	14	750	16	High medium	750.25	766	18	High medium	750.25
23	4	5	4	80	17	750	16	High medium	750.25	797	22	80% High medium 20%High	800.2
24	5	9	2	90	18	770	17	High medium	750.25	796	21	80% High medium 20%High	800.2
25	8	6	1	48	16	935	18	High	1,000.00	898	25	20% High medium 20% High	950.05
26	8	6	2	96	19	935	18	High	1,000.00	906	26	20% High medium 20% High	950.05
27	5	9	6	270	20	940	19	High	1,000.00	952	27	High	1,000

As a summary, the case study demonstrates that with Condition (1) and Condition (2) satisfied, the monotone output property is satisfied. Besides, the output resolution property of the Bowles fuzzy RPN model is improved by using the proposed rule refinement approach.

5 Summary

In this paper, two fuzzy assessment models are explained. We have assessed the two proposed theoretical properties, namely the monotone output property and the output resolution property, of fuzzy assessment models in FMEA methodology. The two properties ensure meaningful measuring scores to be obtained, so that valid and useful comparisons among situations/objects are allowed. We have demonstrated the applicability of the two properties to industrial FMEA applications, with a proposed fuzzy occurrence model and the Bowles fuzzy RPN model. These models are constructed with data and information collected from a real manufacturing facility. The experimental results have shown that by fulfilling the two conditions (Conditions 1 and 2), the monotone output property can be ensured. This can be viewed as a simple and reliable method to obtain a monotonous fuzzy assessment model without resorting to any complicated tuning algorithms. This finding is useful, and is a step further to make fuzzy assessment models a generic tool to be applied in various applications, and to be used by users with very limited knowledge in fuzzy systems. In addition, we have shown that with the rule refinement approach, the output resolution property of the Bowles fuzzy RPN model can be improved.

For further work, the use of the fuzzy assessment models with enhanced techniques needs to be investigated. These include fuzzy assessment models that employ fuzzy rule interpolation techniques or online learning algorithms. In addition, it is necessary to further study the effectiveness of the proposed fuzzy assessment models in different domains in order to ascertain their applicability to real industrial environments.

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