Paper:

Enhancing a Fuzzy Failure Mode and Effect Analysis Methodology with an Analogical Reasoning Technique

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In this paper, a fuzzy Failure Mode and Effect Analysis (FMEA) methodology incorporating an analogical reasoning technique is presented. FMEA methodology was introduced as a formal and systematic procedure for evaluation of risk associated with potential failure modes in the 1960s. Bowles and Peláez [1] proposed a Fuzzy Inference System (FIS)-based Risk Priority Number (RPN) model as an alternative to the conventional RPN model. For an FIS-based RPN (a three-input FIS model), a large set of fuzzy rules are required, and it is tedious to collect the full set of rules. With the grid partition strategy, the number of fuzzy rules required increases in an exponential manner, and this phenomenon is known as the "curse of dimensionality" or the combinatorial rule explosion problem. Hence, a rule selection and similarity reasoning technique, i.e., Approximate Analogical Reasoning Schema (AARS) technique are implemented in a fuzzy FMEA in order to solve the problem. The experiment was conducted using a set of data collected from a semiconductor manufacturing line, i.e., underfill dispensing process, and promising results were obtained.

Keywords: similarity reasoning, failure mode and effect analysis, fuzzy inference system

1. Introduction

Failure Mode and Effect Analysis (FMEA) was introduced as a formal design methodology by the aerospace industry with their well-known reliability and safety requirements [1]. Conventional FMEA has been presented by either developing a Risk Priority Number (RPN) or calculating an item criticality number. The RPN model is used to evaluate the risk associated with each failure mode in FMEA by multiplication of three factors scores, i.e., Severity (S), Occurrence (O), and Detect (D).

A fuzzy FMEA methodology incorporating a Fuzzy Inference System (FIS)-based RPN model allows failure risk evaluation prioritization to be conducted based on experts' knowledge. It aggregates the three factors with an FIS model and produces a fuzzy RPN score. The relationship between S, O, and D, and RPN is expressed using a set of fuzzy production rules. There are several reasons why FIS-based RPN is preferred, instead of the conventional RPN. (1) An FIS-based RPN assumes that the relationship between the RPN score and the S, O, and D to be non-linear, which may be a better representation than that of the conventional RPN [1], (2) FIS could be a good solution against uncertainty and vagueness [1], and (3) scales used may be qualitative instead of quantitative [2]. From the literature review, fuzzy FMEA has been successfully applied to various designs and processes; for example, a fishing vessel [3], an auxiliary feed water system and a chemical volume control system in a nuclear power plant [4, 5], a semiconductor manufacturing line [6], and also health care [7].

Over the years, several enhancements have been proposed to improve the fuzzy FMEA methodology. In [8], a fuzzy rule-based Bayesian reasoning model for prioritization of failures in fuzzy FMEA was proposed. A method to reduce the number of fuzzy rules in fuzzy FMEA was proposed in [9]. Other advanced FMEA methodologies are as follows: (1) a fuzzy weighted geometric mean for risk evaluation was presented and implemented [10]; and (2) fuzzy logic and expert database were integrated with FMEA for system safety and reliability analysis [11]. An Evidential Reasoning (ER) approach was presented to enhance the multiple attribute decision analysis in FMEA [12].

Recent advances in fuzzy modeling focus on rule reduction [13–16] and similarity reasoning [17–20]. The former attempts to reduce the fuzzy rules for a better computation time, storage space, and data collection process [13–16]. In [13], a data-driven fuzzy modeling technique with redundant rules removal and optimization of structure and parameters was presented. A method to reduce fuzzy rule base via singular value decomposition was proposed in [14, 15]. In [16], rule base reduction using orthogonal transform was proposed. The latter focuses on deducing the conclusions for observations in an incomplete rule base. Approximation Analogical Reasoning Schema (AARS) [17] and Fuzzy Rule Interpolation (FRI) [18–20] are examples of similarity reasoning techniques. In a conventional FIS model, unknown consequents are assumed to be zero where this might not be true. This phenomenon is known as the "tomato classification" [20].

The aim of this paper is to develop a fuzzy FMEA methodology with a rule reduction and similarity reasoning technique (i.e., an AARS). The rule reduction technique is used to ease the data collection process. The rule reduction technique systematically selects a set of rules to be collected from the engineer. With the rule reduction procedure, a set of incomplete fuzzy rules that are evenly distributed over the entire input space is selected. The AARS is further used to allow the unknown fuzzy rules to be deduced on the basis of the incomplete rule base. The antecedents for the unknown fuzzy rules are assumed to be observations. The AARS is used to deduce conclusions associated with these observations, which are predictions for unknown consequents. Our proposed method reduces the time required to collect a full set of the rule base by collecting the selected rules only. Hence, it eases the fuzzy FMEA procedure. The proposed fuzzy FMEA procedure is then evaluated using a set of data collected from a semiconductor manufacturing line.

This paper is presented as follows: in Section 2, an FIS, an AARS, and a fuzzy FMEA methodology are reviewed. Our proposed fuzzy FMEA methodology is explained in Section 3. Experimental results are discussed in Section 4. Finally, concluding remarks are presented.

2. Background

2.1. Fuzzy Inference System

A Fuzzy Inference System (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy production rules, and fuzzy reasoning. It has found successful application in a wide variety of fields, such as in achieving classification tasks, offline process simulation and diagnosis, online decision support tools, and process control [21]. An FIS employing *fuzzy if-then* rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses [22].

Generally, a Fuzzy Production Rule (FPR) has the form shown below.

IF (x_1 is $\mu_1^{j_1}$) AND (x_2 is $\mu_2^{j_2}$) ...AND (x_n is $\mu_n^{j_n}$) THEN y is $B^{j_1 j_2 \ldots j_n}$

where x_n and y are the inputs and output of an FIS, respectively; μ and B are the input and output linguistic variables/fuzzy sets, respectively.

The estimated score can be obtained by using a simplified FIS, as given in Eq. (1).

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

where

$$b^{j_1 j_2 \ldots j_n} = rep(B^{j_1 j_2 \ldots j_n}) \quad \ldots \quad (2)$$

$rep(B^{j_1 j_2 \ldots j_n})$ is a representative value of $B^{j_1 j_2 \ldots j_n}$. It represents the overall location where $B^{j_1 j_2 \ldots j_n}$ is. In this paper, $rep(B^{j_1 j_2 \ldots j_n})$ is the point where the membership function value of $B^{j_1 j_2 \ldots j_n}$ is 1.

2.2. Review of the Approximate Analogical Reasoning Schema (AARS)

Analogical reasoning provides a basic mechanism for effective connection between a reasoner's past and present experiences [23]. This notion is further extended; an AARS was proposed to allow unknown fuzzy rules to be deduced from an incomplete rule base in FIS modeling [17].

The AARS can be divided into three steps: (i) determining the similarity measure of an observation with each antecedent of the known fuzzy rules, (ii) selecting the fuzzy rule(s) for deducing the conclusion, (iii) finding the aggregate of conclusions associated with the observation.

In **Fig. 1**, we explained the concept of predicting n_{empty} conclusions, (each conclusion associated to an observation), via the AARS technique from a fuzzy rule base that comprises of $n_{available}$ fuzzy rules. The n_{empty} observations and conclusions are represented as $\mu^{R^i} \rightarrow B^{R^i}$, respectively, $i = 1,2,3,\ldots n_{empty}$. The $n_{available}$ fuzzy rules are represented as $\mu^{R^j} \rightarrow B^{R^j}$, $j = 1,2,3,\ldots n_{available}$.

$\mu^{R^i \cap R^j}$ is the area of overlapping between μ^{R^i} and μ^{R^j}, as shown in **Fig. 2**. In step (i), similarity between an observation and antecedent is determined by their supreme or the maximum point of the $\mu^{R^i \cap R^j}$, i.e., $Sup(R^i \cap R^j) = \max(\mu^{R^i \cap R^j})$. A threshold value λ is adopted to decide the consequent of the antecedent, B^{R^j}, whether it is to be or not to be selected for deducing the conclusion, B^{R^i}. In step (ii), the consequent is selected if $Sup(R^i \cap R^j) > \lambda$. In step (iii), representative value of the conclusion of an observation is calculated using a weighted average in order to obtain the final result as in Eq. (3).

$$b = \frac{\sum_{k=1}^{k=m} Sup(R^i \cap R^k) \times rep\ (B^{R^k})}{\sum_{k=1}^{k=m} Sup(R^i \cap R^k)} \quad \ldots \quad (3)$$

where R^k is the set of selected fuzzy rules, $k \leq n_{selected}$.

2.3. Review of the Fuzzy Failure Mode and Effect Analysis (FMEA) Methodology and its Risk Priority Number (RPN) Models

Conventional FMEA determines the RPN score by multiplying the three input factors which are S, O, and D, as given in Eq. (4).

$$RPN = Severity \times Occurrence \times Detect \quad \ldots \quad (4)$$

The traditional RPN ranking has been well-known for its application in FMEA but it suffers from several weaknesses [1]. FIS-based RPN is introduced as an alternative to conventional RPN [1]. Instead of simple multiplication, an FIS model is used to compute the RPN score. S, O, and D are estimated by experts with reference to scale

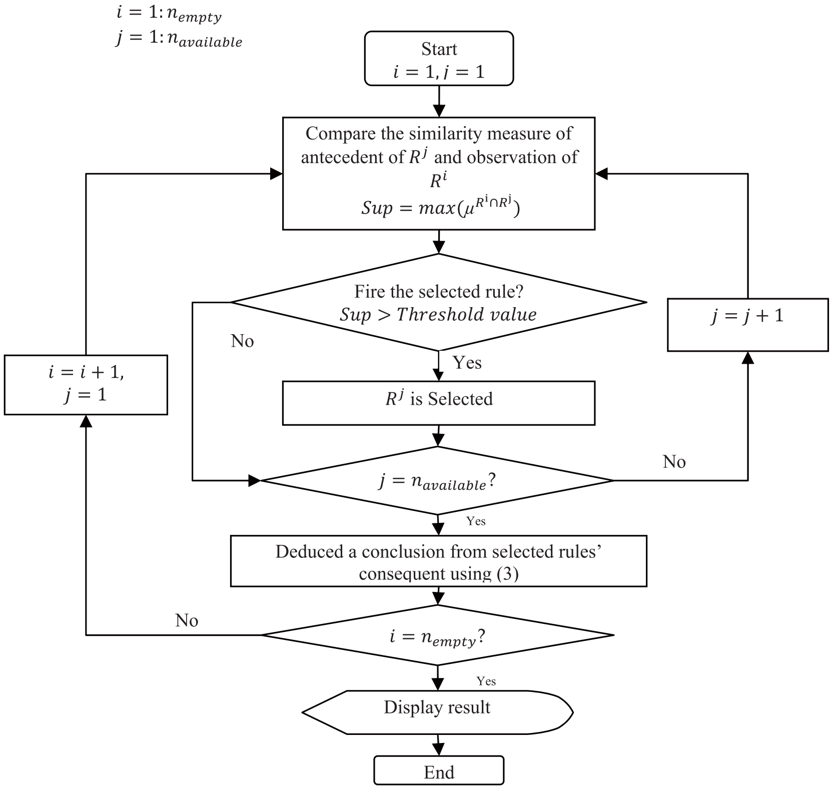

Fig. 1. AARS algorithm.

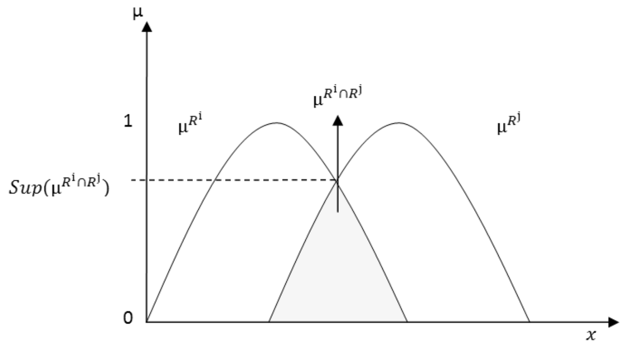

Fig. 2. Depiction of the antecedents' overlapping area.

tables, ranging from 1 to 10 based on a commonly agreed evaluation criteria. **Tables 1**, **2**, and **3** define the scale table for S, O, and D respectively. **Figs. 3**, **4**, and **5** show the membership functions for S, O, and D respectively. The membership function of S, O, and D are denoted as μ_S, μ_O, and μ_D, respectively.

Membership functions for RPN are represented as its representative value. The relationship between S, O, and D, and RPN is described using a set of fuzzy production rules. An example of fuzzy production rules is as follows:

Rule 1:

If Severity is *Extremely 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.*

With the use of grid partition, the number of fuzzy rules required increases in an exponential manner, and this phenomenon is known as the "curse of dimensionality" or the combinatorial rule explosion problem. The Risk Priority Number (RPN) for S, O, and D can be obtained using an FIS model, as given in Eq. (5).

$$RPN = \frac{\sum_{a=1}^{M_S} \sum_{b=1}^{M_O} \sum_{c=1}^{M_D} \mu_S^a \times \mu_O^b \times \mu_D^c \times B^{a,b,c}}{\sum_{a=1}^{M_S} \sum_{b=1}^{M_O} \sum_{c=1}^{M_D} \mu_S^a \times \mu_O^b \times \mu_D^c} \quad (5)$$

where M_S, M_O, and M_D are the numbers of partition for S, O, and D, respectively. M_S, M_O, and M_D are 5, 6, and 6, respectively.

3. The Proposed FIS-Based FMEA Methodology

Our proposed fuzzy FMEA methodology is summarized in **Fig. 6**. A detailed description is as follows:

a) The scale tables for S, O, and D are defined.

b) The membership functions for S, O, and D are designed, i.e., μ_S, μ_O, and μ_D, respectively.

c) 50% of the fuzzy rules (i.e., R^j) are selected for data collection. Fuzzy rules are alternatively selected from the full rule base.

Table 1. Scale table for severity.

Rank	Linguistic terms	Criteria
10	Extremely high	Failure will affect safety or compliance to law
9~8	High	Customer impact Major reliability excursions
7~6	Moderate	Impacts customer yield Wrong package/par/marking
5~2	Low	Yield hit, cosmetic
1	None	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

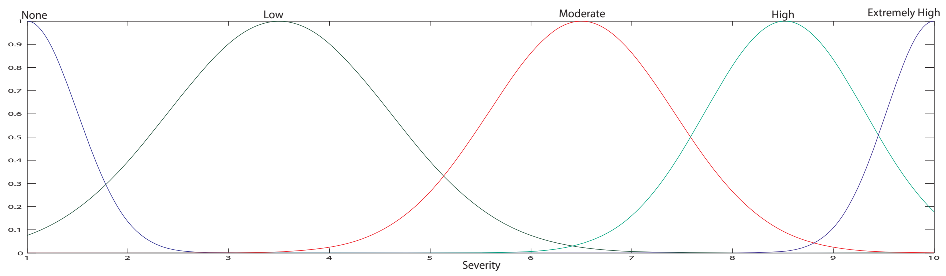

Fig. 3. Membership function of severity.

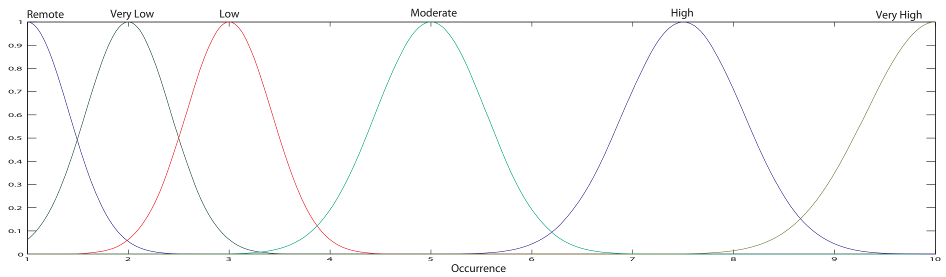

Fig. 4. Membership function of occurrence.

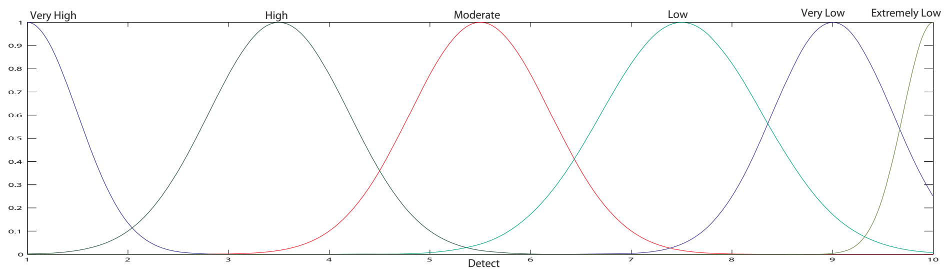

Fig. 5. Membership function of detect.

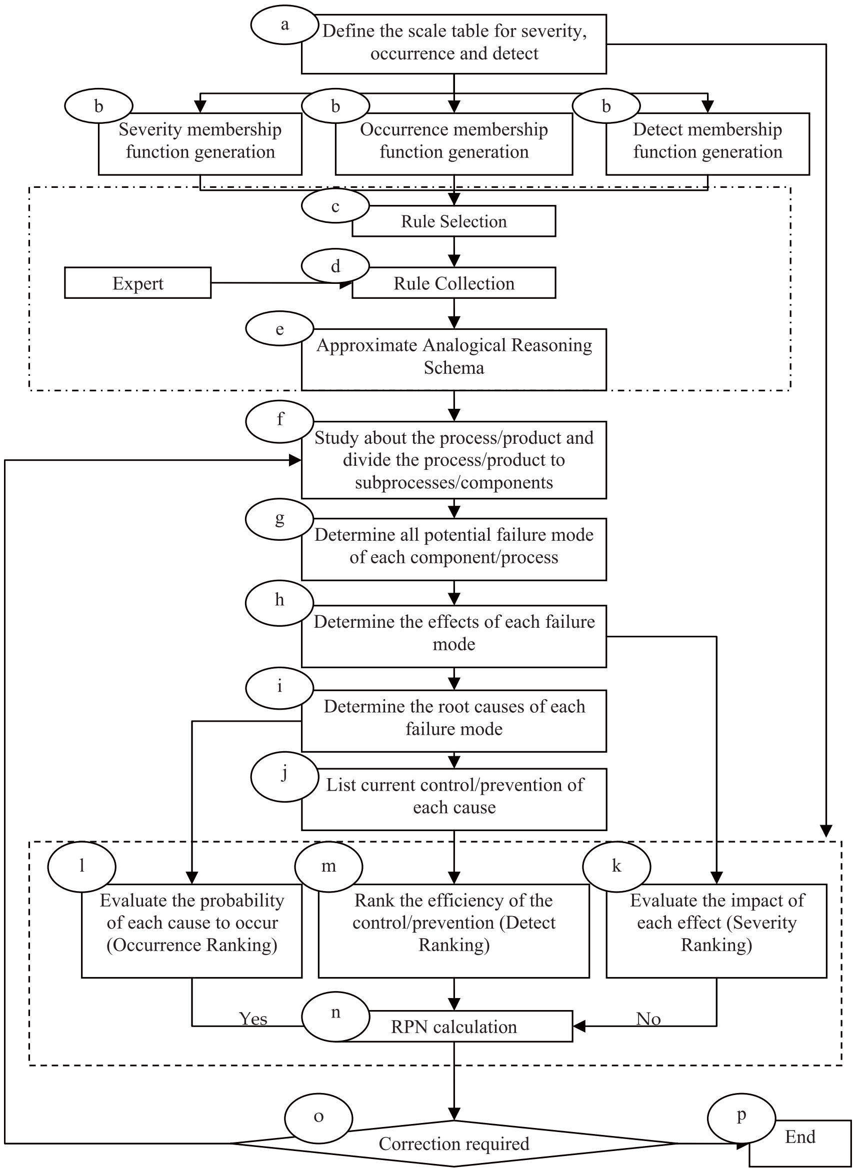

Fig. 6. FMEA with FIS-based RPN model with the AARS technique.

d) R^j are collected from the experts (the process engineer).

e) The process is then continued with the prediction of unknown fuzzy rules R^i, using the AARS.

f) The intention, purpose, goal, and objective of a product/process are studied, which are commonly recognized by interaction among components/processes and followed by task analysis.

g) Potential failures of the product/process which include problems, concerns, and opportunity of improvement are identified.

h) Effects of failure on other components/next processes, operation, customers, and government improvement are identified.

i) The potential root causes of potential failures are identified.

j) The first level method/procedure to detect/prevent failures of the product/process is conducted.

k) Severity score rating is evaluated.

l) Occurrence score rating is evaluated.

m) Detect score rating is evaluated.

n) RPN is computed using Eq. (5).

o) Return to Step f) if there is any correction.

p) End.

Table 4. Failure risk evaluation, ranking, and prioritization results of using the fuzzy RPN model and AARS fuzzy RPN model for the underfill dispensing process.

Failures No.	Inputs ranking			Fuzzy RPN	Fuzzy RPN Rank	AARS Fuzzy RPN	AARS Fuzzy RPN Rank
	S	*O*	*D*				
1	3	1	1	1	1	10	1
2	3	1	2	1	1	78	2
3	3	1	3	1	1	191	4
4	3	2	1	13	3	208	5
5	3	2	2	10	2	148	3
6	4	2	1	15	4	213	6
7	5	2	2	59	7	233	7
8	3	3	2	155	9	267	9
9	4	3	1	230	11	250	8
10	5	1	5	213	10	308	10
11	8	1	1	388	20	438	11
12	3	3	10	40	5	579	13
13	8	1	2	279	15	484	12
14	8	2	1	95	8	588	14
15	8	2	2	255	13	613	15
16	4	4	2	243	12	638	16
17	3	6	1	330	17	727	19
18	3	6	2	360	19	739	20
19	3	7	1	670	25	750	22
20	3	7	2	476	23	761	23
21	4	5	1	44	6	712	17
22	4	5	2	263	14	723	18
23	4	5	4	654	24	746	21
24	5	9	2	331	18	803	24
25	8	6	1	412	21	900	26
26	8	6	2	449	22	909	27

4. Experiments and Results

Our proposed methodology was evaluated using a set of data collected from an underfill dispensing process in a semiconductor manufacturing line. During the 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 reduce the effective thermomechanical stress on the flip chip interconnections. It also intends to protect the flip chip interconnections from environmental effects and absorb harmful alpha particle emissions from the lead in solders, which can cause errors in logic circuits [24].

From **Tables 1**, **2**, and **3**, the complete rule base is expected to have 180 rules [5 (S) × 6 (O) × 6 (D)]. In this experiment, 90 rules are systematically selected. The other 90 rules are predicted using the AARS.

Table 4 summarizes the failure risk evaluation, i.e., the ranking and prioritization results using the FIS-based RPN model (with selected fuzzy rules only) and the FIS-based RPN with the AARS (with selected fuzzy rules and predicted fuzzy rules) of the underfill dispensing process. The column "*Failure No.*" summarizes the 26 potential failure modes. Columns S, O, and D show the three input ranking/rating describing each failure.

The column "*Fuzzy RPN*" shows the predicted RPN score with the FIS-based RPN without the AARS-predicted rule. "*Fuzzy RPN rank*" is the ranking of failure modes with the FIS-based RPN without the AARS-predicted rule. The column "*AARS Fuzzy RPN*" shows the predicted RPN score with FIS-based RPN and the AARS-predicted rule. Its ranking result is presented in the column "*Fuzzy RPN rank*." For example, for failure No.1, S = 3, O = 1, D = 1, fuzzy RPN = 1 and fuzzy rank = 1. The same goes for AARS Fuzzy RPN and its rank.

Figures 7 and **8** depict the surface plot RPN score versus its input without the predicted rules. **Fig. 7** shows the RPN scores versus O and D at S = 1, and **Fig. 8** shows the RPN scores versus S and D at O = 10. **Figs. 9** and **10** illustrate the surface plot RPN score versus its inputs with the AARS predicted rule. **Fig. 9** shows the RPN scores versus O and D at S = 1, and **Fig. 10** shows the RPN scores versus S and D at O = 10.

From the results obtained, it is observed that the surface plots for FIS-based RPN without the AARS are fluctuating. This scenario can be explained as the "tomato classification problem" [20]. Thus, AARS is adopted to predict the empty rules. Smoother surface plots are obtained with the AARS.

It is then noticed that the results for FIS-based RPN with the AARS do not fulfill the monotonicity property. For failure number 5, when S = 3, O = 2, and D = 2, AARS RPN is 148. This value is smaller than that of the condition where S = 3, O = 2, and D = 1, with the AARS RPN of 207. The same goes for failure numbers 9, 13, 21,

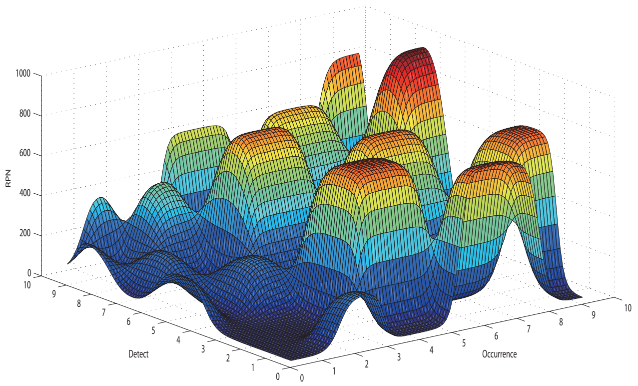

Fig. 7. RPN versus occurrence and detect at severity = 1 for the FIS-based RPN without the AARS.

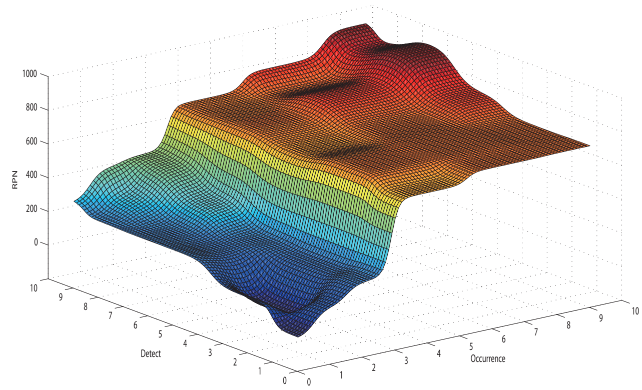

Fig. 9. RPN versus occurrence and detect at severity = 1 for the FIS-based RPN with the AARS.

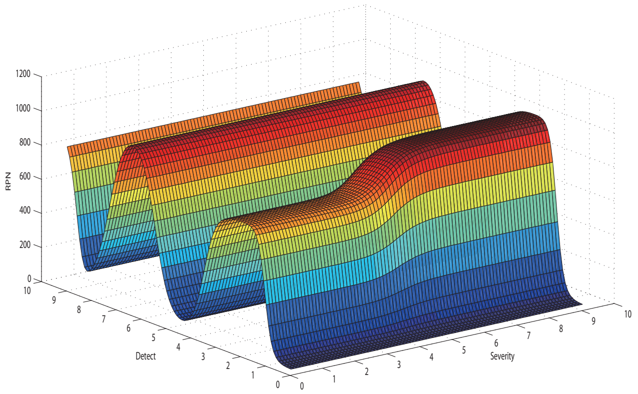

Fig. 8. RPN versus severity and detect at occurrence = 10 for the FIS-based RPN without the AARS.

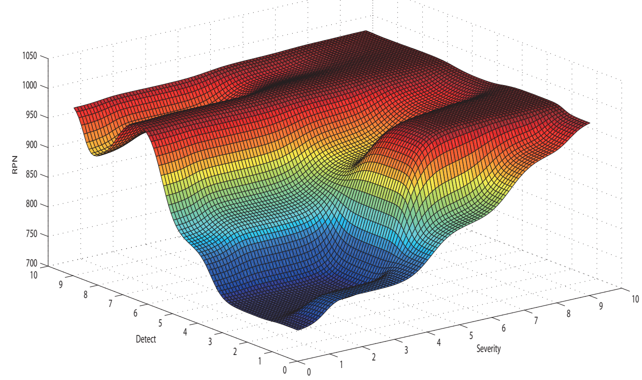

Fig. 10. RPN versus severity and detect at occurrence = 10 for the AARS with FIS-based FMEA.

22, 23, and 27. This non-monotonicity scenario can also be observed in **Figs. 9** and **10**.

5. Conclusions

In this paper, a fuzzy FMEA methodology with the AARS technique is proposed. Collecting a full rule base is tedious, and our proposed procedure reduces the rules collected. Our proposed methodology is able to ease the rule base collection process and reduce the time consumed. The AARS is further used to predict these uncollected fuzzy rules. Our empirical results show that without the AARS, the output has the "tomato classification problem" and that with the AARS, the results are better. However, the results still show that FIS-based RPN with the AARS does not provide a monotonic prediction.

For future studies, the use of fuzzy rule interpolation [18–20] to predict the empty rules will be investigated. Besides, more experiments will be conducted and other optimization tools, e.g., Particle Swarm Optimization (PSO) [25] and Harmony Search (HS) [26], will be investigated. Monotonicity property in FIS modeling will also be studied in order to solve the non-monotonicity problem [2, 6].

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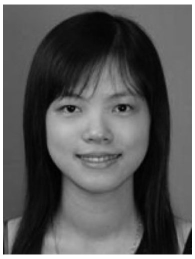

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