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Fuzzy logic-based FMEA robust design: a quantitative approach for robustness against groupthink in group/team decision-making

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Group/team decision-making is an integral part of almost all failure mode and effects analysis (FMEA) projects. A dysfunctional aspect of this decision-making fashion in fuzzy FMEA is that group/team members' designs for membership functions and *IF-THEN* rules may be overshadowed by a member's design. This problem is caused by groupthink, a pitfall known by the Organisational Behaviour science. This study aims to develop a fuzzy FMEA approach which is robust to the problem. We applied the Taguchi's robust parameter design and investigated the effects of various control parameters namely Defuzzification, Aggregation, And and Implication operators for the fuzzy inference system (FIS). Our experiments illustrate that the control parameters, in the above-mentioned order, have the most effect on the signal-to-noise ratio (SNR). These factors' optimal setting consists of the Centroid, Sum, Minimum and Minimum levels, respectively.

Keywords: fuzzy logic; FMEA; Taguchi method; groupthink; fuzzy inference system

1. Introduction

Increased customers' expectations today intensify the pressure on almost all companies to enhance their quality level. Quality improvement endeavours are usually launched by systematic methods such as Failure Mode and Effects Analysis (FMEA).

After its introduction in the 1940s (Su et al. 2014), FMEA is extensively used in the mechanical, chemical, electronic, medical (Liu, Liu, and Liu 2013) and aerospace industries (Bowles and Peláez 1995). It is capable of analysing designs, processes, systems or services systematically, to identify potential failures as well as failure causes and effects. Failure modes are described by Severity (S), Occurrence (O) and Detection (D) factors (hereafter called risk factors). Estimated according to expert knowledge (Braaksma et al. 2012), the risk factors are converted into a single index called Risk Priority Number (RPN) (Chen 2013). A list of RPNs shows risk priorities of failures.

Despite its popularity, traditional FMEA has some limitations including (1) ignorance of relative importance weights of risk factors, (2) computation of RPN through multiplication of risk factors and (3) possibility of obtaining the same RPN from various combinations of risk factors. A comprehensive list of FMEA drawbacks, including the ones mentioned, is presented by Liu, Liu, and Liu (2013). Traditional FMEA, therefore, has almost given way to some modified versions. Application of fuzzy rule-base system to FMEA (fuzzy FMEA) formed the most popular version during 1992 to 2012 (Liu, Liu, and Liu 2013). This popularity/importance brought us to the conclusion that this method should be enhanced further.

FMEA usually needs decision-making of a cross-functional team (Liu et al. 2015). Thus, as with other group/team decision-making-based projects, fuzzy FMEA may suffer from groupthink. Groupthink, an Organisational Behaviour concept, happens when pressures to achieve consensus override the realistic assessment of alternative solutions (Robbins and Judge 2013, 292–293). It mainly occurs in highly cohesive groups/teams (McShane and Von Glinow 2010, 257).

An important symptom of groupthink is the dominance of each member's opinion in group/team discussions. In FMEA projects, it can be avoided by making the output of fuzzy FMEA robust/insensitive to this dominance. To this end, the Taguchi's Robust Parameter Design (RPD) method is applied in this research. RPD is capable of designing controllable parameters in such a way that the response variable becomes robust against uncontrollable factors (Phadke 1995). Here, Defuzzified form of Fuzzy RPN (DFRPN) is considered to be the response variable. The And, Implication,

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Aggregation and Defuzzification parameters of fuzzy FMEA are considered as controllable factors. Moreover, the design for MFs and IF-THEN rules, given by only one group member and overshadowing the others' designs, are considered as a noise level.

2. Literature review

2.1 *FMEA and modified FMEA methods*

In this subsection, applications of traditional FMEA, modified FMEA methods and, in particular, fuzzy FMEA are reviewed.

Chen (2013) utilised an integrated form of FMEA and root-cause analysis for total preventive maintenance of a machine in a semiconductor manufacturing company. Next, the required Autonomous Preventive Maintenance (APM) actions were obtained. As a result, Overall Equipment Effectiveness (OEE) was improved. Resolving the issues caused by numerical interpretation and conversion of risk factors, Franceschini and Galetto (2001) developed a new risk measure called Risk Priority Code (RPC). RPC is of an ordinal scale, which is more compatible with that of risk factors. They showed effectiveness of the method using a numerical example in design of a cooling fan assembly. Their method does not need numerical conversion from the originally qualitative scores expressed by the design team. It also considers risk factors' importance weights. Braaksma et al. (2012) enhanced FMEA for the maintenance purpose by focusing on historical failure data. Indeed, they computed the total cost, including the maintenance and failure costs, based on the failure occurrence probability. The occurrence probability, in turn, was estimated via a logistic regression model. Applicability of the methodology was illustrated using a gas-field case study and a literature example. As it utilises historical, measured data, it is of high repeatability on a consistent manner. Rather than focusing on the most critical failures, represented by the highest RPNs, Silvestri, De Felice, and Petrillo (2012) ranked corrective actions according to multiple criteria and using Analytic Network Process (ANP) and Analytic Hierarchy Process (AHP). The included criteria were RPN, TRPN (Total Risk Priority Number, which is sum of all RPNs) and six more criteria measuring safety, effectiveness and cost. The approach was implemented in a windscreen-producing company's wash station. It led to correction of more than one failure, simultaneously, and to more accident reduction.

Xu et al. (2002) applied Fuzzy Inference System (FIS) to design FMEA in a diesel-engine turbocharger system. The method investigated the items such as (1) interdependencies amongst failures' occurrence factors, (2) relationships amongst failures' severity factors and combination effect severity factors and (3) relationships amongst failures' risk factors and their criticality. Besides considering the interdependencies, the method provided a more realistic interpretation of the FMEA factors, which are naturally uncertain and linguistic. It also combined knowledge of experts from different disciplines. Chin, Chan, and Yang (2008) used fuzzy FMEA to build a product design system to facilitate component and material selection for the design engineers. The approach was utilised in the development project of a printer micromotor. It ranked the components and materials based on combination of their risk, reliability and cost scores. In product architecture, Nepal et al. (2008) applied fuzzy FMEA to analyse the failures caused by component interaction. They studied a coffeemaker product example, leading to a reduced number of interaction failures on which they focused. Calculating severity and detection using linguistic variables and determining occurrence based on the Cpk index, Yeh and Chen (2014) computed a new fuzzy RPN. This RPN is the product of the mentioned risk factors. They implemented the methodology in semiconductor wafer-manufacturing processes. According to the results, the proposed RPN outperformed traditional RPN, two-factor sort RPN ($S \times O$) and simple sort RPN (*SOD*, calculated by putting S, O and D next to each other).

2.2 *Exploration of literature gap*

The literature gap was investigated through study of RPD and fuzzy logic simultaneous applications. The most recent ones are presented next.

Maher et al. (2015) improved quality and productivity in wire-cut electric discharge machining. They conducted a full-factorial experiment and used RPD to optimise the responses including the speed of cutting, roughness of surface and heat-affected zone. Data-set of the experiment was next utilised as the training data for Adaptive Neuro-Fuzzy Inference System (ANFIS). As a result, an ANFIS model was obtained. The ANFIS surface plots were powerful tools to show and analyse the relationships between the machining parameters and responses. Mariajayaprakash, Senthilvelan, and Gnanadass (2015) comparatively applied FMEA and fuzzy FMEA to analyse the cogeneration – power and steam generation at the same time – process failures in a sugar mill boiler. Results of both methods were considerably similar to each other and their most significant failure modes were optimised through RPD. Finally, the model derived from

RPD was improved using Genetic Algorithm (GA). The comparison showed that GA remarkably reduced the defect percentage figures. Abd, Abhary, and Marian (2016) optimised a dynamic scheduling problem in robotic flexible assembly cells. An L_9 experiment was applied to investigate effects of four parameters on three objective functions, total tardiness, makespan and number of tardy jobs, namely, and their Signal-to-Noise Ratios (SNRs). Afterwards, the three SNRs were converted to one performance index. Finally, the performance index was optimised. Huang and Yu (2016) used an L_{12} experimental design to analyse effects of five control factors on temperature uniformity at eight points of a water-cooled condenser. In order to more efficiency, they conducted the experiments using a simulation software. Finally, developing a Multiple-Input, Multiple-Output (MIMO) ANFIS inverse model, they obtained the control factors' optimal design, which provided a more temperature uniformity. Tsai and Liukkonen (2016) investigated three hybrid methods for multi-response optimisation in a stencil printing process. In the first method, the problem was optimised through integration of Response Surface Methodology (RSM) and a desirability function. In the second method, the multiple responses were converted into one response via fuzzy logic, which was next optimised by RPD. In the third method, Artificial Neural Network (ANN) was applied to map the required relationship, which was next optimised by GA. Confirmation experiments indicated that the second method provided the most optimal results.

However, none of these studies addressed the sensitivity of fuzzy FMEA to groupthink. Thus, to the best of the authors' knowledge, this subject is original and requires a profound investigation.

3. Theoretical foundations

3.1 *Fuzzy logic-based FMEA*

In FMEA, RPN is calculated through the *Severity* × *Occurrence* × *Detection* relationship (Silvestri, De Felice, and Petrillo 2012). As mentioned earlier, the relationship is questionable. However, the problem can successfully be resolved using fuzzy logic (Liu, Liu, and Liu 2013). In fact, the real relationship between the three risk factors and DFRPN is unknown. There are no historical data for DFRPN, on the other hand. Therefore, the Mamdani Multi-Input, Single-Output (MISO) inference system-based FMEA is the most appropriate technique here, the process of which will be presented in Section 4.

3.2 *Group decision-making and groupthink*

In contrast to decisions made by only an individual, group decision-making provides more complete knowledge. It also increases solution acceptance and diversity of viewpoints, alternatives or approaches (Robbins and Judge 2013). The diversity reflection capability, however, may be undermined by groupthink. A possible interpretation for this deficiency is dominance of one member or a few members in group discussions (Robbins and Judge 2013). Groupthink occurs when there is an unanimity illusion, and abstention is interpreted as a *yes* vote. It also happens when members who are going to question group/team consensus avoid expressing their differing viewpoints (Robbins and Judge 2013).

It may simply occur in interacting groups, which are usual groups in which members interact face to face with each other. However, it can be controlled by techniques for group decision-making including the electronic meeting, nominal group and brainstorming techniques. It can also be reduced by some other techniques, such as group size monitoring (Robbins and Judge 2013), which need more mastery of interpersonal skills. The present research, however, aims at developing a quantitative solution for the groupthink problem in FMEA projects.

3.3 *Robust Parameter Design*

Taguchi's RPD, also called Robust Design, is a cost-effective approach for quality improvement. It chooses a combination of controllable factor levels, technically called *setting*, that makes the response variable insensitive/robust against the variation imposed by noise(s). Different parameters/factors of RPD include (Phadke 1995): (1) signal factors, which are determined by the product user/operator to express the intended value for the response; (2) controllable/control parameters, which can be controlled and changed by the designer, easily and with a small cost impact; and (3) uncontrollable/noise factors, which are expensive/difficult/impossible-to-control by the designer. They cause response deviation from the target value and, consequently, quality loss.

Each control factor should be assigned some levels covering as extensive a range as possible (Chao and Hwang 1997). Noises, also, are assigned some levels at which they change under experimental conditions. Given m and n settings respectively for control and noise factors, there is a $m \times n$ full-factorial experimental design. These too many experiments are usually inefficient. The efficiency will decline even more once the number of control parameters, noises and/or levels rise. In response to this problem, fractional-factorial designs were introduced, which are called standard Orthogonal Arrays (OAs), technically (Phadke 1995). The OAs used for control parameter experiments are called inner arrays. However, those applied to uncontrollable factor ones are called outer arrays. The OA which is appropriate for a given problem has at least k runs (rows), with k denoting the problem Degree of Freedom (DF).

Once the experiments are conducted through a crossed form of appropriate inner and outer arrays, responses will be observed, recorded and analysed. Then the robust solution is determined using the SNR performance measure. Indeed, the most insensitive level to noise is indicated by the highest mean (average) SNR value for each control parameter (Phadke 1995).

SNRs are (usually) threefold: nominal-the-best, larger-the-better and smaller-the-better (Abd, Abhary, and Marian 2014). For a nominal-the-best response, there is a particular target value to be attained under all noise conditions (Phadke 1995). As DFRPN has only an unknown value to be estimated, the nominal-the-best type of SNR (Equation (1), with μ and σ denoting the mean and standard deviation, respectively) will be applied in this study.

$$\mathrm{SNR}_{\mathrm{NTB}} = 10 \times \log_{10}\left(\mu^2/\sigma^2\right) \tag{1}$$

4. Fuzzy logic-based FMEA robust design

A three-phase framework (Figure 1) is proposed. In the first phase, Identification, the parameter diagram (p-diagram) is identified. The parameter levels are determined as well. In the second phase, Experimentation, an appropriate OA is selected, and a design sheet is prepared. The sheet is used for recording the responses observed from experimentation. In the third phase, Analysis, an appropriate SNR type (nominal-the-best, here) is selected. Afterwards, the control factors are ranked with respect to the effect they have on mean SNR. For each control parameter, the effect (called *delta* in Minitab) is estimated through the difference between the maximum and minimum mean SNRs.

Next, statistical relationships and significance are investigated via a fitted linear model and Analysis of Variance (ANOVA). The most robust setting – combination of the most insensitive levels to noise – is determined, then. Validity of the setting, finally, is checked using three confirmation experiments.

Applicability of the methodology is shown using an illustrative example provided based on the case study of Geramian et al. (2017). Primary calculations are made using MATLAB and Minitab.

The p-diagram's components includes: (1) DFRPN as the response variable; (2) each member's design for MFs and IF-THEN rules, overshadowing the other's designs, as a noise level; (3) the most critical failure mode's risk factors determined in the case study of Geramian et al. (2017), i.e. $S = 8$, $O = 8$ and $D = 7$,as signal factors; and (4) the potential control factors which are specified in Section 4.1.

4.1 *Fuzzy logic-based FMEA*

A Mamdani FIS usually consists of four building blocks, the Fuzzifier, Fuzzy Rule-base, Inference Engine and Defuzzifier, namely (Camastra et al. 2015). Thus, fuzzy FMEA is of the following process:

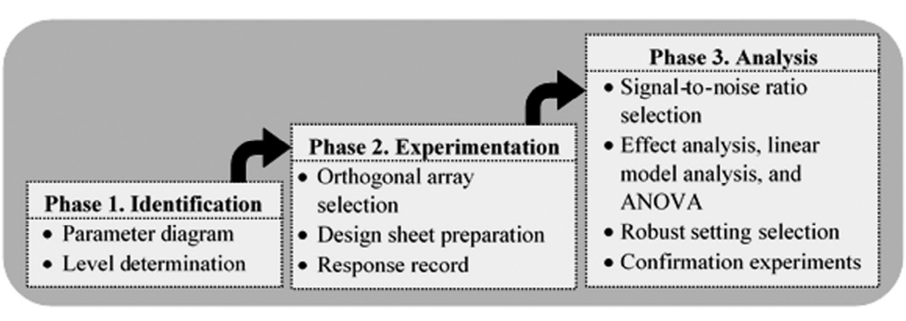

Figure 1. General framework of the proposed methodology.

4.1.1 *Fuzzification*

Conversion of crisp data to fuzzy values via MFs is called fuzzification (Chanamool and Naenna 2016). Each MF corresponds to a linguistic variable such as medium, high, etc. For fuzzy FMEA, the generic sets needed are shown by Equations (2) to (5).

$$S_{set} = \left\{ \begin{array}{c} S, \{1,\ 2, \ldots,\ 10\}, \{VL_S, L_S, M_S, H_S, VH_S\}, \\ \{\mu_{VL_S}(s), \mu_{L_S}(s), \mu_{M_S}(s), \mu_{H_S}(s), \mu_{VH_S}(s)\} \end{array} \right\} \tag{2}$$

$$O_{set} = \left\{ \begin{array}{c} O, \{1,\ 2, \ldots,\ 10\}, \{VL_O, L_O, M_O, H_O, VH_O\}, \\ \{\mu_{VL_O}(o), \mu_{L_O}(o), \mu_{M_O}(o), \mu_{H_O}(o), \mu_{VH_O}(o)\} \end{array} \right\} \tag{3}$$

$$D_{set} = \left\{ \begin{array}{c} D, \{1,\ 2, \ldots,\ 10\}, \{VL_D, L_D, M_D, H_D, VH_D\}, \\ \{\mu_{VL_D}(d), \mu_{L_D}(d), \mu_{M_D}(d), \mu_{H_D}(d), \mu_{VH_D}(D)\} \end{array} \right\} \tag{4}$$

$$\mathrm{FRPN_{set}} = \left\{ \begin{array}{c} \mathrm{FRPN}, \{0,\ 1, \ldots,\ 10\}, \{VL_{\mathrm{FRPN}}, L_{\mathrm{FRPN}}, M_{\mathrm{FRPN}}, H_{\mathrm{FRPN}}, VH_{\mathrm{FRPN}}\}, \\ \{\mu_{VL_{\mathrm{FRPN}}}(rpn), \mu_{L_{\mathrm{FRPN}}}(rpn), \mu_{M_{\mathrm{FRPN}}}(rpn), \mu_{H_{\mathrm{FRPN}}}(rpn), \mu_{VH_{\mathrm{FRPN}}}(rpn)\} \end{array} \right\} \tag{5}$$

Where S_{set}, O_{set}, D_{set} and FRPN_{set}, respectively, denote the sets of Severity (S), Occurrence (O), Detection (D) and Fuzzy RPN (FRPN). MFs can be selected from $\{VL_i, L_i, M_i, H_i, VH_i\}$, with $i = S, O, D$ and FRPN. The set includes Very Low (VL_i), Low (L_i), Medium (M_i), High (H_i) and Very High (VH_i). Through fuzzification, the membership degrees of crisp data (s, o, d and rpn) are determined (e.g. $\mu_{M_{\mathrm{FRPN}}}(rpn)$). The MFs tackle the vagueness/uncertainty of human opinions. In this study, only the triangular and trapezoidal MFs are applied. Also, according to Equations (2) to (5), MFs of the risk factors and FRPN can change in $\{1,\ 2, \ldots,\ 10\}$ and$\{0,\ 1, \ldots,\ 10\}$, respectively.

4.1.2 *Fuzzy rule-base*

A rule-base consists of several rules, with an IF-THEN structure each (Syn et al. 2011). The IF component contains prerequisites needed for occurring the THEN part. These components are also called antecedent and consequent, respectively (Camastra et al. 2015). In each antecedent, conjunction of elements, e.g. $(S\, is\, VL_S), (O\, is\, VL_O)$ and $(D\, is\, L_D)$, is necessary; it can be done using an And method such as Minimum (Min) and Product (Prod). These operators are supported by MATLAB (Syn et al. 2011). The consequent could be, e.g., $(\mathrm{FRPN}\, is\, VL_{\mathrm{FRPN}})$.

Rules explain input-output relationships. They are formulated based on relevant knowledge (Syn et al. 2011). If there are n_S, n_O and n_D MFs for risk factors, there are $n_S \times n_O \times n_D$ rules, at most. Nevertheless, some rules may be neither applicable nor logical in real-life. Once rules are defined, a fuzzy inference engine is built for inputs-to-output mapping.

4.1.3 *Fuzzy implication and aggregation*

Each rule is fired/activated to a specific degree. The degree indicates the truth value of the rule (Lu and Antony 2002; Syn et al. 2011). Next, the implication results are aggregated. Maximum (Max), Sum and Probor are common operators for aggregation (Syn et al. 2011). For simplification, only the first two operators are used here.

4.1.4 *Defuzzification*

The aggregation output is then defuzzified or transformed into a non-fuzzy output (Lu and Antony 2002). The outcome, here, is DFRPN. Centroid, Bisector, Middle of Maximum (MoM), Largest of Maximum (LoM) and Smallest of Maximum (SoM) are common defuzzification methods (Syn et al. 2011). For simplification, only the first three methods are utilised in the present research.

To sum up, the And, Implication, Aggregation and Defuzzification parameters can easily be changed/controlled to modify DFRPN. They, therefore, are regarded as the potential control factors of fuzzy FMEA in the *p*-diagram (Figure 2).

Furthermore, levels of the control parameters (Table 1) are determined according to the fuzzy FMEA process. For simplification, the control factors and levels are denoted by codes presented within parentheses. Code A_1, for instance, denotes the Max level/operator of the Aggregation method (A).

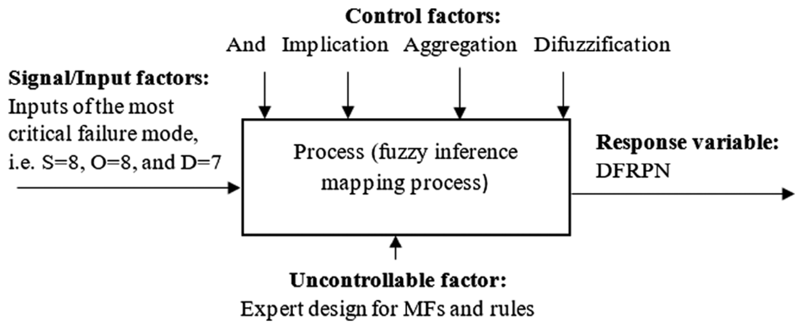

Figure 2. Parameter diagram for the studied problem.

Table 1. Control parameters and their levels along with their codes.

Control factor (code)	Level (code)		
	1	2	3
Aggregation method (A)	Max (1)	Sum (2)	–
And method (B)	Min (1)	Prod (2)	–
Implication method (C)	Min (1)	Prod (2)	–
Defuzzification method (D)	Centroid (1)	Bisector (2)	MoM (3)

With regard to participation of an assumptive three-member/expert team, there is a three-level noise variable. The levels are three different sets of assumptive MFs and rule-bases, each of which is made by assumptive dominance of a member's design over the others' designs. As a result, there are three various FISs. For brevity, features of only the first one are shown in Appendix 1 (A.1–A.5). In this FIS, severity, occurrence, detection and FRPN were designed using five, five, five and seven triangular MFs, respectively (with the three risk factors being of the same design as those of Geramian et al. [2017]). We also assumed that the input-output relationships are expressed using four reduced fuzzy rules. Characteristics of the other two FISs are summarised in Table 2, with *Tri* and *Trap* standing for triangular and trapezoidal MFs.

In regard to Table 1, there are three two-level and one three-level control parameters. According to the authors' experience, the A × D interaction should be investigated as well. The B × D interaction was also included based on trial and error. Thus, the degree of freedom equals 10 ($DF = 3 \times [2-1] + 1 \times [3-1] + 2 \times [[2-1] \times [3-1]] + 1 = 10$). According to the Phadke's (1995) guidelines, the smallest OA at least with 10 runs, being also capable of handling two and three-level factors, is L_{18}. Facilitating the investigation of A × D, we assigned the first (two-level) column of L_{18} to the A parameter. The next two (three-level) columns were assigned to B and C, respectively. Since these two factors are only of two levels, not three, we used the *dummy level technique* (Phadke 1995). The B_2 and C_2 levels were considered as dummy levels. The *two prime* (2') symbol, in Table 3, is to show the dummy levels.

Following the L_{18} design sheet (Table 3), we carried out the experiments in MATLAB. The results are presented in Section 5.

5. Findings

We replicated each run three times using the three assumptive FISs, which resulted in 54 $(18 \times 3 = 54)$ experiments, overall (Table 3).

Table 4 presents average SNRs for the levels. Moreover, the control factors were ranked with respect to deltas.

Figure 3a illustrates the main effects, and Figure 3b shows the interaction effects (Prod' denotes the dummy levels of the B and C factors). Whilst the horizontal pivots represent the levels, the vertical ones show average SNRs. The other findings, including the ANOVA results and the fitted linear model, are presented and discussed in Section 6.

Table 2. Architectures and fuzzy input/output variables of the second and the third FISs.

	Architecture characteristic	The other studied FISs	
		The second FIS	The third FIS
Input	The fuzzy set number	Five (severity)/three (occurrence)/three (detection)	Five (severity)/five (occurrence)/three (detection)
	Shapes and values of fuzzy set	Severity: {(Trap, VL = [1 1 2 4.5]), (Tri, L = [2 4.5 6.3]), (Tri, M = [5.8 7 9.2]), (Tri, H = [7 9 10]), (Tri, VH = [8.5 10 10])}; Occurrence: {(Trap, L = [1 1 2.5 4]), (Tri, M = [3 5 7.5]), (Trap, H = [6 8 10 10])}; and Detection: {(Trap, L = [1 1 2.8 5.2]), (Trap, M = [2.8 5.2 6.8 8.3]), (Trap, H = [6.8 8.3 10 10])	Severity: {(Trap, VL = [1 1 3 4.2]), (Tri, L = [3.5 5.5 6.5]), (Tri, M = [5.8 7.5 8.2]), (Tri, H = [7.5 8.6 9.8]), (Tri, VH = [8.8 10 10])}; Occurrence: {(Tri, VL = [1 1 4]), (Tri, L = [2.5 4 6.2]), (Tri, M = [5.5 6.5 7.2]), (Tri, H = [6.5 7.5 9.3]), (Tri, VH = [7.8 10 10])}; and Detection: {(Tri, L = [0 0 5]), (Tri, M = [2 5 8]), (Tri, H = [5 10 10])}
Output	The fuzzy set number	Five (FRPN)	Five (FRPN)
	Shapes and values of fuzzy set	FRPN: {(Tri, VL = [0 1.5 2.5]), (Tri, L = [2.3 3.5 5]), (Tri, M = [3.5 5 6.5]), (Tri, H = [4.5 6.5 8]), (Tri, VH = [6.5 10 10])}	FRPN: {(Tri, VL = [0 1 3]), (Tri, L = [1 3 5]), (Tri, M = [3 5 7]), (Tri, H = [5 7 9]), (Tri, VH = [6.997 10 10])}
Fuzzy inference engine	Type and the rule number of fuzzy engine	A Mamdani FIS with four reduced rules	A Mamdani FIS with eight reduced rules

Table 3. Experimentation results using L_{18}.

	Control factor				Response			
Run	A	B	C	D	The 1st FIS	The 2nd FIS	The 3rd FIS	SNR
1	1	1	1	1	7.37	6.14	6.91	20.79019
2	1	2	2	1	7.24	5.98	7.29	19.28511
3	1	2′	2′	1	7.24	5.98	7.29	19.28511
4	1	1	1	2	7.10	6.00	7.00	20.83948
5	1	2	2	2	7.10	5.90	7.30	19.02342
6	1	2′	2′	2	7.10	5.90	7.30	19.02342
7	1	1	2	3	7.00	5.00	10.00	9.289705
8	1	2	2′	3	7.00	5.00	10.00	9.289705
9	1	2′	1	3	7.00	5.00	8.70	11.42404
10	2	1	2′	1	7.24	6.11	7.01	21.11091
11	2	2	1	1	7.37	5.95	7.06	19.17973
12	2	2′	2	1	7.24	5.96	7.19	19.43909
13	2	1	2	2	7.10	5.90	7.00	20.01087
14	2	2	2′	2	7.10	5.80	7.20	18.6682
15	2	2′	1	2	7.10	5.80	7.20	18.6682
16	2	1	2′	3	7.00	5.00	7.00	14.78326
17	2	2	1	3	7.00	5.55	8.05	14.75982
18	2	2′	2	3	7.00	5.00	7.00	14.78326

6. Discussion

According to Table 3, each FIS, designed by one of the assumptive experts, leads to almost unique DFRPNs. Thus, viewpoints of other experts will be ignored if groupthink occurs.

Based on Table 4, the D and C parameters have the most and least effects on SNR, respectively. A and B, however, have the second and third ranks in this regard. These facts are also supported by the ANOVA test, in which D has the least *p*-value (0.000), followed by A (0.004), B (0.048) and C (0.423), regardless of *p*-values of the interactions. This order is accepted by the fitted linear model as well, in which the D levels' non-zero coefficients have the least *p*-values, i.e. (0.000) for D_1 and (0.000) for D_2. These are followed by the non-zero coefficients of A_1, B_1, B_2, C_2 and C_1, with *p*-values of 0.004, 0.025, 0.043, 0.257 and 0.292, respectively. Therefore, the order of impacts on SNR is Defuzzification (D)>> Aggregation (A)>> And (B)>> Implication (C). This order is also in agreement with Figure 3a where the D, A, B and C factors, respectively, lead to the most line fracture or slope.

Table 4. Average SNRs for the levels as well as delta values.

Level	Aggregation (A)	And (B)	Implication (C)	Defuzzification (D)
1	16.47	17.80	17.61	19.85
2	17.93	16.70	16.97	19.37
3	–	17.10	17.03	12.39
Delta	1.46	1.10	0.64	7.46
Rank	2	3	4	1

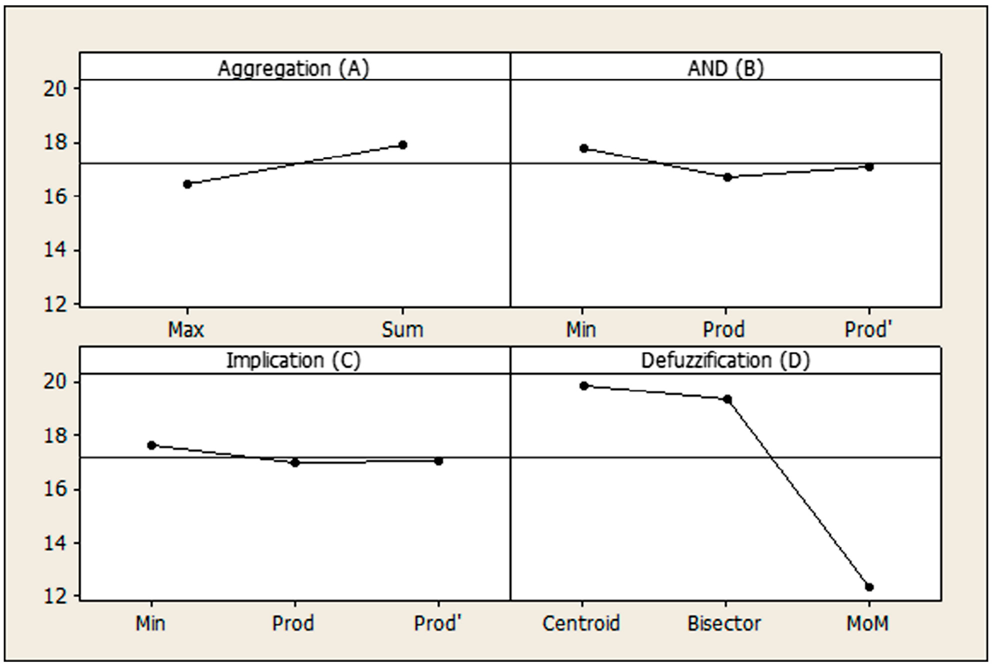

Figure 3a. Main-effect plot.

The ANOVA test also indicates that the A×D interaction has a significant impact on SNR (p-value = 0.002) in alpha-level 0.05. B × D, nonetheless, does not so (p-value = 0.119). The results are consistent with outcomes of the fitted model, amongst which the non-zero coefficients of $A_1 \times D_1$ and $A_1 \times D_2$ are of the p-values (0.017 and 0.004) less than alpha-level 0.05. However, the non-zero coefficients of $B_1 \times D_1$ and $B_1 \times D_2$ (with p-vales of 0.229 and 0.152) are insignificant in the alpha-level. The same facts are visible also from Figure 3b, where A × D has an *anti-synergistic interaction*, but B × D has an approximately *synergistic interaction*. In other words, the lines related to A × D are not parallel nor are they of the same improvement directions. However, those pertaining to B × D are almost parallel and of the same improvement directions (for more details on the interaction typology, see Phadke [1995]). Therefore, the A × D interaction has a significant influence and has correctly been taken into consideration.

The p-values of C and B × D, derived from both the ANOVA and the fitted model, show that these factors have no significant impact on SNR in the mentioned significance level. However, the model still has a high coefficient of determination (R^2), 99.6%. In fact, elimination of either C, B × D or both of them will reduce the R^2. Hence, we kept them in the model.

All in all, well-chosen levels for the D, A, B and C parameters, respectively, can remarkably reduce the groupthink effect, indirectly. According to Table 4/Figure 3a, the optimal setting is predicted to be $A_2B_1C_1D_1$ in this study. The setting refers to the Centroid level for Defuzzification, Sum for Aggregation, Min for And and Min for Implication, resulting in $SNR = 21.12140$. Unsurprisingly, the SNR is higher than the SNRs of all the 18 experiments conducted.

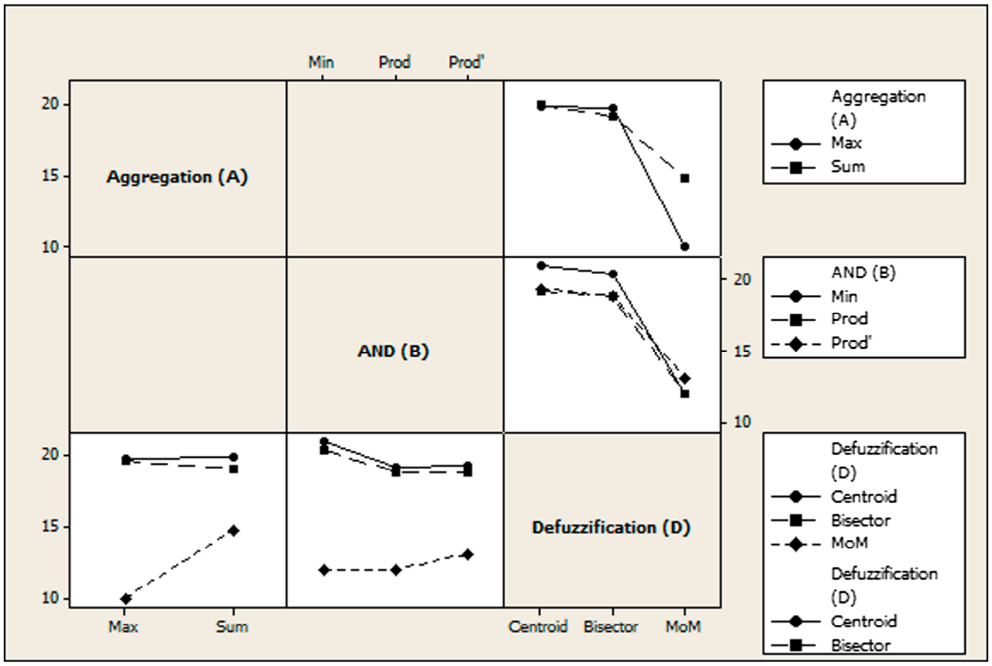

Figure 3b. Interaction-effect plot.

7. Practical implications

7.1 *Statistical implications*

Achieving robustness has been a primary aim in this research, so the most robust setting was called the optimal setting. More precisely, estimation of DFRPN is a nominal-the-best problem needing two optimisation steps: (1) minimisation of sensitivity to noise; and (2) adjustment of mean DFRPN on target; however, since the DFRPN's target value (its actual value to be estimated) is unknown in FMEA, the later step of the optimisation cannot be carried out.

Furthermore, here where the aim is not to reduce DFRPN, it should not be considered as a smaller-the-better response, with the zero target value. Strictly speaking, the control parameters included in this research logically affect only the response robustness, not its reduction. For the reduction purpose, the right factors are failure causes, which are not investigated here.

Also, we validated the predicted optimal setting using three confirmation experiments. The validation is to investigate to what extent the predicted results, including SNR and the mean response, are close to the actual ones. So, the three studied FISs were used under the predicted optimal setting, leading to three confirmation experiments. The actual results for the optimal setting predicted using the L_{18} are $SNR = 20.55496$ and mean (average) response $= 6.79667$. Thus, the Percentage Prediction Error (PPE) (Abd, Abhary, and Marian 2016) for SNR is 2.76%, and, for the mean response, it is 0.20%.

$$\text{PPE} = \frac{\text{Experimental(actual)value} - \text{Predictedvalue}}{\text{Experimental (actual) value}} \tag{6}$$

Since these errors are small, the predicted optimal setting can be adopted for the studied numerical example.

There used to be no systematic method for selecting the studied control factor levels. Therefore, every possible level combination can be considered as an initial setting. Therefore, regardless of the one optimal setting ($A_2B_1C_1D_1$), there are potentially 23 (3 × 2^3−1 = 23) initial settings (it was calculated based on the number of the levels and factors). In terms of robustness (SNR), the confirmation experiments outperform 19 out of the 23 initial settings. In three out of the four failure situations (23 − 19 = 4), the dominance over the optimal setting (on average, 1.74%) is small and negligible. Nevertheless, the other failure situation, with 3.55% outperformance relative to the predicted optimal setting, is attributable to a setting not existing in the used L_{18}. The reason is that L_{18} is a fractional-factorial design, which does not contain some possible level combinations.

Since this study's experiments are conducted in MATLAB and are not too costly by nature, we applied a full-factorial design as well. Given the three replications, the design comprises 72 (3 × [3 × 2^3] = 72) experiments, resulting in the $A_1B_1C_2D_1$ optimal setting with $SNR = 21.28374$. This is exactly the setting missing from the L_{18}. To sum up, it is also important to consider a trade-off between the time-efficiency of the L_{18} and the accuracy of the full-factorial design.

Moreover, whenever accuracy of fitted linear models is not satisfactory enough, the backward elimination procedure should be tried. The procedure is initiated with removing the factor with the highest *p*-value. Nonetheless, it should be kept in mind that the procedure may not always improve coefficients of determination (R^2). For example, elimination of the Implication (C) parameter reduces the R^2 from 99.6% to 99.4%.

Finally, in this study, there was a hypothesis as to what the potential interaction (A×D) is. However, if there is no previous knowledge about potential interactions, as many interactions as possible should be included, first. Next, only the anti-synergistic one(s) should be kept.

7.2 *Managerial implications*

Despite its advantages, group/team decision-making could result in groupthink, of which managers should be aware. A reason is that it can undermine the productivity of this decision-making type by reducing the outputs obtained from the invested inputs. In other words, whilst all members are paid (inputs) for their participation in groups/teams, their technical decisions/viewpoints (outputs) may be overshadowed by one member or a few members. Their presence, thus, would be ineffective, in practice (reduced productivity). In this sense, productivity of group/team decision-making in FMEA projects can be improved by the proposed approach.

Also, those managers in charge of quality in group/team decision-making had better overcome groupthink, particularly in the situations mentioned in sub-section 3.2. In this regard and in FMEA projects, the proposed methodology could facilitate participation of each group/team member in decision-making, separately. Therefore, group/team pressures on a member for unanimity/abstention would be reduced. It, in turn, would enable the member to question the dysfunctional consensus of the group/team, which would contribute to more innovation.

The methodology can also enhance the time-efficiency and flexibility of group/team decision-making in FMEA projects. Indeed, often it is difficult, if not impossible, to bring whole experts/members together at the same time and/or place. This issue will be more acute where members are from top-management levels and will most often result in frustrating project delays. However, allocating separate participation opportunities to each member, the approach can solve the problem.

With respect to the above advantages, in FMEA projects, the quantitative methodology of this research can be a powerful complementary approach to the Organisational Behaviour's qualitative methods for minimising groupthink (for more information about the qualitative methods see, e.g., Robbins and Judge [2013, 293]). As these qualitative approaches require mastery of human skills, the fuzzy FMEA robust design method can be an appropriate substitute where there are a few interpersonal skills. The method would even be preferred in that it minimises groupthink effects indirectly, in contrast to the direct pressures put by Organisational Behaviour's qualitative methods during the decision-making sessions.

8. Conclusions

We enhanced fuzzy FMEA with application of the Taguchi's method for robustness. Accordingly, calculation of the risk priorities was made insensitive against groupthink. As most of the FIS parameters played a significant role in robustness of DFRPN, we did not set them haphazardly. The systematic selection of the levels led to magnificent results. In fact, through a fractional-factorial design, it was ascertained that the optimum setting included the Centroid, Sum, Min and Min levels for the Defuzzification, Aggregation and Implication factors respectively. The full-factorial design, however, resulted in a more robust setting ($A_1B_1C_2D_1$), but at the cost of $18\,(72 - 54 = 18)$ more experiments. Thus, a trade-off is necessary.

Other advantages mentioned for the proposed approach are capability of improving the productivity, time-efficiency and flexibility in FMEA projects. It would also be a complementary method to Organisational Behaviour's groupthink-minimising approaches.

However, we applied the approach only to group/team decision-making in fuzzy FMEA. Moreover, dominance of only one member over the other group/team members was investigated; the risk factors of only the most critical failure mode were considered as signal factors; some levels of the Aggregation and Defuzzification factors were not taken into account; for simplification, the group and team words were used interchangeably, but they are different concepts; and separate participation of each member in decision-making, would deprive him/her of being informed of the others' valuable technical comments.

Accordingly, future studies could expand application of the methodology into other real-life problems. However, four prerequisites should be investigated before any potential application, including: (1) data uncertainty – data are fuzzy/qualitative/linguistic; (2) unknown inputs-to-output relationships – these relationships are unknown/complex/questionable and have to be determined by experts; (3) necessity of decision-making by groups/teams; and (4) necessity of protecting the members' diverse ideas against groupthink. In short, everywhere a MISO Mamdani FIS can be used for group/team decision-making, the proposed methodology could be used too.

In addition, other scenarios, i.e. dominance of two, three, … and n − 1 members, different risk factors' values and the other levels of Aggregation and Defuzzification could be investigated.

Moreover, given the inherent differences between a group and a team, the methodology may need to be tailored to each of the concepts. Also, it appears that the field is open to further empirical research on comparison of Organisational Behaviour's techniques for groupthink minimisation and that of this study. Finally, both the fuzzy FMEA robust design and the electronic meeting approaches limit interpersonal discussion and communication and can provide the opportunity of distance-participating, even from different time zones. These similarities build a basis for possible integration of these two methods, which may resolve limitations of each of the methods or both of them.

Disclosure statement

No potential conflict of interest was reported by the authors.

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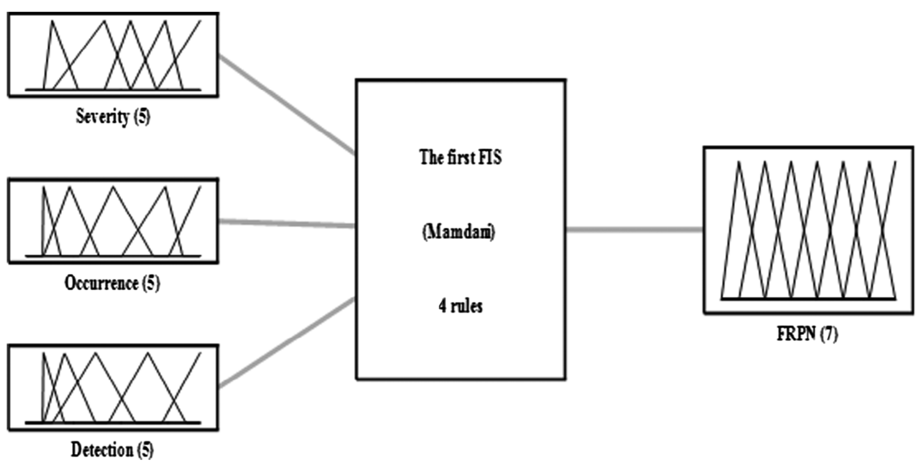
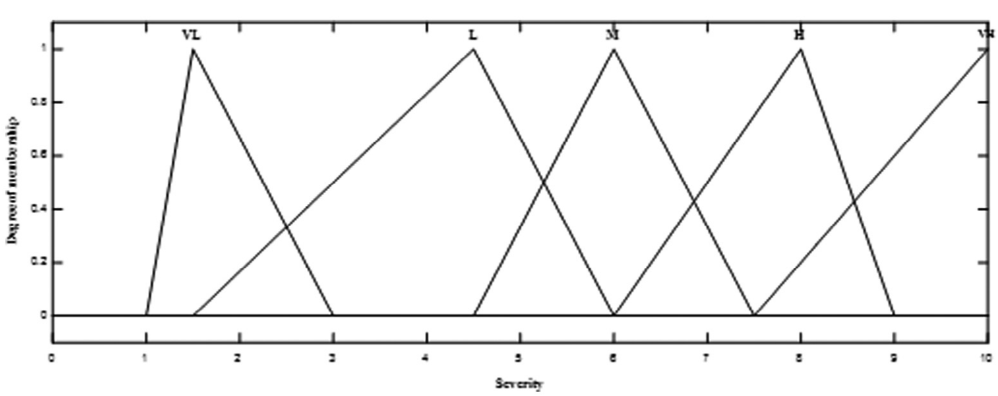
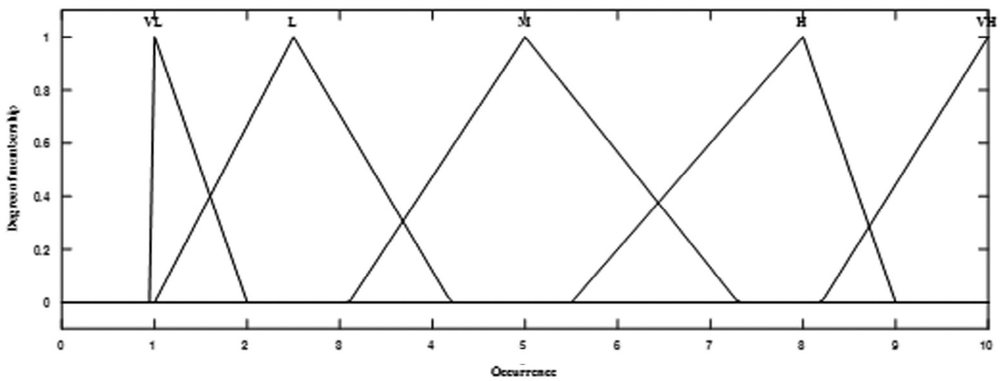
Appendix 1.



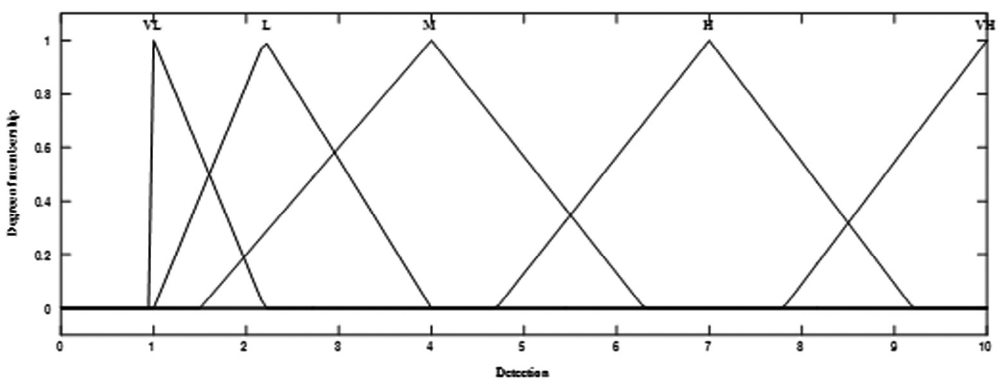
Appendix A.1. Architecture of the first FIS.



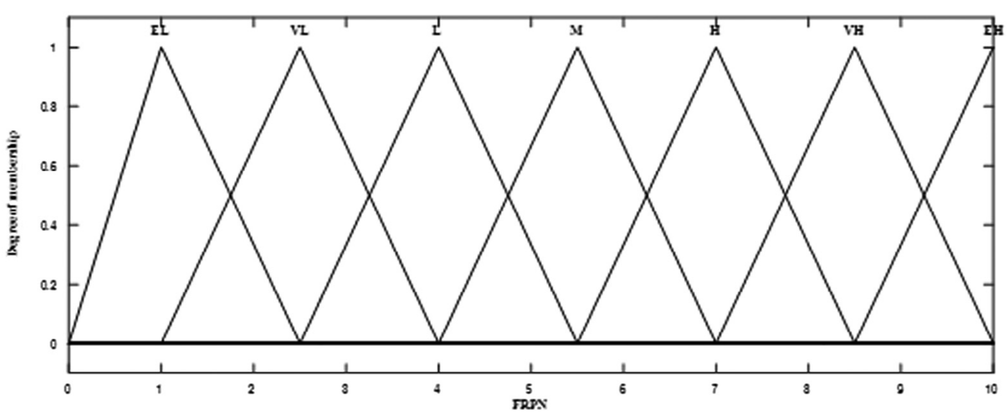
Appendix A.2. Severity variable of the first FIS.



Appendix A.3. Occurrence variable of the first FIS.



Appendix A.4. Detection variable of the first FIS.



Appendix A.5. FRPN variable of the first FIS.

Appendix 2. Validation using confirmation experiments.

		SNR	Mean
Optimal setting obtained from the full-factorial design ($A_1B_1C_2D_1$)		21.28374	6.82333
Optimal setting obtained from the L_{18} ($A_2B_1C_1D_1$)	Predicted	21.12140	6.81037
	Actual	20.55496	6.79667
Prediction Error		2.76%	0.20%
SNR of the full-factorial design's optimal setting outperforms those of all the 23 possible initial settings			
SNR of the confirmation experiments, which were conducted under the predicted optimal setting, outperforms 19 out of the 23 initial settings			