Enhanced FMEA: An integrative approach of Fuzzy Logic-based FMEA and collective process capability analysis

The aim of this study is to modify and enhance the quantitative/mathematical features of both computational and analytical aspects of the process failure modes and effects analysis (FMEA). For this purpose, a hybrid approach including the Fuzzy Logic-based FMEA (FFMEA) and collective process capability analysis (CPCA) has been developed in three phases. First, failure modes have been defined based on lack of quality in quality characteristics under investigation, and then, they have been prioritised using FFMEA. Second, the most critical failure has been selected for statistical analysis using CPCA, leading to the corrective actions in the third phase. The proposed approach was investigated in an electrical-equipment-manufacturing company. Findings indicated that the diameter deviation in Insulator A was the most critical failure effect caused by a rightward mean shift of 0.32 centimetre. In addition, Cpk has been improved from 0.41 to 1.12, and defective products have been reduced from 115,083.09 to 336.98 parts per million.
Keywords: quality improvement; Six Sigma; Fuzzy Inference System (FIS); fuzzy FMEA; process capability; Voice of Customer (VOC)

1. Introduction

Industrial processes usually deal with many failures. However, removing all the failures relevant to a process, simultaneously, seems difficult. That is why application of a failure-ranking method such as Failure Modes and Effects Analysis (FMEA) is highly advantageous.

FMEA has been applied in a wide range of industries since its introduction. FMEA endeavours can be divided into design FMEA, process FMEA, system FMEA and service FMEA (Abbasgholizadeh Rahimi et al, 2015). Addressing the failures occurring in some stages/functions of a process, the present study focuses only on process FMEA.

In FMEA, the failure occurrence, severity and detection (risk factors) scores, determined by experts, are used to calculate Risk Priority Number (RPN). The RPN values are utilised to rank failures. These scoring and calculation steps are attributable to the FMEA computational aspect. Besides, the FMEA analytical aspect entails investigating failure causes and effects, current controls and recommended corrective actions. The aim of this study is to modify and enhance both aspects, quantitatively/mathematically.

The following are some limitations of the FMEA computational aspect: i) questionable calculation of RPN, i.e. multiplication of risk factors; ii) uncertainty in determination of risk factors; and iii) possibility of allocating the same relative importance weights to risk factors. A comprehensive list of FMEA shortfalls can be found in Liu et al (2013).

The literature-review article of Liu et al (2013) indicated that Artificial Intelligence (AI), with a 40.00% share of all the papers reviewed, was the most popular methodology amongst those devoted to resolve the mentioned shortcomings. More precise is that Fuzzy Logic-based FMEA (FFMEA) was addressed as the most popular methodology in AI. This fact led the authors of the present research to modify FMEA using Fuzzy Logic, resulting in an enhanced FMEA computational aspect.

Fuzzy Logic/Fuzzy Inference System (FIS) was, first, applied in Failure Mode, Effects and Criticality Analysis (FMECA) (Bowles and Peláez, 1995; Moss and Woodhouse, 1999), with riskiness and risk factors represented by linguistic variables. Crisp inputs were fuzzified, combined, inferred and finally converted into crisp values. Xu et al (2002) utilised FFMEA for failure analysis of a diesel-engine turbocharger system. They used FIS to explore interdependencies amongst different failures and to facilitate knowledge sharing amongst experts of different disciplines by incorporating their knowledge in the fuzzy rule base. Sharma et al (2005) used FFMEA in a paper-mill case, with integration of Mean Time between Failures (MTBF) data and expert experience to calculate occurrence. Chin et al (2007) proposed an expert product development system employing FFMEA to determine risks of design materials/components. The risk scores were combined with the reliability and cost scores to determine the best alternative. Nepal et al (2008) focused on component interaction failures and used FFMEA to analyse them in product architecture. Jong et al (2013) applied FFMEA in the food/agriculture industry to systematically analyse failures of Edible Bird Nest (EBN) production. Yeh and Chen (2014) calculated severity and detection via fuzzy linguistic variables, and occurrence using failure times or process capability (Cpk) in semiconductor wafer-manufacturing processes. Their approach outperformed traditional RPN, simple sort RPN and two-factor sort RPN. The subsidence-risk analysis of metro tunnels was another application of FFMEA in which severity and detection were calculated using FIS, and occurrence was computed by means of Artificial Neural Network (ANN) (Rafie and Namin, 2015). Mariajayaprakash et al (2015) used the basic and fuzzy FMEA methodologies to determine the most critical failures of a sugar-mill-boiler process. Next, the most important parameters were optimised using the Taguchi method. Moreover, they were further optimised using Genetic Algorithm (GA). Geramian et al (2017) comparatively utilised the traditional and fuzzy FMEA methodologies to analyse failures of some manufacturing processes of a car-part producer. Recently, the Taguchi's Robust Parameter Design (RPD) was applied to design the Fuzzy Logic operators in such a way that the defuzzified fuzzy RPN became robust against groupthink in group/team decision-making (Geramian et al, 2018).

It appears that the reviewed studies – except for two of them – did not include the ratio (and interval) scale of measurement in FMEA, whilst it is the richest/highest scale with more permissible statistical calculations amongst the four measurement scales of nominal, ordinal, interval and ratio types (Stevens, 1946). Strictly speaking, to the best of our knowledge, the literature addressed only the failure modes and effects of a nominal scale. Nevertheless, Yeh and Chen (2014) calculated occurrence more accurately, i.e. through failure times of the processes that they studied. Moreover, considering the quality characteristic-related failure modes, Geramian et al (2017) calculated failure frequencies accurately via dividing the out-of-tolerance items by total items or based on equation $Non-Conforming\ \ Rate\,(NCR) = 1 - P(LSL \leq x \leq USL)$ (Kotz and Johnson, 2002) – with x, LSL and USL denoting the quality characteristic, lower and upper specification limits, respectively. However, there is still no direct indication of the opportunity of including the ratio (and interval) scale in FMEA.

Inspired by the Geramian et al (2017) research, the authors of the present study define failure modes based on different types of lack of quality which usually occur for quality characteristics during the relevant process. Accordingly, failure effects are quality characteristic deviations, which are statistically caused by mean shifts and/or standard deviations (Phadke, 1995). Therefore, data of quality characteristics and the two statistical causes, which are continuous – versus discrete data (Park, 2003) – and of ratio/interval scales, are included in FFMEA. As a result, FFMEA are enhanced from the aspect of failure effect investigation. Moreover, similar to the research of Geramian et al (2017), this study computes occurrence rates based on NCRs, leading to reflection of Voce of Customer (VOC) in FMEA and FFMEA through the path below:

VOC (represented by USL and LSL values, defined by customer(s)) → NCRs → occurrence rates → occurrence scores → RPNs and Fuzzy RPNs.

As the continuous data included are typically the inputs for Process Capability Analysis (PCA), two extra layers of statistical calculation can be added to FMEA and FFMEA, including the PCA and Collective PCA (CPCA, detailed in Subsection 4.2). The former layer is useful for controlling the process quality condition/capability (Section 3) based on the most critical failure mode identified by FFMEA. Hence, it enhances FFMEA from the current control viewpoint. The latter layer is beneficial to unravelling the twisted threads of the two statistical causes mentioned (Subsection 4.2). Therefore, it contributes to FFMEA in terms of failure cause investigation.

Moreover, based on the CPCA approach (Palmer and Tsui, 1999), some statistical guidelines for corrective actions are given in Subsection 4.3, which improve FFMEA from the aspect of recommended corrective action. Further, the following illuminates the other path through which VOC is included in the proposed hybrid approach:

VOC (represented by USL and LSL) → Cp, Cpk and k indices (detailed later) → FFMEA-CPCA.

The present study, thus, contributes to the FMEA analytical and computational dimensions and facilitates the data utilisation and analysis that ratio-scale data of a process deserve. Additionally, the following are the contributions made by using the FFMEA part in the proposed approach:

i) experts' judgment uncertainty – in scoring the risk factors – is tackled using the fuzzy approach (Ghorbani et al, 2013; Shahin et al, 2017); ii) the Fuzzy Logic relationship-mapping capability is used for valid computation of RPN (Geramian et al, 2017); iii) the rule-designing capability is beneficial to weighting the risk factors (Geramian et al, 2017); iv) the weighting capability has a remarkable impact on resolving an FMEA problem, i.e. computation of the same RPN for different combinations of risk factors (Geramian et al, 2017); and v) the FFMEA risk indicator (Fuzzy RPN) is continuous and free of the RPN problem, i.e. having many holes (Liu et al, 2013).

Once failure modes have been prioritised using FFMEA, the most critical failure is analysed using PCA and CPCA. Finally, statistical corrective actions are proposed. All these phases are illustrated in Figure 1.

2. Basic FMEA

In FMEA, risk priorities are determined using RPN, as the product of the three risk factor scores (Equation 1) with a scale of 1-10 such as what is addressed in Table 1.

$$RPN = Occurrence \times Severity \times Detection \tag{1}$$

Table 1. Descriptions and scales of risk factors (Sharma et al, 2005; Geramian et al, 2017)

Score	Occurrence	Severity	Detection rate (%)
10 9	> 0.1 0.05-0.1	A failure that would seriously affect the ability to complete the task or cause damage, serious injuries or death	0-5 6-15
8 7	0.02-0.05 0.01-0.02	A failure that causes deterioration in system performance and/or leads to minor injuries	16-25 26-35
6 5 4	0.005-0.01 0.002-0.005 0.001-0.002	A failure that would cause high degree of operator dissatisfaction, or that causes noticeable but slight deterioration in system performance	36-45 46-55 56-65
3 2	0.0005-0.001 0.0001-0.0005	A failure that would cause slight annoyance to the operator, but would cause no deterioration to the system	66-75 76-85
1	≤ 0.00001	A failure that has no effect on the system performance and the operator probably will not notice	86-100

Although severity and detection scores are determined based on experience of expert-teams, occurrence can be computed based on NCR (Geramian et al, 2017). The larger the RPN, the more critical the failure.

3. Process capability analysis

In 1986, Motorola described its quality-improving and defect-measuring approaches using the new phrase Six Sigma (Arumugam et al, 2016). Regarding a process mean shift by 1.5 sigma, Six Sigma aims to achieve 3.4 Defects per Million Opportunities (DPMO) (Antony et al, 2008). Besides DPMO, other Six Sigma measures are Process Capability Indices (PCIs), used to compare a stable process performance with the specified tolerance. Juran (1962) proposed the idea of comparing the width of natural control limits to that of the tolerance limits. Later, the idea was utilised in the introduction of a ratio directly indicating the process capability (Juran and Gryna, 1980). An inverse form of the ratio is known as Cp (Equation 2).

$$Cp = \frac{USL - LSL}{6.\sigma} \tag{2}$$

Where σ depicts the standard deviation (Std). Cp values are useful for interpretation of process quality conditions. In fact, processes with $Cp < 0.68,\ \ 0.68 \le Cp < 1,\ \ 1 \le Cp < 1.33,\ \ 1.33 \le Cp < 1.67,\ \ 1.67 \le Cp < 2$ and $Cp \ge 2$ are considered as poor, inadequate, capable, satisfactory, excellent and super excellent, respectively (Tsai and Chen, 2006). Since Cp does not reflect the process mean shift, the Cpk and k indices were developed (Palmer and Tsui, 1999):

$$Cpk = \min(Cpu, Cpl) = \min(\frac{USL - \mu}{3.\sigma}, \frac{\mu - LSL}{3.\sigma}) \tag{3}$$

$$k = {(\mu - M)} \Big/ {(USL - LSL)/2} \tag{4}$$

where μ and M denote the process mean and $midpoint = (USL + LSL)/2$, respectively. Index k indicates the process mean location with respect to the midpoint. μ and σ are estimated by $\hat{\mu}$ and $\hat{\sigma}$, respectively. The main focus of this study is on the collective analysis of Cp, Cpk and k (explained in Subsection 4.2).

4. New approach: integration of FFMEA and CPCA

The hybrid approach FFMEA-CPCA consists of three phases (Figure 1), detailed in Subsections 4.1 to 4.3.

“Insert Figure 1 here”

Figure 1. FFMEA-CPCA framework

4.1. Failure ranking using FFMEA

First, failure modes are defined based on typical items of lack of quality which occur for quality characteristics during a process. Then they are prioritised using FFMEA, with a Mamdani type FIS (Pourjavad and Shahin, 2018) of Multiple Inputs and Single Output (MISO). The reason is that FMEA has three inputs, one output together with an unknown inputs-to-output relationship. The FFMEA steps (Geramian et al, 2017) are described in subsections below:

4.1.1. Fuzzification

Membership degrees of crisp inputs (risk factor scores) in their relevant Membership Functions (MFs) are determined in the fuzzification step. MFs are fuzzy sets corresponding to linguistic variables (Wang et al, 2016), such as very low, low, etc., which are useful to computing with words (Shahin et al, 2017). Each linguistic variable corresponds to a fuzzy number with a trapezoidal shape, triangular shape, etc. Equations (5) to (7) indicate risk factor vectors (Geramian et al, 2017).

$$Occurrence_{vector} = \left\{ \begin{array}{l} O, \{1,\ 2,\ \ldots\ 10\}, \{VL_O,\ L_O,\ M_O,\ H_O, VH_O\}, \\ \{\mu_{VL_O}(o), \mu_{L_O}(o), \mu_{M_O}(o), \mu_{H_O}(o), \mu_{VH_O}(o)\} \end{array} \right\} \tag{5}$$

$$Severity_{vector} = \left\{ \begin{array}{l} S, \{1,\ 2,\ \ldots\ 10\}, \{VL_S,\ L_S,\ M_S,\ H_S, VH_S\}, \\ \{\mu_{VL_S}(s), \mu_{L_S}(s), \mu_{M_S}(s), \mu_{H_S}(s), \mu_{VH_S}(s)\} \end{array} \right\} \tag{6}$$

$$Detection_{vector} = \left\{ \begin{array}{l} D, \{1,\ 2,\ \ldots\ 10\}, \{VL_D,\ L_D,\ M_D,\ H_D, VH_D\}, \\ \{\mu_{VL_D}(d), \mu_{L_D}(d), \mu_{M_D}(d), \mu_{H_D}(d), \mu_{VH_D}(d)\} \end{array} \right\} \tag{7}$$

Where O, S and D denote the variables occurrence, severity and detection changeable in the discrete range of $\{1, \quad 2, \quad \ldots \quad 10\}$. For $i = O, S$ and D, the general set of linguistic variables is $\{VL_i, \quad L_i, \quad M_i, \quad H_i, \quad VH_i\}$, standing for very low, low, medium, high and very high, respectively. Regarding the crisp values, $c = o, s$ and d, the general set of membership degrees is $\{\mu_{VLi}(c), \mu_{Li}(c), \mu_{Mi}(c), \mu_{Hi}(c), \mu_{VHi}(c)\}$. The Fuzzy RPN (FRPN) vector (Equation 8) has similar components except for FRPN, which is changeable in the discrete range of $\{0, \quad 1, \quad \ldots \quad 10\}$ and has the crisp rpn value.

$$FRPN_{vector} = \left\{ \begin{array}{l} FRPN, \{0, \quad 1, \quad \ldots \quad 10\}, \{VL_{FRPN}, \quad L_{FRPN}, \quad M_{FRPN}, \quad H_{FRPN}, VH_{FRPN}\}, \\ \{\mu_{VL_{FRPN}}(rpn), \mu_{L_{FRPN}}(rpn), \mu_{M_{FRPN}}(rpn), \mu_{H_{FRPN}}(rpn), \mu_{VH_{FRPN}}(rpn)\} \end{array} \right\}$$

(8)

The MFs designed in this study are illustrated in Figure 3.

4.1.2. Fuzzy rule base

A rule base consists of several rules, with an If-Then structure, in which the If/antecedent part results in the Then/consequent part. The antecedent is obtained by conjunction of input MFs, e.g. $(O \text{ is } VL_O)$ and $(S \text{ is } VL_S)$ and $(D \text{ is } L_S)$. The conjunction operator is a t-norm (Geramian et al, 2017) or an *AND* method (Ries and Beullens, 2015). The consequent is a linguistic output such as $(FRPN$ is $VL_{FRPN})$. Antecedent-consequent relationships are determined based on expert knowledge. If risk factors have n_O, n_S and n_D MFs, the full number of rules are, potentially, $n_O \times n_S \times n_D$. However, some of them are negligible or not logical in real-life applications (Geramian et al, 2017).

4.1.3. Fuzzy inference and aggregation

Once the fuzzy rule base was designed, the fuzzy inference engine is fed with inputs. Each rule is fired/activated to a particular extent based on the received inputs and is implicated using operators such as Minimum:

$$\mu\left(R^j\right)=Min\left(\alpha^j,\mu_{output\ MF^j}\right) \tag{9}$$

where α^j is the conjunction result for the j^{th} rule antecedent, and $\mu_{output\ MF^j}$ is the j^{th} rule output MF, for $j=1,\ 2,\ \ldots\ n_O \times n_S \times n_D$. Next, the $\mu(R^j)$ values are aggregated using an *or* operator such as Maximum (Lu and Antony, 2002):

$$\mu_{FRPN} = Max\left\{\ \mu\left(R^1\right)\ ,\ \ \mu\left(R^2\right)\ ,\ \ \ldots\ \ \mu\left(R^{n_O \times n_S \times n_D}\right)\ \right\} \tag{10}$$

4.1.4. Defuzzification

In this step, μ_{FRPN} is defuzzified to be perceptible by experts. Amongst various defuzzification methods, Centroid (Equation 11) is of high popularity (Rafie and Namin, 2015). Hence, it was applied in this study.

$$Estimated\ Crisp\ RPN = \frac{\int_{-\inf}^{+\inf} \mu_{FRPN}(y) \times y \times dy}{\int_{-\inf}^{+\inf} \mu_{FRPN}(y) \times dy} \tag{11}$$

Where y denotes the input of the aggregated MFs.

4.2. Collective process capability analysis

Having determined via FFMEA, the most critical failure mode was analysed, further, using the Cp, Cpk and k indices (both separately and collectively). The CPCA, specifying how much deviation is caused by mean shift and/or how much by Std, is explained below (the comprehensive details of CPCA can be found in Palmer and Tsui, 1999):

a) compare Cp and Cpk:

a.1) if $Cpk = Cp$, then the process has no mean shift from the target

a.2) if $Cpk < Cp$, then the process suffers from a mean shift

b) compare Cp and 1.0:

b.1) if $Cp \geq 1.0$, then the process Std is acceptable

b.2) if $Cp < 1.0$, then Std is not acceptable

4.3. Statistical guidelines for corrective actions

Regarding the CPCA conditions, including $(a.1)$, $(a.2)$, $(b.1)$ and $(b.2)$, four main scenarios are conceivable, $(a.1-b.1)$, $(a.1-b.2)$, $(a.2-b.1)$ and $(a.2-b.2)$, namely. These scenarios along with the following statistical guidelines for correction are mentioned below based on the instructions made by Palmer and Tsui (1999):

- in $(a.1-b.1)$, engineers face the best scenario. However, the process Std could be reduced more to achieve higher Cp values.
- in $(a.1-b.2)$, the process Std should be reduced in order for Cp to be higher than or equal to one.

For the other scenarios, comprising the $(a.2)$ condition, both $(a.2.1)$ and $(a.2.2)$ steps should be investigated (Palmer and Tsui, 1999):

(a.2.1) if $k < 0$, the process mean has shifted to left side of the target

(a.2.2) if $k > 0$, the process mean has shifted to the right side of the target

Thus, it is more accurate to split scenario $(a.2-b.1)$ into $(a.2.1-b.1)$ and $(a.2.2-b.1)$, and scenario $(a.2-b.2)$ into $(a.2.1-b.2)$ and $(a.2.2-b.2)$:

- in $(a.2.1-b.1)$, the process mean should be increased until it is adjusted on the target, or $Cpk = Cp$.

- in $(a.2.1 - b.2)$, first, Std should be reduced in order for Cp to be higher than or equal to 1.0; then the process mean should be increased until it is adjusted on the target, or $Cpk = Cp$.
- in $(a.2.2 - b.1)$, the process mean should be decreased until it is adjusted on the target, or $Cpk = Cp$.
- in $(a.2.2 - b.2)$, first, Std should be reduced in order for Cp to be higher than or equal to 1.0; then the process mean should be decreased until it is adjusted on the target, or $Cpk = Cp$.

5. Case study and findings

An electrical-equipment-manufacturing company, producing insulators and bushings, was selected as the case study. Manufactured insulators are used in electric networks to bear weight of and to insulate distribution-line conductors. Bushings are both an insulator for environment and an electric conductor through which electrical flow is passed. Insulators and bushings are produced through the same production process with five specific steps, including material preparation, mold-injection preparation, heat curing, quality control and post curing.

Material preparation refers to combination of materials forming the main body of each insulator/bushing based on a specific chemical formula. Each product has its specific mold, equipped with thermal elements and vacuum pumps. Mold-injection preparation refers to vacuuming molds before the material injection. The high pressure made by the vacuum pump brings about suction of the combined material within the mold. Next, the chemical mixture is hardened under a specific heat and time, technically called heat curing. Afterwards, removed from the mold is a solid product which is ready to be tested in the quality control section. In this case study, the quality of produced insulators and bushings are investigated based on the height, weight and diameter quality characteristics. In the process, it is only non-defective products which pass another curing process called post curing, under a specific time to be hardened more.

An expert team was formed. Interviews with the team along with statistical figures resulted in identification of four product types (Table 2) that caused most customer dissatisfaction. Beyond these initial diagnostic endeavours, this study adopted an approach similar to the Six Sigma methodology, in which a subset of Critical-to-Quality (CTQ) items, called Critical-to-Customer (CTC), was selected to be further analysed and improved (for more details on Six Sigma see Park, 2003, p. 34).

Table 2. Technical specifications for the studied quality characteristics

Product	Quality characteristic								
	Height (centimetre)			Weight (gram)			Diameter (centimetre)		
	LSL	T	USL	LSL	T	USL	LSL	T	USL
Insulator A	7.50	8.00	8.50	595	600	605	7.50	8.00	8.50
Insulator B	8.00	8.50	9.00	460	470	480	5.50	6.50	7.50
Insulator C	20.50	21.00	21.50	105	110	115	7.00	8.00	9.00
Bushing A	14.40	15.00	15.60	693	700	707	9.00	10.00	11.00

Strictly speaking, the application of Six Sigma in manufacturing is based on the Define, Measure, Analyse, Improve and Control (DMAIC) strategy. In the Define phase, CTQs are identified. Considering the four products with the three quality characteristics, this study dealt with 12 CTQs. Nonetheless, due to time and budget limitations and according to Six Sigma, they were ranked and narrowed down to the most critical failure via FMEA (Table 3) and FFMEA (Table 4).

Sampling and data collection are necessary to calculate NCR – or, finally, occurrence – and to conduct CPCA. The total number of each of the four product types produced during one month (the statistical population unit) was around 1300. Thus, the appropriate sample size for each type was computed around 300 (Krejcie and Morgan, 1970). Each sampling was conducted through 60 subgroups of size five, each $(60 \times 5 = 300)$, and by Systematic Random Sampling. Regarding the NCRs calculated in the samples, the relevant Occurrence (O) scores were obtained. These scores together with those of the other two risk factors – S and D – were utilised to calculate RPN values (Table 3).

Table 3. FMEA for the studied failures*

Process function	Failure mode	Potential failure effect(s)	Statistical failure cause(s)	S	O	D	RPN	Priority
Material preparation	Lack of weight quality in Insulator A	Weight deviation of Insulator A $(W_{I(A)})$	Mean shift and/or Std	2	6	2	24	9
	Lack of weight quality in Insulator B	Weight deviation of Insulator B $(W_{I(B)})$	Mean shift and/or Std	3	3	2	18	10
	Lack of weight quality in Insulator C	Weight deviation of Insulator C $(W_{I(C)})$	Mean shift and/or Std	1	3	2	6	11
	Lack of weight quality in Bushing A	Weight variability of Bushing A $(W_{B(A)})$	Mean shift and/or Std	1	4	1	4	12
Mold injection	Lack of diameter quality in Insulator A	Diameter deviation of Insulator A $(D_{I(A)})$	Mean shift and/or Std	6	10	3	180	1
	Lack of diameter quality in Insulator B	Diameter deviation of Insulator B $(D_{I(B)})$	Mean shift and/o Std	6	6	3	108	4
	Lack of diameter quality in Insulator C	Diameter deviation of Insulator C $(D_{I(C)})$	Mean shift and/or Std	6	7	3	126	3
	Lack of diameter quality in Bushing A	Diameter deviation of Bushing A $(D_{B(A)})$	Mean shift and/or Std	6	5	1	30	8
	Lack of height	Height deviation of Insulator A	Mean shift and/or Std	7	7	2	98	5

quality in Insulator A	($H_{I(A)}$)						
Lack of height quality in Insulator B	Height deviation of Insulator B ($H_{I(B)}$)	Mean shift and/or Std	7	10	2	140	2
Lack of height quality in Insulator C	Height deviation of Insulator C ($H_{I(C)}$)	Mean shift and/or Std	7	6	2	84	6
Lack of height quality in Bushing A	Height deviation of Bushing A ($H_{B(A)}$)	Mean shift and/or Std	7	5	1	35	7

* almost similar to the ASQ's FMEA template (http://asq.org/learn-about-quality/quality-tools.html)

Therefore, FMEA resulted in the following prioritisation order (For simplification, each failure mode will, hereafter, be represented by its only failure effect – e.g. $\mathrm{D}_{\mathrm{I(A)}}$ represents the lack of diameter quality in Insulator A.):

$$\mathrm{D}_{\mathrm{I(A)}} >> \mathrm{H}_{\mathrm{I(B)}} >> \mathrm{D}_{\mathrm{I(C)}} >> \mathrm{D}_{\mathrm{I(B)}} >> \mathrm{H}_{\mathrm{I(A)}} >> \mathrm{H}_{\mathrm{I(C)}} >> \mathrm{H}_{\mathrm{B(A)}} >> \mathrm{D}_{\mathrm{B(A)}} >> \mathrm{W}_{\mathrm{I(A)}} >> \mathrm{W}_{\mathrm{I(B)}} >> \mathrm{W}_{\mathrm{I(C)}} >> \mathrm{W}_{\mathrm{B(A)}}.$$

However, it is questionable due to the following three problems:

(a) $\mathrm{D}_{\mathrm{I(C)}}$ with $(O,S,D)=(7,6,3)$ has almost the same occurrence and detection as $\mathrm{H}_{\mathrm{I(A)}}$ with $(O,S,D)=(7,7,2)$. However, it is known more critical than $\mathrm{H}_{\mathrm{I(A)}}$, even with a less severity $(6<7)$.

(b) $\mathrm{D}_{\mathrm{I(B)}}$ with $(O,S,D)=(6,6,3)$ is known more critical than $\mathrm{H}_{\mathrm{I(A)}}$ with $(O,S,D)=(7,7,2)$, even with less occurrence and severity $(6<7$ and $6<7)$ and almost the same detection.

(c) $\mathrm{D}_{\mathrm{I(B)}}$ with $(O,S,D)=(6,6,3)$ has nearly the same occurrence and detection as $\mathrm{H}_{\mathrm{I(C)}}$ with $(O,S,D)=(6,7,2)$. However, $\mathrm{D}_{\mathrm{I(B)}}$ is known more critical than $\mathrm{H}_{\mathrm{I(C)}}$, even with a less severity $(6<7)$.

With regard to these problems, discussed in Section 6, application of FFMEA is necessary. The main part of FFMEA calculations was made using MATLAB software, with a general architecture shown in Figure 2.

"Insert Figure 2 here"

Figure 2. FFMEA architecture of the present study

According to the expert team's opinion and the data of Table 1, each fuzzy input was designed using five MFs of Very Low (VL), Low (L), Medium (M), High (H) and Very High (VH). The fuzzy output, however, was designed with two more MFs, i.e. Extremely Low (EL) and Extremely High (EH) (Figure 3).

"Insert Figure 3 here"

Figure 3. Designed fuzzy inputs and output

The three inputs, with the five MFs, resulted in $125\,(5\times 5\times 5=125)$ potential rules, many of which were not necessarily applicable in the case study. Therefore, they were reduced to 40 appropriate rules covering the crisp inputs (Geramian et al, 2017), such as:

$$Rule\ 1: if\ (Occurrence\ is\ VH)\ and\ (Severity\ is\ VH)\ and\ (Detection\ is\ L)\ then\ (FRPN\ is\ EH)$$
$$Rule\ 4: if\ (Occurrence\ is\ VH)\ and\ (Severity\ is\ H)\ and\ (Detection\ is\ VL)\ then\ (FRPN\ is\ VH)$$
$$Rule\ 29: if\ (Occurrence\ is\ M)\ and\ (Severity\ is\ VL)\ and\ (Detection\ is\ L)\ then\ (FRPN\ is\ VL)$$
$$Rule\ 40: if\ (Occurrence\ is\ L)\ and\ (Severity\ is\ VL)\ and\ (Detection\ is\ VL)\ then\ (FRPN\ is\ EL)$$

Derived from the designed FIS are the three-dimension plots illustrated in Figure 4.

"Insert Figure 4 here"

Figure 4. FRPN surface plots relative to occurrence-severity, detection-occurrence and detection-severity

The plots show ascending trends of FRPN relative to the inputs. Once the FIS received the crisp inputs, the rules were fired, implicated, aggregated and defuzzified, leading to the FFMEA prioritisation (Table 4).

Table 4. FFMEA prioritisation

Failure mode	Defuzzified FRPN	Defuzzified FRPN-based priority
$H_{I(A)}$	6.84	3
$W_{I(A)}$	2.25	9
$D_{I(A)}$	7.98	1
$H_{I(B)}$	7.87	2
$W_{I(B)}$	1.97	10
$D_{I(B)}$	5.81	6
$H_{I(C)}$	6.21	5
$W_{I(C)}$	1.35	11
$D_{I(C)}$	6.81	4
$H_{B(A)}$	5.26	7
$W_{B(A)}$	0.82	12
$D_{B(A)}$	4.09	8

Therefore, FFMEA resulted in the following prioritisation order:

$D_{I(A)} >> H_{I(B)} >> H_{I(A)} >> D_{I(C)} >> H_{I(C)} >> D_{I(B)} >> H_{B(A)} >> D_{B(A)} >> W_{I(A)} >> W_{I(B)} >> W_{I(C)} >> W_{B(A)}$.

It is important to note that $H_{I(A)}$ received more priority than $D_{I(C)}$ and $D_{I(B)}$ through FFMEA, while it wrongly received less priority via FMEA. Moreover, in contrast to FMEA, FFMEA ranked $H_{I(C)}$ as more critical than $D_{I(B)}$. The first phase was finished at this point.

According to the specific requirement of the case study, only the most critical failure, $D_{I(A)}$, was selected for analysis in the second phase. A CPCA technique, using Equations (2) and (3), has three data prerequisites including stability, normality and symmetry (Palmer and Tsui, 1999). The Capability Sixpack option of Minitab software was used to analyse the sample data collected from $D_{I(A)}$ (Figure 5). In Figure 5, Xbar Chart, R Chart and the run chart of the last 25 Subgroups indicate the stability of the subgroups. In addition, Normal Probability Plot indicates observations are distributed almost normally, with an Anderson-Darling p-value of 0.206. Being almost normal, the data are almost symmetric. Thus, it can be analysed by the CPCA technique.

Based on Capability Plot of Figure 5, for within-subgroup Std of 0.1446, PCIs are

$Cp = 1.15$ and $Cpk = 0.41$ for $\mathrm{D}_{\mathrm{I(A)}}$. Therefore, it is capable according to Cp, but poor on the basis of Cpk. Moreover, the process mean-location index is $k = 0.65$. As $Cpk < Cp,\ \ Cp \geq 1$ and $k > 0$, the $(a.2.2 - b.1)$ scenario occurred, indicating that the process suffered from a remarkable mean shift to the right. The shift can be seen also through Capability Histogram and Capability Plot of Figure 5. The process pre-improvement statistical indices are summarised in Table 5. The second phase was finished at this point.

Interviews with the expert team outlined that diameter failures are usually caused by i) mold deformation, bringing about insulators with shorter diameters than the target; and ii) erosion of mold internal wall due to thermal stresses during casting operation, causing insulators with longer diameters than the target. Shifting to the right, the $\mathrm{D}_{\mathrm{I(A)}}$ diameter mean was larger than its target, indicating that the second cause was occurred to the mold. An eroded mold could either be repaired or replaced depending on the erosion intensity. In this case study, the former was adopted. Repairing had three steps including sintering (coating the mold internal wall with a specific tin alloy), polishing the mold internal wall and hard Chrome plating. According to the third phase, since the $(a.2.2 - b.1)$ scenario happened, the mold internal diameter should be reduced exactly by $0.32\ (\hat{\mu} - m = 8.32 - 8.00)$ centimetres.

Once the failure cause was resolved, 300 extra samples were collected from $\mathrm{D}_{\mathrm{I(A)}}$. The pre and post indices of process improvement are summarised in Table 5.

“Insert Figure 5 here”

Figure 5. Capability Sixpack chart for $\mathrm{D}_{\mathrm{I(A)}}$

Table 5. Six Sigma pre- and post-improvement indices for $\mathrm{D}_{\mathrm{I(A)}}$

Improvement stage	Cp	Cpk	K	Sigma level	DPMO

Pre stage	1.15	0.41	0.65	2.73	115,083.09
Post stage	1.18	1.12	0.05	4.86	336.98
Improvement (%)	2.61	173.17	0.60	78.02	114,746.11

The sigma quality levels (long run) were calculated through: $Sigma\ level = 3 \times Cpk + 1.5$ (Park, 2003). The DPMOs – with one defect opportunity – were calculated based on the table of relationship between defective items and sigma levels (Breyfogle et al, 2001). The Third phase was finished at this point.

6. Discussion

The FMEA computational aspect limitations, mentioned in Section 1, were resolved by i) calculating RPNs via the 40 rules designed by experts, not through Equation (1); ii) designing the fuzzy inputs, which tackled the uncertainty in the determination of risk factors; and iii) considering different risk factor weights through the fuzzy rules. Despite the weight ignorance in FMEA, by means of FFMEA the severity factor was considered more important than occurrence and detection, which seems reasonable (Geramian et al, 2017). The weight ignorance is the main reason behind the FMEA limitations indicated by the (a), (b) and (c) problems mentioned in Section 5. More precisely, the $[\mathrm{H_{I(A)}} \text{ and } \mathrm{D_{I(C)}}]$, $[\mathrm{H_{I(A)}} \text{ and } \mathrm{D_{I(B)}}]$ and $[\mathrm{H_{I(C)}} \text{ and } \mathrm{D_{I(B)}}]$ failure pairs, which were wrongly ranked via FMEA, were ranked correctly through FFMEA by considering the risk factor weights. That is why the order of the third to sixth priorities in FMEA – $\mathrm{D_{I(C)}} >> \mathrm{D_{I(B)}} >> \mathrm{H_{I(A)}} >> \mathrm{H_{I(C)}}$ – were inconsistent with those in FFMEA – $\mathrm{H_{I(A)}} >> \mathrm{D_{I(C)}} >> \mathrm{H_{I(C)}} >> \mathrm{D_{I(B)}}$. Hence, the FMEA computational aspect was enhanced using FIS.

In Figure 4, the ascending trends of FRPN relative to the inputs indicated that a valid logic was considered in the rule definition: the higher the risk factors, the higher the FRPN.

On the one hand, the proposed approach is limited to the new definitions of the failure mode and failure effect, mentioned earlier in the Introduction section. On the other hand, the definitions are of significant contributions, mentioned in the section. For example, by defining the failure mode as the lack of diameter quality in Insulator A, FFMEA was enhanced by inclusion of the continuous data from the $D_{I(A)}$ effect. It was also enriched by inclusion of the ratio-scale data from the rightwards mean shift of 0.32 (the statistical cause). More precisely, it is of a derived-type ratio scale because of being a mathematical function of length (diameter, here), which in turn is a fundamental magnitude with a ratio scale (Stevens, 1946). The definition also facilitated obtaining the occurrence score 10 via the NCR relationship, leading to reflection of VOC in RPNs and, finally, in Fuzzy RPNs through the mentioned path. The definition, further, facilitated completing the FFMEA results with the analyses, VOC reflection and corrective action provided by means of PCA and CPCA. Accordingly, it appears that the advantages gained by the specific definition of failures modes considerably outweigh the limitation imposed by it.

Furthermore, the limitation can be alleviated by inclusion of other failures and effects, e.g. those with the nominal measurement scale. Important to note is that the second and third phases of the methodology are not applicable for those other types.

Mean shift was the only cause of the $D_{I(A)}$ effect. However, if it is combined with the other type of cause, Std, diagnosing the sources of deviation or share of these two in deviation will be difficult. That is where the genuine value of the added CPCA layer in unravelling the twisted threads of the two statistical causes is understood.

It was assumed in this study that there is no interaction/interdependency amongst the failures. In fact, the relevant production knowledge indicated that height and diameter deviations were caused by mold deformations in the height and diameter directions. The weight deviations, however, were caused by erroneous mixing of materials. Moreover, since each mold was filled with a fixed amount of material, there was no interaction between weight and the other two deviations. However, some inverse interdependencies were possible between height and diameter, which was small and negligible.

Nonetheless, failure interactions may be significant in future applications of the approach and, thus, should be taken into consideration. A suggestion may be the adoption of an approach similar to that of Xu et al (2002) in which interdependencies of failure modes and effects are considered using the fuzzy rule base approach.

The effectiveness of the methodology, demonstrated through comparing the pre- and post-improvement PCIs in Table 5, indicated that the proposed methodology strongly contributed to an important task of a well-established FMEA, i.e. the failure occurrence elimination/reduction (Xu et al, 2002). Furthermore, the weight ignorance problem of FMEA, addressed in many studies such as Liu et al (2013), was resolved in the present research. Similar to Sharma et al (2005) and Geramian et al (2017), FMEA and FFMEA were analysed comparatively. Moreover, as with Jong et al (2013), designing valid rules and FRPNs was emphasised in this study. Additionally, similar to Geramian et al (2017), occurrence was determined based on NCR.

Before the application of Equations (2) and (3), the stability, normality and symmetry of collected samples should be investigated. Also, as with Geramian et al (2017), this study included only the MFs covering the problem crisp inputs. Therefore, the reduced rules must be readjusted by variation of the crisp values from one problem to another. Additionally, the validity of defined rules should be investigated using surface plots (such as Figure 4). An accurate rule base generates ascending trends for FRPN relative to risk factors; otherwise, rules must be revised.

Moreover, in the $(a.2.1-b.2)$ and $(a.2.2-b.2)$ scenarios, Std reduction precedes mean adjustment. This is because under the quadratic loss function interpretation of capability indices, variability reduction is a more important and challenging matter than process location adjustment (Palmer and Tsui,1999).

FFMEA-CPCA calculations were performed using MATLAB and Minitab software. However, it can be done simply by Minitab if the FFMEA ranking precedes the Capability Analysis and Capability Sixpack options of this software. Therefore, as a suggestion, the two mentioned options of Minitab software – located in Stat Menu → Quality tools – can be replaced/enhanced by two new options of i) Fuzzy FMEA-Capability Analysis; and ii) Fuzzy FMEA-Capability Sixpack, respectively. It would be advantageous also because the capability analysis would be conducted with respect to failure priorities, not randomly.

7. Managerial and practical implications

If accurately deployed, the FFMEA-CPCA approach not only can cut the scrap, rework and tool costs pertaining to the most critical failure mode, but also can reduce the customer complaints arising from it. Therefore, the approach can significantly lead to more profitability and customer satisfaction. In this regard, this case study illustrated a 114,746.11 reduction in the DPMO.

Besides cross-functional expert teams, customers can be involved in improvement endeavours by the use of the approach – indirectly through the reflection of VOC. In the studied case, for instance, an expert team was involved thanks to the rule base design capability used in the methodology. In addition, the customers' standpoint was considered through the statistical pathways presented earlier. Hence, the approach can pave the way for more involvement of organisational talents and external customers in quality decision-making processes, which is typically of the utmost importance to top management.

Further, not only the hybrid approach of FFMEA-CPCA benefits from the synergistic effect of its isolated ingredients (FMEA, FIS, PCA and CPCA, namely), but also its analyses are based on multiple sources – ranging from qualitative expert knowledge to quantitative process data. Thus, it is a streamlined, enhanced approach.

In essence, the approach is more precise because provides more technical details for corrective actions – e.g., the statistical root cause(s) and its (their) intensity. Moreover, it is more efficient since it focuses capability analysis efforts only on the most critical failure. It is also more customer-oriented in the sense that it reflects VOC in failure analysis.

This study illuminated how the approach was helpful to a manufacturing company. However, it is possible to use it successfully in service provision or other manufacturing processes. Nonetheless, those managers adopting the methodology may confront the following challenges:

- lack of the knowledge essential for successful adoption of the statistical/engineering aspects of the approach;
- absence of accurate definitions of CTQs or, in this study, the failure modes, as well as failure effects;
- resistance to the changes necessary for non-stop progress of implementation of the approach;
- lack of indication of suppliers' viewpoints in FFMEA-CPCA.

As there are significant commonalities of concepts, tools and techniques between FFMEA-CPCA and Six Sigma, i.e. CTQ/CTC, VOC, FMEA and PCA, borrowing the Six Sigma belt system – including the White Belt, Yellow Belt, Black Belt, Master Black Belt and Six Sigma Champion roles – seems logical for the training purpose (for more information in this regard see Laureani and Antony [2011] and Antony and Karaminas [2016]). Also, to define CTQs, failure modes and effects accurately, clear understanding of customer complaints, business processes, process functions and characteristics is necessary. Additionally, the resistance challenge could be responded to via the solution to the same challenge in Six Sigma implementation: the business units/functions/divisions accepting the new initiative had better be involved prior to those that may resist (Park, 2003, p. 155). It may also be tackled through developing a viable coordination and communication system clearly informing the relevant expert team about achievements and shortcomings of the approach implementation. Finally, while FFMEA-CPCA has a built-in mechanism for customer participation, it lacks such an inherent component for supplier participation. Despite this, managers should not ignore the important role which suppliers may play in quality improvement.

8. Conclusions

Some of the issues resolved by the hybrid approach of FFMEA-CPCA were the questionable calculation of RPN, the uncertainty in determination of risk factor scores and the ignored risk factor weights. Therefore, it enhanced the computational aspect of FMEA. Moreover, as it improved the investigation of the failure cause and effect, current control and recommended corrective action, it quantitatively/mathematically enhanced the FMEA analytical aspect too. Additionally, it reflected the VOC considerations in FFMEA.

The key message of this study is that by appropriate definitions of failure modes and failure effects, FFMEA results can be analysed further via PCA and CPCA. Using this idea, the present study improved Cpk and sigma level by 173.17% and 78.02%, respectively. It also reduced DPMO by 114,746.11.

There were some limitations in this study. More precisely, i) FFMEA-CPCA is applicable only for normally distributed data; ii) risk factors as well as failure modes were assumed independent; and iii) PCA, CPCA and statistical improvement were conducted only for the most critical failure mode.

Hence, the focus of future studies can be on i) developing a FFMEA-CPCA approach with distribution-free PCIs (in this regard, see, e.g., Kotz and Johnson, 2002); ii) considering possible interdependencies amongst risk factors and amongst failure modes (the latter type of interactions were explained in the Discussion section); and iii) conducting CPA, CPCA, and statistical improvement for all of ranked failures, sequentially and with respect to their priorities.

Finally, as almost all FMEA endeavours deal with decision-making of cross functional expert teams, they would be susceptible to groupthink – a dysfunctional aspect of group/team decision-making. Therefore, the FFMEA-CPCA methodology can be enhanced further via the approach of Geramian et al (2018).

References

Abbasgholizadeh Rahimi S, Jamshidi A, Ait- Kadi D and Ruiz A (2015). Using fuzzy cost based FMEA, GRA and profitability theory for minimizing failures at a healthcare diagnosis service. *Quality and Reliability Engineering International* 31(4): 601-615.

Antony J and Karaminas H (2016). Critical assessment on the Six Sigma Black Belt roles/responsibilities, skills and training: A global empirical study. International Journal of Quality & Reliability Management 33(5): 558-573.

Antony J, Kumar M and Labib A (2008). Gearing Six Sigma into UK manufacturing SMEs: results from a pilot study. *Journal of the Operational Research Society* 59(4): 482-493.

Arumugam V, Antony J and Linderman K (2016). The influence of challenging goals and structured method on Six Sigma project performance: A mediated moderation analysis. *European Journal of Operational Research* 254(1): 202-213.

Bowles JB and Peláez CE (1995). Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. *Reliability Engineering & System Safety* 50(2): 203-213.

Breyfogle III FW, Cupello JM and Meadows B (2001). *Managing Six Sigma: A practical guide to understanding, assessing, and implementing the strategy that yields bottom-line success*. John Wiley & Sons: New York.

Chin KS, Chan A and Yang JB (2007). Development of a fuzzy FMEA based product design system. *The International Journal of Advanced Manufacturing Technology* 36(7-8): 633-649.

Geramian A, Mehregan MR, Garousi Mokhtarzadeh N and Hemmati M (2017). Fuzzy inference system application for failure analyzing in automobile industry. *International Journal of Quality & Reliability Management* 34(9): 1493-1507.

Geramian A, Abraham A and Ahmadi Nozari M (2018). Fuzzy logic-based FMEA robust design: a quantitative approach for robustness against groupthink in group/team decision-making. *International Journal of Production Research* (in press).

Ghorbani M, Arabzad SM and Shahin A (2013). A novel approach for supplier selection based on the Kano model and fuzzy MCDM. *International Journal of Production Research* 51(18), 5469-5484.

Jong CH, Tay KM and Lim CP (2013). Application of the fuzzy failure mode and effect analysis methodology to edible bird nest processing. *Computers and electronics in agriculture* 96: 90-108.

Juran J (1962). *Quality Control Handbook*. McGraw-Hill: New York.

Juran J and Gryna F (1980). *Quality Planning and Analysis*. McGraw-Hill: New York.

Kotz S and Johnson NL (2002). Process capability indices—a review, 1992–2000. *Journal of Quality Technology* 34(1): 1-19.

Krejcie RV and Morgan DW (1970). Determining sample size for research activities. *Educational and psychological measurement* 30(3): 607-610.

Laureani A and Antony J (2011). Standards for lean six sigma certification. *International Journal of Productivity and Performance Management* 61(1): 110-120.

Liu HC, Liu L and Liu N (2013). Risk evaluation approaches in failure mode and effects analysis: A literature review. *Expert Systems with Applications* 40(2): 828-838.

Lu D and Antony J (2002). Optimization of multiple responses using a fuzzy-rule based inference system. *International Journal of Production Research* 40(7); 1613-1625.

Mariajayaprakash A, Senthilvelan T and Gnanadass R (2015). Optimization of process parameters through fuzzy logic and genetic algorithm–A case study in a process industry. *Applied Soft Computing* 30: 94-103.

Moss TR and Woodhouse J (1999). Criticality analysis revisited. *Quality and Reliability Engineering International* 15(2): 117-121.

Nepal BP, Yadav OP, Monplaisir L and Murat A (2008). A framework for capturing and analyzing the failures due to system/component interactions. *Quality and Reliability Engineering International* 24(3): 265-289.

Palmer K and Tsui KL (1999). A review and interpretations of process capability indices. *Annals of Operations Research* 87: 31-47.

Park SH (2003). *Six Sigma for Quality and Productivity Promotion*. Asian Productivity Organization: Tokyo.

Phadke MS (1995). *Quality Engineering Using Robust Design*. Prentice Hall PTR: New Jersey.

Pourjavad E and Shahin A (2018). The application of Mamdani Fuzzy Inference System in evaluating Green Supply Chain Management performance. *International Journal of Fuzzy Systems*, 20(3): 901-912.

Rafie M and Namin FS (2015). Prediction of subsidence risk by FMEA using artificial neural network and fuzzy inference system. *International Journal of Mining Science and Technology* 25(4): 655-663.

Ries J and Beullens P (2015). A semi-automated design of instance-based fuzzy parameter tuning for metaheuristics based on decision tree induction. *Journal of the Operational Research Society* 66(5): 782-793.

Shahin A, Barati A and Geramian A (2017). Determining the Critical Factors of Radical Innovation Using an Integrated Model of FAHP-Fuzzy Kano With a Case Study in Mobarakeh Steel Company. *Engineering Management Journal* 29(2): 74-86.

Sharma RK, Kumar D and Kumar P (2005). Systematic failure mode effect analysis (FMEA) using fuzzy linguistic modelling. *International Journal of Quality & Reliability Management* 22(9): 986-1004.

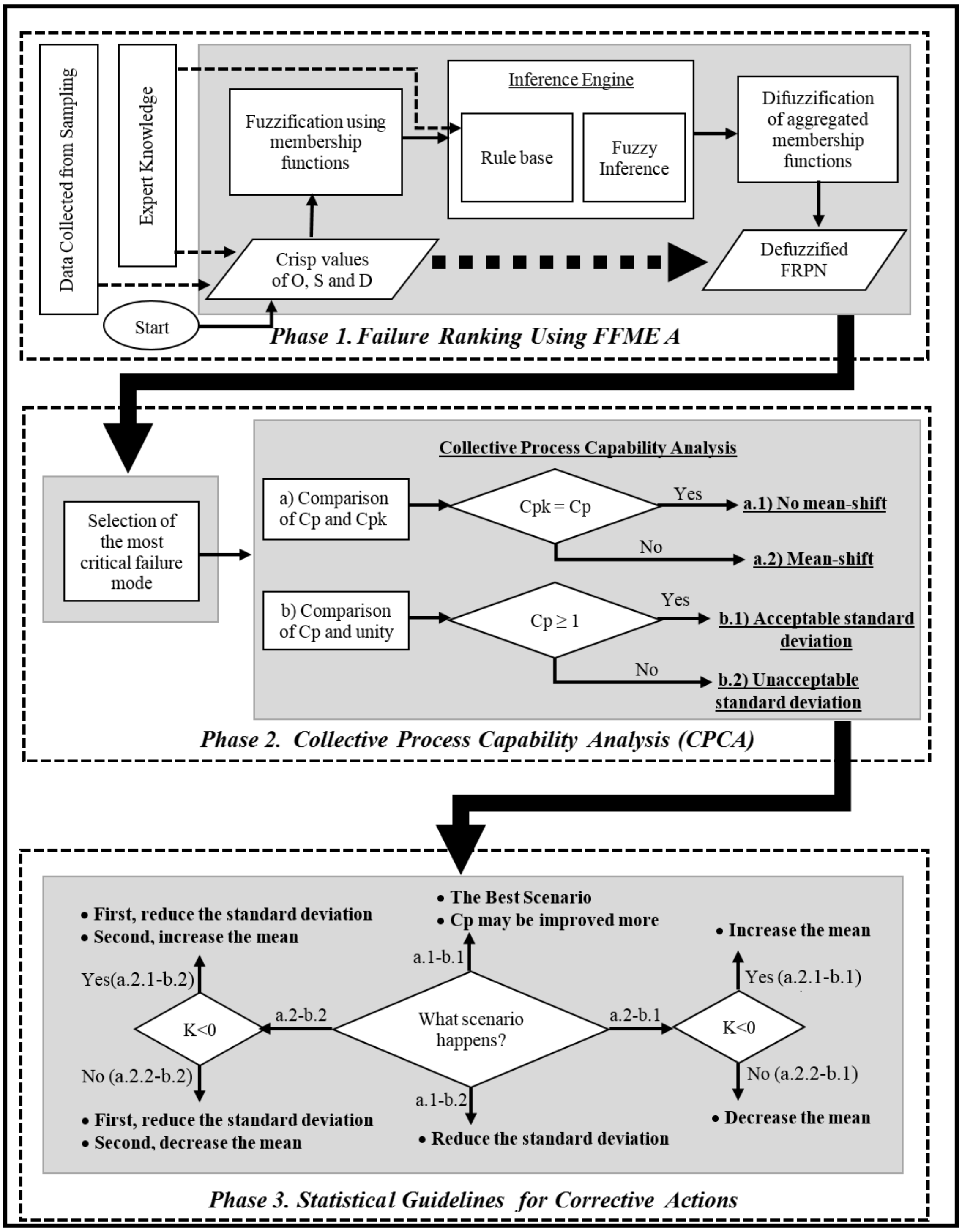
Stevens SS (1946). On the theory of scales of measurement. *Science* 103(2684): 677-680.

Tsai CC and Chen CC (2006). Making decision to evaluate process capability index C p with fuzzy numbers. *The International Journal of Advanced Manufacturing Technology*, *30*(3-4): 334-339.

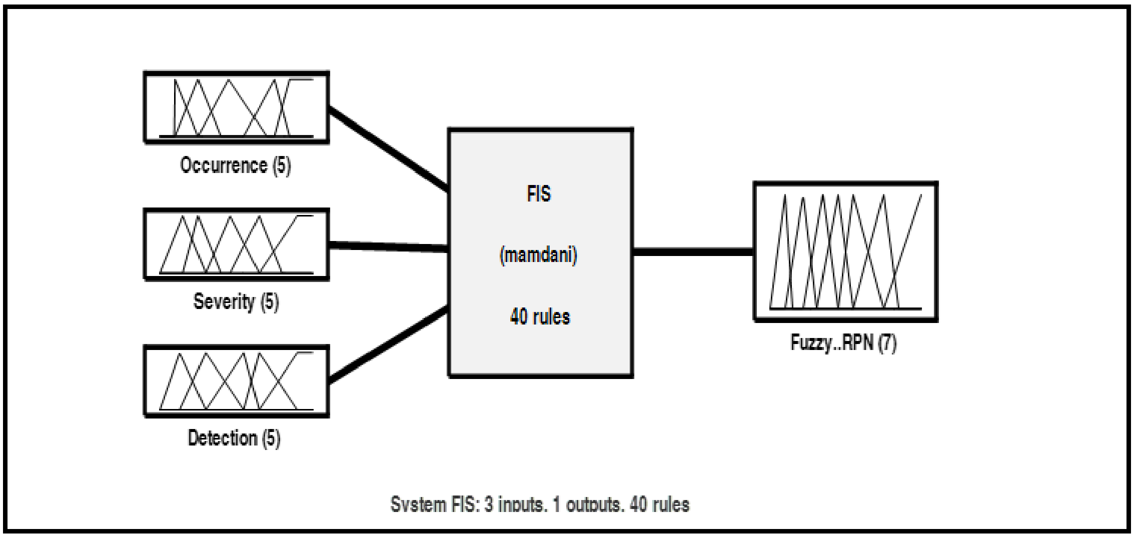
Wang K, Huang Y and Qin H (2016). A fuzzy logic-based hybrid estimation of distribution algorithm for distributed permutation flowshop scheduling problems under machine breakdown. *Journal of the Operational Research Society* 67(1): 68-82.

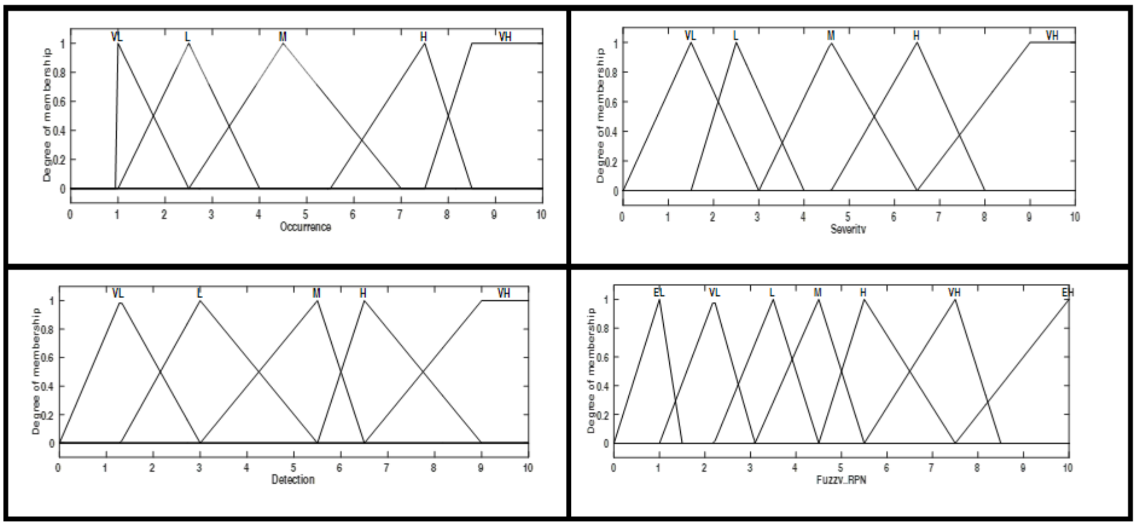
Xu K, Tang LC, Xie M, Ho SL and Zhu ML (2002). Fuzzy assessment of FMEA for engine systems. *Reliability Engineering & System Safety* 75(1): 17-29.

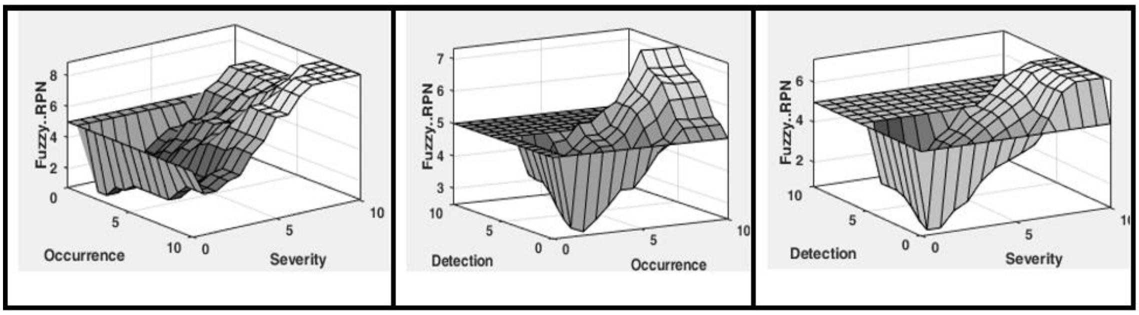
Yeh TM and Chen LY (2014). Fuzzy-based risk priority number in FMEA for semiconductor wafer processes. *International Journal of Production Research* 52 (2): 539–549.

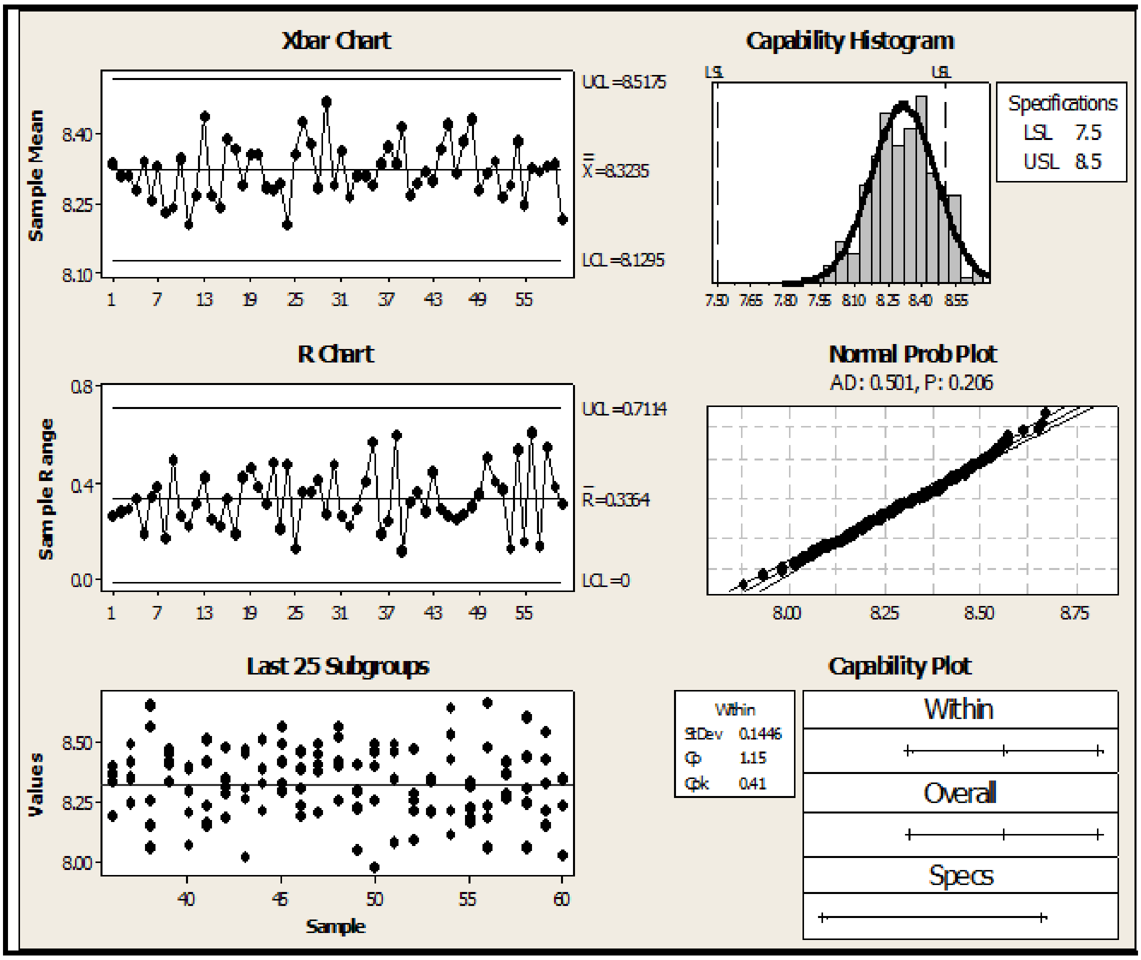


Data Collected from Sampling
Expert Knowledge
Fuzzification using membership functions
Inference Engine
Rule base
Fuzzy Inference
Difuzzification of aggregated membership functions
Crisp values of O, S and D
Defuzzified FRPN
Start
Phase 1. Failure Ranking Using FFME A
Selection of the most critical failure mode
Collective Process Capability Analysis
a) Comparison of Cp and Cpk
Cpk = Cp
Yes
a.1) No mean-shift
No
a.2) Mean-shift
b) Comparison of Cp and unity
Cp ≥ 1
Yes
b.1) Acceptable standard deviation
No
b.2) Unacceptable standard deviation
Phase 2. Collective Process Capability Analysis (CPCA)
• First, reduce the standard deviation
• Second, increase the mean
• The Best Scenario
• Cp may be improved more
• Increase the mean
a.1-b.1
Yes(a.2.1-b.2)
Yes (a.2.1-b.1)
K<0
a.2-b.2
What scenario happens?
a.2-b.1
K<0
No (a.2.2-b.2)
a.1-b.2
No (a.2.2-b.1)
• First, reduce the standard deviation
• Second, decrease the mean
• Reduce the standard deviation
• Decrease the mean
Phase 3. Statistical Guidelines for Corrective Actions


Occurrence (5)
Severity (5)
Detection (5)
FIS
(mamdani)
40 rules
Fuzzy..RPN (7)
System FIS: 3 inputs, 1 outputs, 40 rules


VL L M H VH
Occurrence
Severity
Detection
EL VL L M H VH EH
Fuzzy..RPN
Degree of membership


Fuzzy..RPN
Occurrence
Severity
Detection


Xbar Chart
Sample Mean
UCL=8.5175
X=8.3235
LCL=8.1295
Capability Histogram
LSL
USL
Specifications
LSL 7.5
USL 8.5
R Chart
Sample Range
UCL=0.7114
R=0.3364
LCL=0
Normal Prob Plot
AD: 0.501, P: 0.206
Last 25 Subgroups
Values
Sample
Capability Plot
Within
StDev 0.1446
Cp 1.15
Cpk 0.41
Within
Overall
Specs