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Sqfemethod Under Uncertain Conditionsby Generating Fuzzy Membership Function

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Abstract: The quality-based approach SQFE (Suivi Qualite Par le Fournisseur Exterieur) has been introduced by three automotivecorporationstomeasure the quality of supplier products. This approach proposesa general criterionby which inspection samples are classified to different demerit categories with different weights, to compute mean unit demerit (Dmr) for each measurable quality characteristic. However, the assignment of an actual and crisp demerit weight to each sampleis unrealistic, in the face of the unavoidable measurement errors as well as the inevitable uncertainty involved in human judgment. In this paper an improved estimation procedure which is based on fuzzy logic instead of bivalent logic,is presented to calculate Dmrs. The fuzzy set theory is used to add more accuracy and flexibility to the analysis. For this aim, "likelihood view" has been adapted to generate fuzzy membership function, in order to assign the appropriate demerit weight to each sample. In addition, a numerical example that evaluates productsbased on the proposed methodand compares it with the current standard procedureis presented.

Key words: SQFE;Demerit category; Dmr; Fuzzy membership function; Likelihood view.

INTRODUCTION

Many kindsof classification systems have been provided in various military and International organizations for Standardization (ISO)such as, quality rating systems which have been applied and extended to define, classify, and evaluate none conformities in various industrial situations(D.A.Nembhard and H.B.Nembhard, 2000). As one of those approaches,SQFE which introducedby three automotive corporations:Peugeot, Citroen and Renault, has been applying by them to measure and monitor the quality of their supplier's products. As the guidance of quality department audits, it defines a method for measuring the quality of prepared products for delivering by supplier, based on the score that is assigned to each category of product demerit related to each quality characteristic. It aims to ensure that products arriving on the production lines from external suppliers meet manufacturer's quality and reliability requirements. This approach, proposes that the quality of a supply can be measured by two main indices as follows: 1) Mean number of demerit points for the product (*DUM*) that gives a relative measure of quality. 2) Thelevel of delivered quality (*NQL*) that showes the observed maximum deviation from the target value.The supplier can prioritize the corrective and preventive actionsthrough the results obtained by these indices(SQFE, 1993).

The indices calculate based on demerit weights that are assigned to demerit classes.Typically, weights increase as the degree of severity increases. Although a general demerit classificationanddemerit weights have been suggested by SQFE standard, the final demerit rating system is decided by the agreement of manufacturer and supplier to reflect their current relative levels of concern for each failure type.Each sample taken is subjected to rating of the chosen characteristics based on a demerit system. The general demerit categories and their corresponding weights have been listed in Table 1. For measurable quality characteristics, demerit weights are determined as a function of the distance from the center of the tolerance interval as shown in Table 2,based on Fig 1, where m denotes the target value of ith quality characteristic, $T$is its tolerance, A_R and A_L are upper specification limit and lower specification limit. Moreover, using B_R and C_R determined on the right side of the target value and $B_L$and C_L on its left side, the tolerance band divides to 4 classes in each side, that every sample should be judged based on them. The mathematical formulas are as follows:

$$B_R = m + 0.33T \qquad (1)$$

$$C_R = A_R + 0.1T \qquad (2)$$

$$B_L = m - 0.33T \qquad (3)$$

$$C_L = A_L - 0.1T \qquad (4)$$

The sum of demerits for ith quality characteristic which is denoted by Dr_i can be obtained as follows:

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$$Dr_i = \sum_{j=1}^{n_i} W_{ij}\; i = 1,2,\dots,q\; j = 1,2,\dots,n_i \qquad (5)$$

Where W_{ij} is the demerit weight of jth inspection sample, with respect to ith quality characteristic which is obtained for each sample, based on the criteria defined in advanced and n_i is total number of samples which must be collected to monitor the ith quality characteristic. For ith quality characteristic, Dmr_i which indicates the mean demerit is determined by:

$$Dmr_i = \frac{Dr_i}{n_i} \qquad (6)$$

Then we can obtain *DUM* for the product as:

$$DUM = \sum_{i=1}^{q} Dmr_i \qquad (7)$$

Table 1: Demerit categories and their weights.

Demerit category	Demerit weight
None defect	0
Meriting improvement	3
Meriting rework	5
Imperative rework	15
Recall necessary	55

Table 2: Demerit rating criteria for double-limit measurable quality characteristics.

Demerit category	Criteria	Demerit weight
1	$B_L \le x \le B_R$	0
2	$A_L \le x \le B_L OR B_R \le x \le A_R$	3
3	$C_L \le x \le A_L OR A_R \le x \le C_R$	Standard rating:5 Ifdefect requires rework:15 If defect require recall:55
4	$x \le C_L OR x \ge C_R$	Standard rating:15 If defect requires recall:55

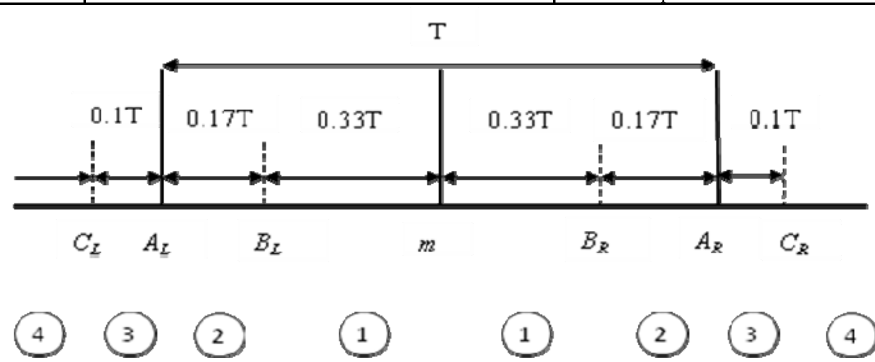


Fig. 1: The criteria for classification of double-limit measurable quality characteristics.

Here the question is “is there any certainty that all the defects related to a specific measurable quality characteristic located in one demerit category, have the same degree of severity?”. The classical SQFE assigns the same crisp weight to each none conformity of the same demerit category, regardless of their degree of severity. However, for the defects classified to the same category, the degree of severity might be different.

This model is still lacking of the capability to handle the inherent uncertainty which is usually unavoidable in most of problems including human judgments, beliefs and subjective decision making processes. A human's thought process cannot directlydetermine the weight value, which can describe by language (Cheng *et al*., 1999).The problem of natural language by which most of human knowledge is expressed is that it is intrinsically imprecise. Imprecision of natural language comes from perception that is also intrinsically imprecise. As the logic of imprecision, fuzzy logic is a much better choice than bivalent logic that is naturally unsuited to present natural language(Zadeh, 2008). Fuzzy logic introduced by Zadeh, in 1965, has been considered as an appropriate method for subjective judgment and qualitative assessment in the evaluation processes of decision-making to handle the impreciseand uncertain information(Tai and Chen, 2009).According toZadeh (2008) as more often than not, reality is fuzzy;thereforeitis need to use fuzzy logic, to construct the realistic models.

There has been a rapid growth in applying fuzzy logic to a variety of issues in manufacturing during the past two decades(Azadegan *et al*., 2011). Therefore to solve the problem of weight assignment, the aim of this paper is to propose an efficient frameworkto measure and improve supplier performance, in which the quality level obtained through SQFE could be measured based on the reality and more flexible than the classical one. We generate fuzzy membership function, through fuzzy set theory (FST), considering the different defect's degree of severity, which was not seriously treated by the researchers. The paper is organized as follows: In section 2, weintroduce the basic of fuzzy logic and fuzzy membership function; Section 3 includes generating fuzzy membership function of demerit categories, as well as calculation of fuzzyDmr for each measurable quality characteristic. In Section4, the applicability of the proposed models in practice is demonstrated with a numerical example. Finally the last section concludes the present research.

2. Fuzzy Logic And Fuzzy Membership Function:

Boolean logic has only 'yes' and 'no', and nothing between them, by contrast, In fuzzy logic which is extension of Boolean logic(Yaqiong *et al*., 2011), any fuzzy set can be uniquely determined by its membership function or according to Zadeh(1975)by compatibility function which assigns a value within the range between 0 and 1 to each variable in the fuzzy set. This value represents the variable's compatibility with the fuzzy restriction (Zadeh, 1975); for example the assigned value 1 or 0 indicates the element which totally belongs to the set or not, whereas the value within the interval (0, 1), denotes the element that only partially belongs to the set.

It is important to notice that Zadeh has stated that fuzzy logic is characteristically distinct from probability, and is not a replacement for it. Although probability only allows for considering stochastic uncertainty which is the uncertainty of whether a certain event will take place or not (Azadegan *et al*., 2011), for a long time probability theory considered as the only tools for representing uncertainty(Masson and DenWux, 2006).Nevertheless, modeling based on fuzzy logic has been superior to modeling based on probability (Azadegan *et al*., 2011).

The generation of membership function is one of the fundamental issues inmany applications of fuzzy theory. However, there are no guidelines or rules that we can choose the appropriate membership generation technique based on it. Indeed, it depends on the kind of the problem and the type of the available data. In other words, there are no measures to evaluate the correctness of the method by which the membership function has been generated (Ang and Quek, 2012). Moreover, there is a lack of agreement on the meaning and definition of membership functions. In this direction,Turksen(2006)pointed out that the statement: " the membership value of John in the class of big men is 0.8" has different interpretation as: (a) 80% of a given population declares that John is big(Likelihood view), (b) 80% of a given population describes bigas an interval containing John's height(Random set view), (c) John's height is at a normalized distance equal to 0.2 away from the prototypical object (Similarity view), (d) 0.8 is the utility of asserting that John is big (Utility view), (e)When compared to others John is bigger than some and this fact can be encoded as 0.8 on some scale (Measurement view).

Here we generate membership function based on the"likelihood view" which has been advocated by Hisdal in 1985 (Turksen, 2006). Itis in the group of methods that are used in the situation that we need to generate membership function based on subjective perceptions of vague or imprecise information rather than on data or other objective entities (Medasani *et al*., 1998). One of the proposed method of eliciting the membership function that Hisdalhas considered, is Yes-No experiment (Turksen, 2006), or the polling technique (Medasani *et al*., 1998). In this method, the values of membership function are obtained through randomly and repeatedly presenting a subject with elements and getting either yes or no response to this question "does X belong to A?"(Medasani *et al*., 1998).For exampleYang and Bose(2006), generated membership functions for fuzzy variables tall and short in heights among a group of people, by using likelihood view in which, the analyst asks an explicit but imprecise descriptive question and the subject gives an explicit two-valued verification (Turksen, 2006).In this method the membership value of X is proportional to the probability of positive answer to the mentioned question (Medasani *et al*., 1998).

3. Developmentof The Fuzzy Dmr:

3.1Generating Fuzzy Membership Function Of Demerit Categories:

According to classical SQFE, the data obtained through a measurement system with an acceptable error, are assigned to one of the 4 classes located on two sides of the target, respect to each measurable quality characteristic. The grade of belonging to each class is binary, as Fig.2 shows the crisp grade of belonging to demerit category A. The proposed method generates fuzzy membership function for each demerit category, related to each especial quality characteristic, based on the "Likelihood view" method and inspired by the "Analytic method" which is according to the work of McCaslin and Gruska in 1976 and is presented in the reference manual entitled MSA, to form the Gauge Performance Curve(GPC)(Sweet *et al*., 2005).

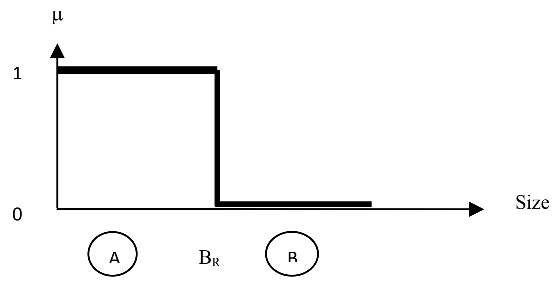


Fig. 2: The crisp grade of belonging to demerit category A

The procedure of the analytic method is briefly describedas follows: "The first stage of the attribute measurement system study consists of part selection as the reference values, eight parts should be selected at as nearly equidistant intervals as practical. The eight parts must be run through the gage, $m = 20$times, and the number of accepts (a), recorded. For the total study, the smallest part must have the value$a = 0$; the largest part$a = 20$; and the six other parts, $1 \le a \le 19$. If six of the parts do not have$1 \le a \le 19$, additional parts can be taken at selected points throughout the range. If necessary, the procedure can be repeated until the criteria are met. Once the data collection criteria have been satisfied, the probability of acceptance is calculated for each part using the following equations:"

$$P_a = \begin{cases} \frac{a+0.5}{m} if \frac{a}{m} < 0.5, a \neq 0 \\ \frac{a-0.5}{m} if \frac{a}{m} > 0.5, a \neq 20 \\ 0.5 \quad if \frac{a}{m} = 0.5 \end{cases} \tag{8}$$

Note that, $P_a = 0$where$a = 0$, except for the largest reference value with $a = 0$ in which $P_a = 0.025$ and$P_a = 1$ where $a = 20$except for the smallest reference value with $a = 20$ in which $P_a = 0.975$(MSA, 2002). The reason is that $P_a$cannot reach 0 or 1 for finite *x*, but it can be arbitrarily close to these values(Vágó and Kemény, 2010).

In this paper the generation of fuzzy membership function is proposed for the data that are greater than target value. For the sample data that are less than target, is analogous. According to Zadeh(1975) we adopt a hierarchical structure of linguistic variables whose first level includes linguistic variable, and second level contains linguistic terms that are assigned to the linguisticvariable as its values and are extracted from experts during knowledge acquisition phase(Türkşen, 2006). The third level includes basic variables which are assigned to different linguistic terms by the numbers as their degree of membership (see Fig. 3). Here the linguistic variable is "demerit", the linguistic terms are expressed by "demerit classes"and the basic Variables indicate the data obtained through measuring samples.For example D.A.Nembhard and H.B.Nembhard(2000)grouped none conformities into three classes as follows: Critical, Major and Minor, to develop a new demerit control

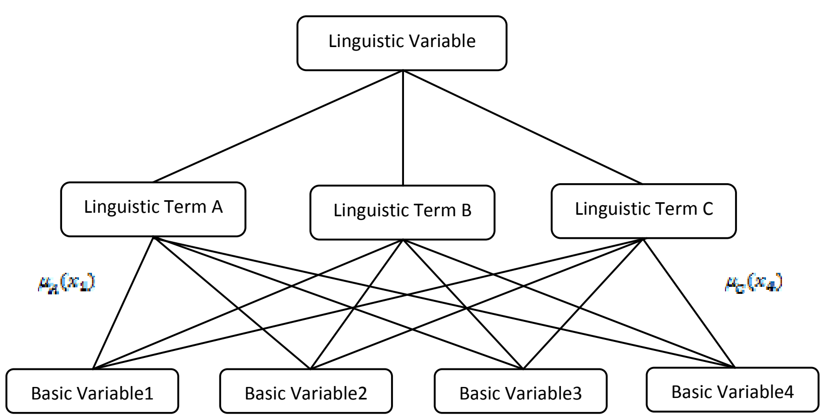


Fig. 3: Hierarchical structure of a linguistic variable.

chart, Also Chen (2005) used Very Serious, Serious, Moderately Serious and Minor to extend the demerit control chart by linguistic weights. Therefore, depending on how influential and crucial the quality of part in the performance of final product is, the most proper classification of demerits should be identified.

The rest of the method consists of measuring ith quality characteristic in several selected partsthroughout the range.In other words,the selected parts should be as a proper representative of the tolerance. Let m be the number of experts by which the selected parts are evaluated and $a_A(x_{ij})$be the number of assignments to demerit category A by the experts. For x_{ij} that denotes the measured value of jth selected part, related to$i$th quality characteristic, the $\mu_A(x_{ij})$which is the probability of positive answer to the question "doesx_{ij}belong to demerit category A?", is obtained as bellow:

$$\mu_A(x_{ij}) = \begin{cases} \frac{a_A(x_{ij})+0.5}{m} if \frac{a_A(x_{ij})}{m} < 0.5 \ , a_A(x_{ij}) \neq 0 \\ \frac{a_A(x_{ij})-0.5}{m} if \frac{a_A(x_{ij})a}{m} > 0.5, \ a_A(x_{ij}) \neq 20 \\ 0.5 \qquad if \frac{a a_A(x_{ij})}{m} = 0.5 \end{cases} \quad (9)$$

$\mu_A(x_{ij})$is also the degree of membership of x_{ij} to demerit category A. Like analytical method, note that, $\mu_A(x_{ij}) = 0$ where $a_A(x_{ij}) = 0$, except for the largest selected part with $a_A(x_{ij}) = 0$ in which $\mu_A(x_{ij}) = 0.025$ and$\mu_A(x_{ij}) = 1$ where $a_A(x_{ij}) = m$ except for the smallest selected part with $a_A(x_{ij}) = m$ in which $\mu_A(x_{ij}) = 0.975$. when $\mu_A(x_{ij})$ calculated for each selected part, fuzzy membership function of belonging to demerit category A, could be developed through a best curve fitting as Fig. 4. It is important to note that the goodness of this estimate depends on the size of selected parts. The larger the sample, the better the estimate.

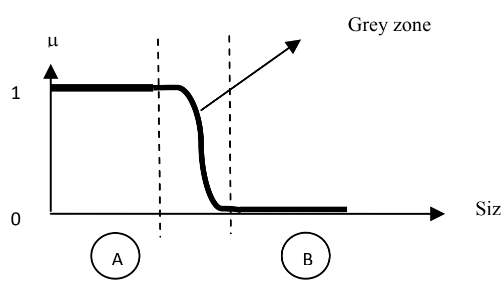


Fig. 4: The membership function of demerit category A

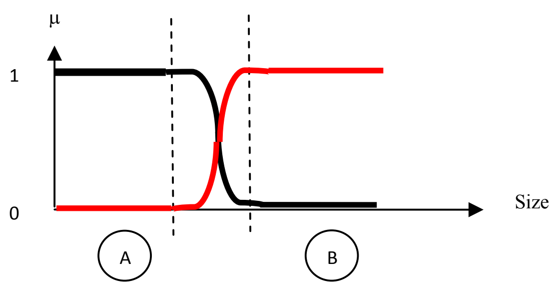


Fig. 5: The membership function of demerit category A,The membership function of demerit category B.

3.2 Calculation Of Fuzzy Dmr For Each Measurable Quality Characteristic:

According to Fig. 4, if a measured characteristic for one sample is out of the grey zone, the sample is surely judged as only class A or class B. The case where a sample comes from the grey zone,it is judged as partially belongs to class A and class B, thereforethe demerit rate must be determined considering the demerit weight of both class A and B. After generating fuzzy membership function for each demerit category of each characteristicas is shown in Fig.5, the fuzzy aggregated demerit weight of jth sample data considering ith quality characteristic is calculated as:

$$\widetilde{W}_{ij} = \mu_A(x_{ij}).W_A + \mu_B(x_{ij}).W_B + \mu_C(x_{ij}).W_C + \mu_D(x_{ij}).W_D \quad (10)$$

Where A, B, C and D are the demerit classes which have been identified in advanced, and $\mu_A(x_{ij}), \mu_B(x_{ij}), \mu_C(x_{ij}), \mu_D(x_{ij})$, are the degree of membership of x_{ij} to 4 demerit classes, and W_A, W_B, W_C, W_D are the weight of demerit category A,B,C and D according to classical SQFE. Then for ith measurable quality characteristic $\widetilde{D}r_i$ and $D\widetilde{m}r_i$ are calculated as follows:

$$\widetilde{D}r_i = \sum_{j=1}^{n_i} \widetilde{W}_{ij} \quad i = 1,2,\dots,q \quad j = 1,2,\dots,n_i \tag{11}$$

$D\widetilde{m}r_i = \frac{\widetilde{D}r_i}{n_i}$ (12) To sum up, the algorithm of generating fuzzy Dmr in order to measure the quality level of supplier's product through SQFE, is organized into six steps, displayed in Fig. 6.

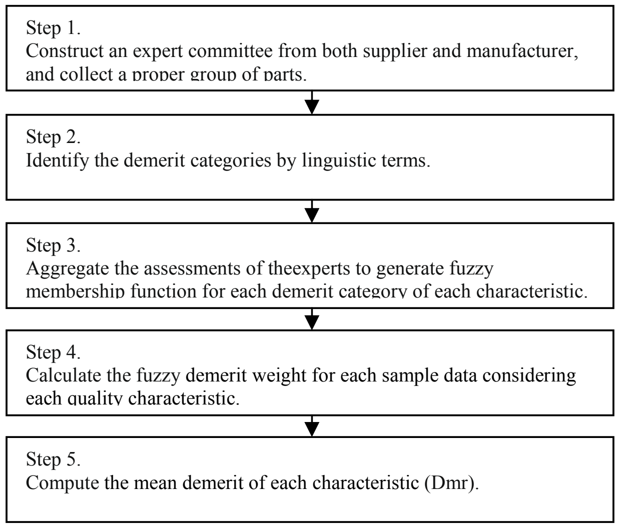
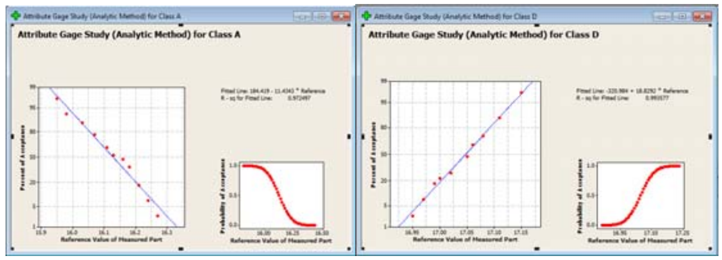


Fig. 6: The Procedure of the proposed fuzzy approach.

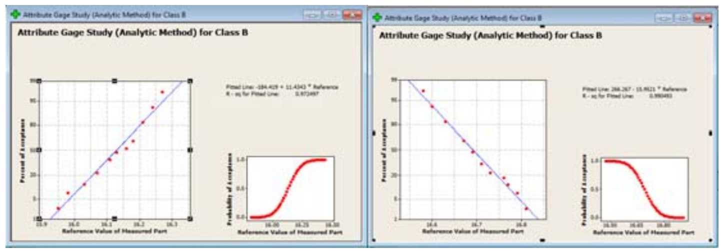
4. Numerical Example:

In order to explain further the proposed method and its application, we employed a numerical example. For a dimension that has a target value of 15 and the tolerance of ± 1.7, assume that demerits have been grouped into 4 classes, in the form of a hierarchical structure of linguistic variable as Fig. 3 shows, which are: "none defect", "minor", "major" and "critical". 51 selected parts have been evaluated by 20 experts (m=20) as the representative of supplier and manufacturer. The sorted measured data, and the number of assignments of each part to each demerit category, as well as the results of the degree of membership of x_{ij} to each demerit category which are calculated by using Eq. (9) are listed in Table 3. Finally, the membership function of each demerit category could be developed, as Fig. 7 illustrates the output of Minitab software obtained through the best curve fitting.

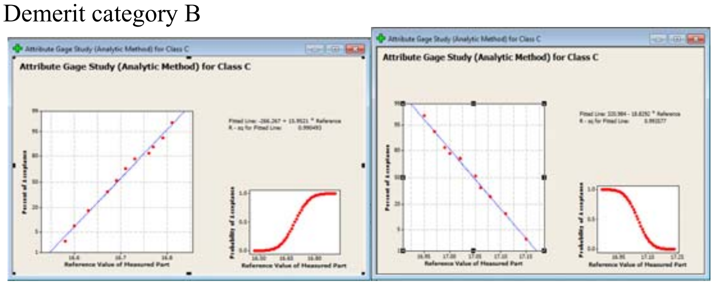
After generating fuzzy membership function for each demerit category, to calculate mean demerit for ith quality characteristic (Dmr_i), assume that the data obtained through measuring 20 samples are as Table 5. The degree of membership of each sample to each demerit category has been obtained through Minitab outputs (see Fig. 8. As an example), as well as demerit weight of each sample ($\widetilde{W}_{ij}$) has been calculated by Eq. (9), considering the weight of demerit categories in classical SQFE as is mentioned in Table 4. The final result of computation is listed in Table 5. For ith measurable quality characteristic $\widetilde{D}r_i$ and $D\widetilde{m}r_i$ are calculated by using Eqs.(10),(11) which are listed in Table 6 and can be compared with the value of classical Dr_i , Dmr_i in that table.



Demerit categoryA Demerit category D



Demerit category B



Demerit category C

Fig. 7: Fuzzy membership functions for demerit categories based on Minitab output.

Table 3: The result of judgments and the degree of membership of x_{ij} to demerit categories.

Part	Value	A=None	B=Minor	C= Major	D= Critical	μ_A	μ_B	μ_C	μ_D
1	15.00	20	0	0	0	1.000	0.000	0.000	0.000
2	15.08	20	0	0	0	1.000	0.000	0.000	0.000
3	15.22	20	0	0	0	1.000	0.000	0.000	0.000
4	15.49	20	0	0	0	1.000	0.000	0.000	0.000
5	15.63	20	0	0	0	1.000	0.000	0.000	0.000
6	15.78	20	0	0	0	1.000	0.000	0.000	0.000
7	15.86	20	0	0	0	1.000	0.000	0.000	0.000
8	15.95	20	0	0	0	0.975	0.025	0.000	0.000
9	15.98	19	1	0	0	0.925	0.075	0.000	0.000
10	16.03	18	2	0	0	0.875	0.125	0.000	0.000
11	16.07	16	4	0	0	0.775	0.225	0.000	0.000
12	16.11	13	7	0	0	0.625	0.375	0.000	0.000
13	16.13	11	9	0	0	0.525	0.475	0.000	0.000
14	16.16	9	11	0	0	0.475	0.525	0.000	0.000
15	16.18	7	13	0	0	0.375	0.625	0.000	0.000
16	16.21	3	17	0	0	0.175	0.825	0.000	0.000
17	16.24	1	19	0	0	0.075	0.925	0.000	0.000
18	16.27	0	20	0	0	0.025	0.975	0.000	0.000
19	16.29	0	20	0	0	0.000	1.000	0.000	0.000
20	16.33	0	20	0	0	0.000	1.000	0.000	0.000
21	16.36	0	20	0	0	0.000	1.000	0.000	0.000
22	16.42	0	20	0	0	0.000	1.000	0.000	0.000
23	16.48	0	20	0	0	0.000	1.000	0.000	0.000
24	16.53	0	20	0	0	0.000	1.000	0.000	0.000
25	16.56	0	20	0	0	0.000	1.000	0.000	0.000
26	16.58	0	20	0	0	0.000	0.975	0.025	0.000
27	16.60	0	19	1	0	0.000	0.925	0.075	0.000
28	16.63	0	17	3	0	0.000	0.825	0.175	0.000

29	16.67	0	13	7	0	0.000	0.625	0.375	0.000
30	16.69	0	9	11	0	0.000	0.475	0.525	0.000
31	16.71	0	6	14	0	0.000	0.325	0.675	0.000
32	16.73	0	4	16	0	0.000	0.225	0.775	0.000
33	16.76	0	3	17	0	0.000	0.175	0.825	0.000
34	16.77	0	2	18	0	0.000	0.125	0.875	0.000
35	16.79	0	1	19	0	0.000	0.075	0.925	0.000
36	16.81	0	0	20	0	0.000	0.025	0.975	0.000
37	16.83	0	0	20	0	0.000	0.000	1.000	0.000
38	16.88	0	0	20	0	0.000	0.000	1.000	0.000
39	16.92	0	0	20	0	0.000	0.000	1.000	0.000
40	16.95	0	0	20	0	0.000	0.000	0.975	0.025
41	16.97	0	0	19	1	0.000	0.000	0.925	0.075
42	16.99	0	0	17	3	0.000	0.000	0.825	0.175
43	17.00	0	0	16	4	0.000	0.000	0.775	0.225
44	17.02	0	0	15	5	0.000	0.000	0.725	0.275
45	17.05	0	0	11	9	0.000	0.000	0.525	0.475
46	17.06	0	0	7	13	0.000	0.000	0.375	0.625
47	17.08	0	0	5	15	0.000	0.000	0.275	0.725
48	17.11	0	0	2	18	0.000	0.000	0.125	0.875
49	17.15	0	0	0	20	0.000	0.000	0.025	0.975
50	17.19	0	0	0	20	0.000	0.000	0.000	1.000
51	17.25	0	0	0	20	0.000	0.000	0.000	1.000

Table 4: Demerit categories and their corresponding weights.

Sample data	Demerit category	Demerit weight
$315 \leq x_{ij} \leq 315.264$	None defect (A)	0
$315.264 < x_{ij} \leq 315.4$	Minor (B)	3
$315.4 < x_{ij} \leq 315.48$	Major (C)	15
$x_{ij} > 315.48$	Critical (D)	55

Table 5: Classical and fuzzy W_{ij}sbased on the result of inspection.

Number	x_{ij}	W_{ij}	$\mu_A(x_{ij})$	$\mu_B(x_{ij})$	$\mu_C(x_{ij})$	$\mu_D(x_{ij})$	$\widetilde{W}_{ij}$
1	16.05	0.00	0.79	0.21	0.00	0.00	0.63
2	16.17	3.00	0.28	0.72	0.00	0.00	2.16
3	16.33	3.00	0.00	1.00	0.00	0.00	3.00
4	15.74	0.00	1.00	0.00	0.00	0.00	0.00
5	15.82	0.00	1.00	0.00	0.00	0.00	0.00
6	15.33	0.00	1.00	0.00	0.00	0.00	0.00
7	16.25	3.00	0.09	0.91	0.00	0.00	2.73
8	16.76	15.00	0.00	0.13	0.87	0.00	13.44
9	15.79	0.00	1.00	0.00	0.00	0.00	0.00
10	16.84	15.00	0.00	0.00	1.00	0.00	15.00
11	16.55	3.00	0.00	1.00	0.00	0.00	3.00
12	17.01	15.00	0.00	0.00	0.76	0.24	24.60
13	16.68	3.00	0.00	0.56	0.44	0.00	8.28
14	15.62	0.00	1.00	0.00	0.00	0.00	0.00
15	17.09	55.00	0.00	0.00	0.16	0.84	48.60
16	15.22	0.00	1.00	0.00	0.00	0.00	0.00
17	15.03	0.00	1.00	0.00	0.00	0.00	0.00
18	15.05	0.00	1.00	0.00	0.00	0.00	0.00
19	15.11	0.00	1.00	0.00	0.00	0.00	0.00
20	15.25	0.00	1.00	0.00	0.00	0.00	0.00

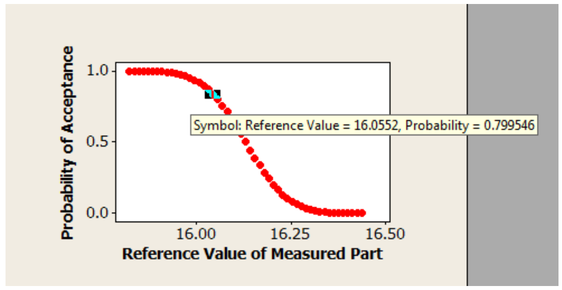


Fig. 8: The degree of membership to class A for a sample with the value of 16.05

Table 6: Classical and fuzzy Dr and Dmr for ith quality characteristic.

Dr_i	Dmr_i	$\tilde{D}r_i$	$D\tilde{m}r_i$
115	5.75	121.44	6.07

Conclusions:

Apart from measuring the quality of supplier products, the results of the SQFE approach, provides suppliers with valuable information to set the new targets by focusing on the priority areas. Because of the importance that *Dmr*as one of the SQFE indiceshas, in order to determining the supplier quality level, more flexibility and sensitiveness should be added to it.In real-world conditions, uncertainty may be caused by human, machine or systems related issues.The uncertainty reaches its maximum at each demerit border. Since the observations that are close to the demerit category boundaries, may cause false calculation of *Dmr*s,The use of likelihood view to generate fuzzy membership function in the proposed approach allows to assign a more meaningful value as demerit weight to each sample, considering thatthe membership value of X to subset A is proportional to the probability of positive answers to the question" does X belong to A?" by the experts. Thefuzzy based proposed approach can sufficiently deal with theuncertainty which is at the heart of human judgment and decision-making process. It improves the applicability of the SQFE and makes the decision making process more realistically. For further research, the other method can be adopted to generate fuzzy membership function for demerit categories.

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