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CLASSIFICATION ALGORITHM FOR CUSTOMER COMPLAINT USING FUZZY APPROACH

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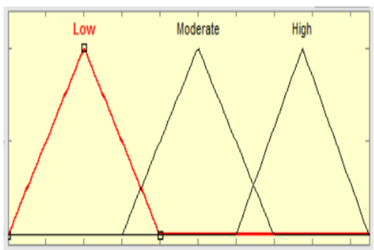
Graphical abstract



Abstract

Customer complaint contains valuable information to realize the opportunity to enhance service for customer satisfaction. The main challenge to extract the valuable information is a proper approach managing the complaint data, classification process and high level of uncertainties on the complaint and involvement of experts' opinion. Besides, most of the existing complaint system still running the complaint handling process manually. The impact is on time processing issue. Another problem, current complaint system focused on the English keyword, while in Malaysia, the complaint system is using *Malay* wording and keyword. Hence, an effective approach is needed to tackle these issues properly. This paper presents Fuzzy Logic Complaint Handling Algorithm (FLCHA) to handle the complaint handling process. The FLCHA used fuzzy logic approach to classifying real complaint, and non-real complaint, improve time processing and automate the complaint handling process. Customer complaints data from local government in Kuala Lumpur is used for this study to prove the efficiency of the proposed approach. Seven experts from the local government are working together in this study. The domain of the complaint data focused on landscaping and 406 data provided for the testing. Results show that the proposed approach is highly consistent with the human benchmark, efficient and good processing time. Overall GGTrap (fuzzy type-1) membership function using fuzzy number is the best membership function for customer handling process with accuracy 93.35% and processing time 0.441 seconds.

Keywords: Customer complaint, complaint handling, classification algorithm, fuzzy approach, uncertainties

1.0 INTRODUCTION

Customer complaint is not a new topic to discuss when relating to service oriented company or government sector. In Malaysia, customer complaint has become one of the important attributes to know the level of services. Even in the government sector, most of the servicing related department will implement a mechanism to capture customer opinion towards provided services. The only matter this approach being treated seriously just because of, it is the easiest and fastest way to improve the quality of service. One of local government in Kuala Lumpur is using complaint management system to handle customer complaint related to their services. Even though the local government is using the system but the complaint handling process still done manually. A group of staff who are experts in their area need to identify and classify each of the complaints either it is valid or not valid before proceeding with the solution phase. A lot of time and energy need to dedicate to entertain all the customer complaint. The growing of the complaints data and the urgency to solve especially on the high priority issues needs the staff to stay longer period from the actual working hours. It is a good opportunity if a proper approach can be applied to solve the complaint handling process focus on rectifying real and non-real complaints, classify and ranking the complaints based on priority. All the process should be done automatically which a lot of time and energy can save, and the most important, proper approach to handling the complaint data will benefit the local government in term of the valuable information from the customer complaints.

A customer is referring to a person who receives a product or service [1]. The complaint is natural human behavior on responding towards something that not satisfied their expectation. Trappey *et al*. defined complaint is a manner for humans to convey their frustration on the provided services and in return the service provider should take proper action to improve the quality of service [2]. Customer complaints reveal important information to the service provider to indicate that the service provider does not fulfill the customer needs properly. This kind of signal needs immediate action from the service provider to recover the failure service [3]. This type of action is called complaint handling.

Complaint handling is a process to isolate real complaints and non-real complaints. Besides, it also needs to determine the ranking of the complaints [4]. This process is also known as service recovery which has a great impact on customer retention and the beneficial usage of complaint information for quality improvements [5]. Service provider acknowledges the important of handling customer complaints and increasing the performance of services. Hence, the customers' feedback is essential for the service provider to know the service failure so they can find a solution to solve the problem [6]–[8].

Handling customer complaints is not an easy task for most of the service provider. A lot of them facing a great challenge in term of managing and processing record of complaints [9]. Priceless information of complaint is very important for the service provider to use it to plan a proper strategy to increase the performance of service [2], [10]. The success of processing and retrieving the valuable information within the complaint depends on the complaint management process. Complaint management is a process to manage the complaint activities start from receiving customer complaint until resolving the complaint [11]. Complaint management is also known as a process to disseminate information at identifying and correcting customer dissatisfaction [3]. Thus, a reliable information system needs to handle the complaint, which can profit the business and support the customers to increase their satisfaction level [12]. This kind of system is normally known as customer complaint management system (CCMS). The fundamental of developing a successful CCMS is depend on the spirit of improvement towards total customer satisfaction and energized by full support from top management.

Typically complaint handling process for the specific complaint involves experts with experiences and uncertain, difficult and complex customer complaint [13]. The complaint is constructed based on the customer's wording and perceptions. Customer perception towards services provided will determine the level of dissatisfaction. Once customer perception towards the failure service increased, the level of dissatisfaction also will increase. Hence, this situation increases the level of uncertainties [14]. Next, the resolution of the complaint relied on experts who have specific knowledge and experiences about services provided and the organization itself. With the knowledge and experience that they possess, they will give their viewpoints to solve the complaints. Each expert has their opinion towards the complaint, and normally discussions and meetings will be held among the experts to consolidate final decision. Thus, this situation also increases the level of uncertainties [14].

With various approaches of complaint handling process, Park and Lee presented a framework to establish product specification by transforming customer opinions from websites. The process is using text-mining to transform customer opinions that collected from an online customer center into customer needs. The proposed framework allows designing better online customer centers to collect and analyze customer opinions in producing useful information [15].

Pyon *et al*. proposed a web-based decision support system namely Voice of the Customer (VOC) to handle customer complaints for business process management, and improve the service based on the data extraction. The received data will through the process of comparison, exception and summarization for data enrichment [16].

Trappey *et al*. analyzed and developed framework of complaint handling system for a Japanese restaurant chain. The authors showed the benefits of the proposed work by learning the process between the headquarter and branches [2].

Next, a group of researchers created and developed complaint handling process based on ontology schema for consumer complaint dialogues to automatically text mine consumer dialogues, create significant dialogue clusters, and, from these clusters, derive meaningful trends, baselines, and interpretations of consumer satisfaction and dissatisfaction. Later, the authors improved the method by presented intelligent complaint handling based on interoperable ontology. Next, case-based reasoning to offers an informative and knowledge-based methodology to resolve customer complaints systematically with self-learning feature [13], [17], [18].

Then, other researchers developed a new approach to handle customer complaints based on Service Oriented Architecture (SOA) [19], rule mining technique [20], customer-company dialogues [21], agent-based Complaint Management System (ACM) [22] and automatic email classification system [23].

Next, authors want to present few related research with the ranking approach using a fuzzy method. Doctor *et al*. proposed three novel approaches for ranking job applicants by employing; (i) type-1 fuzzy agents (ii) a neuro-fuzzy based agent approach and (iii) type-2 fuzzy sets for handling the uncertainties and inconsistencies in group decisions of a panel of experts. The presented systems will enable automating the processes of requirements specification and applicant's matching/ranking [24]–[26].

In summary, work in the field of fuzzy approach ranking method has been focused more on English based wording and keyword while this research directed on local government complaints that based on *Malay* wording and keyword. Furthermore, the work on complaint handling that involves many uncertainties has focused on other approaches except fuzzy approach. Whereas, cases that involve with high levels of uncertainties are proper to be handled with a fuzzy approach [24], [27]–[31]. Hence, this paper proposes Fuzzy Logic Complaint Handling Algorithm (FLCHA) to handle the complaint handling process. The FLCHA used fuzzy logic approach to classifying real complaint, and non-real complaint, improve time processing and automate the complaint handling process. Through further simulation and testing, it can prove that the approach can automate the complaint handling efficiently and less time consuming.

This paper organized as follows. Section 2 describes the methodology of the research. Section 3 discusses the results of the simulation. Section 4 summarizes the study and highlights direction for further research.

2.0 METHODOLOGY

This section explains the methodology used in this study which involves fuzzy approach. In this study, two proposed algorithms that used for classification and ranking are presented. Real complaints data from CCMS of local government in Kuala Lumpur used for the testing purposes. The complaints domain is landscaping, and seven experts involved.

The keywords extracted from each complaint are used to form complaint specification references. The complaint keywords possibly retrieved from complaint database, files, services or complaint areas identified within an organization. The FLCHA involves five main steps; (i) Data extraction and experts selection (ii) Form complaint specification (iii) Generate fuzzy rules (iv) Complaint characteristics weighted calculation and (v) Complaint scoring and classification.

In step 1, a set of data will be extracted from the database. The data will be used to form complaint specification in the next phase. In this phase also, a group of complaint experts will be identified. In this case, 406 complaints data were extracted from the CCMS.

In step 2, the experts will select the characteristics of complaints to form the requirement's criteria that will be used to form complaint specification. From actual exploratory complaint specifications for different complaint area, it was discovered that the requirement's criteria have usually divided into three categories i.e. 'Very Important,' 'Important' and 'Normal.' Most organizations would rank complaints on the basis that they initially satisfy the 'Very Important' characteristics for the complaint area followed by the 'Important' and finally the 'Normal' characteristics. The 'Very Important' characteristics have higher weighting and importance than the 'Important' characteristics and also have higher weighting and importance than the 'Normal' characteristics. Hence, this categorizing scheme is used to guide the experts to select and classify characteristics of the complaint specifications. The experts then will be requested to value the significance of the selected characteristics using a predefined scale.

In step 3, the differences value for each of characteristic from all experts is solved by using Fuzzy Delphi approach. The identified complaint categories in step 2 have different weights based on the meaning of the word itself, so the weights have been assigned to the categories on this basis. Then, each characteristic weighted average is calculated by multiply each characteristic value that has been assigned by experts with categories weights. There are two types characteristics value is used for this study; (i) real number and (ii) fuzzy number. The calculation for real number is show as follows [32]:

$$
\begin{array}{cc}
 & C_1 \quad C_2 \quad C_3 \\
 & E_1 \quad E_2 \quad \cdots \quad E_m \\
\begin{array}{c} c_1 \\ c_2 \\ \vdots \\ c_n \end{array} & \begin{bmatrix} L_{11} & L_{12} & \cdots & L_{1m} \\ L_{21} & L_{22} & \cdots & L_{2m} \\ L_{n1} & L_{n2} & \cdots & L_{nm} \end{bmatrix}
\end{array} \tag{1}
$$

$$W_i = [(C_k L_{11})(C_k L_{12})(C_k L_{ij})]^\wedge {}^1/_j \tag{2}$$

Where W_i = weighted average of i^{th} characteristic and i = 1,2,…,n. C_k = categories and k = 1,2,3, while j = expert and j = 1,2,…,m and L_{ij} = characteristic value. Table 1 and Table 3 show the weightage for each of the characteristics.

The calculation for fuzzy number is show as follows [33]:

$$a_i = Min_j(a_{ji}),\ b_i = \frac{1}{n}\sum_{i=1}^{n} b_{ji},\ c_i = Max_j(c_{ji}) \tag{3}$$

Where the evaluation value of the significance of No. i characteristic given by No. j expert of m experts is $\widetilde{w}_{ji} = (a_{ji}, b_{ji}, c_{ji})$, i = 1, 2, …n, j = 1, 2, …m. Then the fuzzy weightage $\widetilde{w}_i$ of No. i element is $\widetilde{w}_i = (a_i, b_i, c_i)$, i = 1, 2, …n. Next to get the final weightage using simple center of gravity method to defuzzify the fuzzy weight $\widetilde{w}_i$ of each alternate element to definite value W_i, the following are the calculation:

$$W_i = \frac{a_i + b_i + c_i}{3} \tag{4}$$

Where i = 1, 2, …n. Table 2 and Table 4 show the weightage for each of the characteristics.

From the identified characteristics weighted, fuzzy rules is established by the experts to use in the later phase. They are seven linguistics terms that being employed as follows: very low, low, medium low, medium, medium-high, high and very high.

In this phase also the fuzzy rules for the input, process and output are identified. Two variables are created to describe the relationship between them in producing the final results. The identified variables for input are *Tajuk* (principal complaint) and *Butir* (complaint details). Each of the variables has three linguistics terms which are 'Low', 'Moderate' and 'High'.

Table 1 *Tajuk* (principal complaint) weightage (real number)

Characteristics	Exp1				Exp2				Exp3				Exp4				Exp5				Exp6				Exp7				W_i
	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	
Pokok (Tree)			8	7.20			10	9.00			10	9.00			10	9.00			10	9.00			9	8.10			9	8.10	8.46
Lampu (Lamp)			5	4.50			9	8.10			7	6.30			8	7.20			8	7.20			9	8.10			8	7.20	6.83
Taman (Park)		5		3.00		7		4.20		8		4.80		8		4.80		6		3.60		8		4.80		6		3.60	4.06
Sampah (Trash)		5		3.00	6			1.80		7		4.20	8			2.40		8		4.80		5		3.00		7		4.20	3.18
Rumput (Grass)	5			1.50	3			0.90	7			2.10	7			2.10	5			1.50	5			1.50	5			1.50	1.54

Table 2 *Tajuk* (principal complaint) weightage (fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			Defuzzification
Pokok (Tree)	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.900	1.000	1.000	0.967
Lampu (Lamp)	0.7	0.9	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.700	0.986	1.000	0.895
Taman (Park)	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.100	0.471	0.700	0.424
Sampah (Trash)	0.1	0.3	0.5	0	0.1	0.3	0.3	0.5	0.7	0	0.1	0.3	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.000	0.329	0.700	0.343
Rumput (Grass)	0	0	0.1	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0	0.1	0	0	0.1	0.000	0.029	0.300	0.110

Table 3 *Butir* (complaint details) weightage (real number)

Characteristics	Exp1				Exp2				Exp3				Exp4				Exp5				Exp6				Exp7				W_i
	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	N	I	VI	W	
Pokok (Tree)			10	9.00			10	9.00			10	9.00			10	9.00			10	9.00			9	8.10			9	8.10	8.73
Bahaya (Dangerous)			8	7.20			9	8.10			7	6.30		8		4.80			8	7.20			9	8.10			8	7.20	6.89
Lampu (Lamp)		8		4.80			7	6.30		10		6.00			8	7.20			7	6.30			7	6.30			6	5.40	6.00
Tinggi (High)	8			2.40	6			1.80		5		3.00	8			2.40	6			1.80		5		3.00	7			2.10	2.31
Jatuh (Fall)		5		3.00	9			2.70	9			2.70	9			2.70		5		3.00		7		4.20	9			2.70	2.96
Sampah (Trash)		8		4.80		9		5.40	10			3.00	7			2.10	9			2.70		7		4.20	9			2.70	3.38
Reput (Rot)			8	7.20			6	5.40			6	5.40			6	5.40			7	6.30			9	8.10			9	8.10	6.46
Menyala (Light)	5			1.50	7			2.10	9			2.70	5			1.50	5			1.50	5			1.50	6			1.80	1.76
Rosak (Damage)			8	7.20			9	8.10			6	5.40			9	8.10			6	5.40			7	6.30			8	7.20	6.73
Selenggara (Maintenance)			5	4.50		9		5.40			7	6.30		9		5.40			8	7.20			7	6.30			6	5.40	5.73
Panjang (Long)		8		4.80		6		3.60		8		4.80		7		4.20		5		3.00		7		4.20		5		3.00	3.88
Semak (Bush)		5		3.00		8		4.80		4		2.40		7		4.20		5		3.00		7		4.20		5		3.00	3.42
Mati (Dead)			8	7.20		10		6.00			5	4.50			7	6.30			7	6.30			7	6.30			6	5.40	5.95
Gelap (Dark)		5		3.00		8		4.80		7		4.20		8		4.80		5		3.00		5		3.00		5		3.00	3.60
Ular (Snake)		8		4.80		10		6.00		10		6.00			7	6.30		9		5.40		10		6.00		9		5.40	5.68
Berfungsi (Function)	5			1.50	7			2.10	5			1.50	3			0.90	6			1.80	5			1.50	5			1.50	1.50
Nyamuk (Mosquito)	5			1.50	9			2.70		7		4.20	10			3.00	6			1.80		8		4.80	10			3.00	2.79

Table 4 *Butir* (complaint details) weightage (fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			Defuzzification
Pokok (Tree)	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.9	1	1	0.900	1.000	1.000	0.967
Bahaya (Dangerous)	0.9	1	1	0.9	1	1	0.7	0.9	1	0.3	0.5	0.7	0.9	1	1	0.9	1	1	0.9	1	1	0.300	0.914	1.000	0.738
Lampu (Lamp)	0.3	0.5	0.7	0.7	0.9	1	0.3	0.5	0.7	0.9	1	1	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.300	0.800	1.000	0.700
Tinggi (High)	0	0.1	0.3	0	0.1	0.3	0.1	0.3	0.5	0	0.1	0.3	0	0.1	0.3	0.1	0.3	0.5	0.3	0.5	0.7	0.000	0.214	0.700	0.305
Jatuh (Fall)	0.1	0.3	0.5	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.000	0.271	0.700	0.324
Sampah (Trash)	0.3	0.5	0.7	0.3	0.5	0.7	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.3	0.5	0.7	0.3	0.5	0.7	0.000	0.329	0.700	0.343
Reput (Rot)	0.9	1	1	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.9	1	1	0.9	1	1	0.700	0.943	1.000	0.881
Menyala (Light)	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0	0.1	0	0	0.1	0.3	0.5	0.7	0.000	0.100	0.700	0.267
Rosak (Damage)	0.9	1	1	0.9	1	1	0.7	0.9	1	0.9	1	1	0.7	0.9	1	0.7	0.9	1	0.9	1	1	0.700	0.957	1.000	0.886
Selenggara (Maintenance)	0.7	0.9	1	0.3	0.5	0.7	0.7	0.9	1	0.3	0.5	0.7	0.9	1	1	0.7	0.9	1	0.7	0.9	1	0.300	0.800	1.000	0.700
Panjang (Long)	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.100	0.443	0.700	0.414
Semak (Bush)	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.100	0.386	0.700	0.395
Mati (Dead)	0.9	1	1	0.3	0.5	0.7	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.300	0.857	1.000	0.719
Gelap (Dark)	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5	0.100	0.386	0.700	0.395
Ular (Snake)	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.7	0.9	1	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.300	0.557	1.000	0.619
Berfungsi (Function)	0	0	0.1	0	0.1	0.3	0	0	0.1	0	0	0.1	0	0.1	0.3	0	0	0.1	0	0	0.1	0.000	0.029	0.300	0.110
Nyamuk (Mosquito)	0	0	0.1	0	0.1	0.3	0.3	0.5	0.7	0	0.1	0.3	0	0.1	0.3	0.3	0.5	0.7	0	0.1	0.3	0.000	0.200	0.700	0.300

Next, there is final fuzzy inference system (FIS) rule need to establish to process the final results for the output. FIS rule presentation is a set of fuzzy IF-THEN rules. In this case, the number of fuzzy rules is established based on this formula:

$$FR = V_1L_1 \text{ x } V_2L_2 \tag{5}$$

Where *FR* = Number of fuzzy rules, *VnLn* = Number of variable linguistics terms. Based on formula (5) there are nine fuzzy rules as shown in Table 5. These rules will be used to determine the final value of the complaints.

Table 5 Fuzzy Inference System Rules

No of Rules	IF-THEN Rules	Results
1.	If (Principal is Low) and (Details is Low)	Very Low
2.	If (Principal is Low) and (Details is Moderate)	Low
3.	If (Principal is Low) and (Details is High)	Medium Low
4.	If (Principal is Moderate) and (Details is Low)	Medium Low
5.	If (Principal is Moderate) and (Details is Moderate)	Medium
6.	If (Principal is Moderate) and (Details is High)	Medium High
7.	If (Principal is High) and (Details is Low)	Medium High
8.	If (Principal is High) and (Details is Moderate)	High
9.	If (Principal is High) and (Details is High)	Very High

In step 4, complaint's characteristics are extracted from the complaint data set based on complaint specifications that being derived in step 2. The extracted characteristics are assigning a value by comparing against identified characteristics weight in the complaint specification. In each complaint, all identified characteristics value will have added up to produce aggregated value that will have used during classification process in the final phase. The calculation for complaint characteristics aggregated value is show as follows:

$$FW_i = \sum_{i=1}^{n} wc_i \tag{6}$$

Where FW_i = aggregated weighted value for identified characteristics, wc_i = weighted value for complaint characteristics and i = 1,2,…,n. There are two levels of characteristics aggregated value as mentioned earlier which are *Tajuk* (principal complaint) and *Butir* (complaint details).

In step 5, the characteristics aggregated value for both *Tajuk* (principal complaint) and *Butir* (complaint details) are used to produce the final score for each of the complaints. The process will be done based on fuzzy rules that have established as mentioned in step 3. The final value is generated based on Mamdani FIS. Five fuzzy membership functions and ten combination membership functions are use. The membership functions are; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve. The combination membership functions are; (i) Gaussian-Trapezoidal-Triangular (GTTrim) (ii) Gaussian-Triangular-Trapezoidal (GTTrap) (iii) Triangular-Gaussian-Trapezoidal (TGTrap) (iv) Trapezoidal-Gaussian-Triangular (TGTrim) (v) Trapezoidal-Triangular-Gaussian (TrapTG) (vi) Triangular-Trapezoidal-Gaussian (TrimTG) (vii) Gaussian2-Triangular-Trapezoidal (G2TTrap) (viii) Bell-Triangular-Trapezoidal (BTTrap) (ix) Gaussian-Gaussian-Triangular (GGTrim) and (x) Gaussian-Gaussian-Trapezoidal (GGTrap). The final result from this process is the scoring and classification of the complaint.

The proposed methodology used fuzzy sets rules for complaint classification process by representing the meaning based on linguistics labels. This linguistic label makes the user easy to understand about the classification of the data. Besides, the identified process of the complaint characteristics also is transparent of how the experts rated the characteristics. Later, it can be used to provide justification on the characteristics selection and complaint classification process.

In a situation of the changes of the group of experts or the changes of the opinion such as incoming of new experts or resignation of the existing experts and adding a new opinion from the experts, the proposed methodology allows the changes process. Means new rules and values can be updated to the existing complaint specification. This methodology is important to allow the methodology to improve the fuzzy rules based on latest opinion, suggestion, and update from the experts. Due to that, it also will improve the accuracy of the classification process of the complaints.

3.0 RESULTS AND DISCUSSION

The analysis for complaint handling process in this study consists of three categories. First, is the accuracy compare to human experts' decision benchmark. The second is the differences of the complaint based on classification categories with human experts' decision. The last is the processing time taken based on membership function. This analysis has divided into two types of fuzzy approach which are type-1 and type-2.

3.1 Fuzzy Type-1

Figure 1 shows the accuracy using real numbers for five fuzzy type-1 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. It can see that Gaussian 2 Curve has the highest accuracy of 84.98%, follow by Gaussian Curve with 82.76% accuracy. The third one is General Bell with 81.28% accuracy follow by Triangular for the fourth with 79.31% accuracy and last follow by Trapezoidal with 75.26% accuracy.

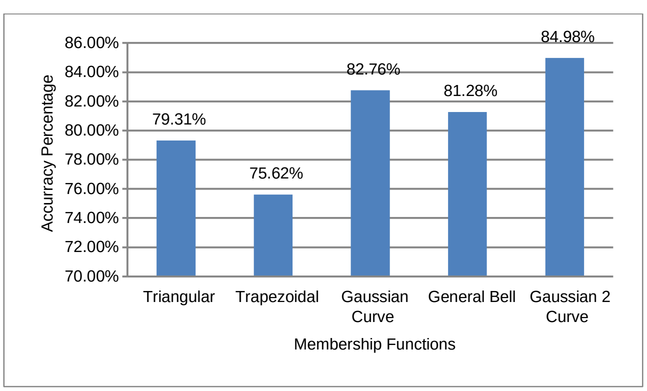


Figure 1 Accuracy Percentage Comparison Between Type-1 FIS Membership Functions (Real Numbers)

Figure 2 shows the accuracy using real numbers for ten combination fuzzy type-1 membership functions. The results show in sequence starting from highest accuracy are; (i) GGTrim and GGTrap with 86.95% accuracy (ii) GTTrap with 86.70% accuracy (iii) GTTrim with 86.45% accuracy (iv) G2TTrap with 86.20% accuracy (v) BTTrap with 82.76% accuracy (vi) TGTrap with 76.35% accuracy (vii) TrapTG with 74.14% accuracy (viii) TrimTG with 74.14% accuracy and (ix) TGTrim with 72.41% accuracy.

From these two results as shown in Figure 1 and Figure 2, GGTRim and GGTrap membership functions have the highest accuracy using real numbers.

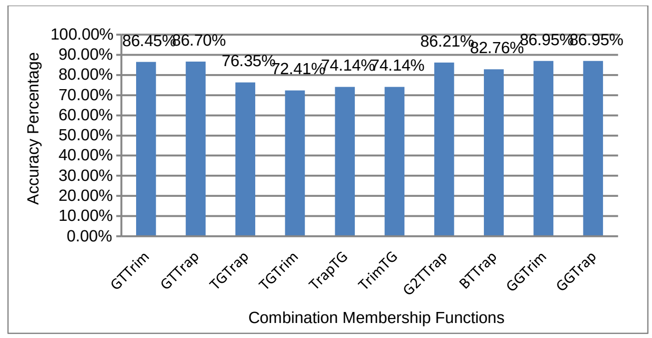


Figure 2 Accuracy Percentage Comparison Between Type-1 FIS Combination Membership Functions (Real Numbers)

Figure 3 shows the accuracy using fuzzy numbers for five fuzzy type-1 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. It shows that Gaussian Curve and Gaussian 2 Curve have the highest accuracy of 88.67%, follow by General Bell with 87.19% accuracy, the third follow by Triangular with 85.71% accuracy and last is Trapezoidal with 83.74% accuracy.

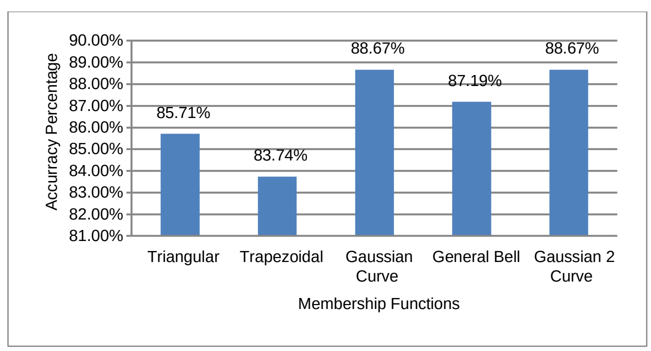


Figure 3 Accuracy Percentage Comparison Between Type-1 FIS Membership Functions (Fuzzy Numbers)

Figure 4 shows the accuracy using fuzzy numbers for ten combination fuzzy type-1 membership functions. The results show that GGTrim and GGTrap have the highest accuracy with 93.35% compare to others.

From these four results, as shown in Figure 1, Figure 2, Figure 3 and Figure 4, GGTRim and GGTrap membership functions using fuzzy numbers have the highest accuracy for fuzzy type-1 membership functions.

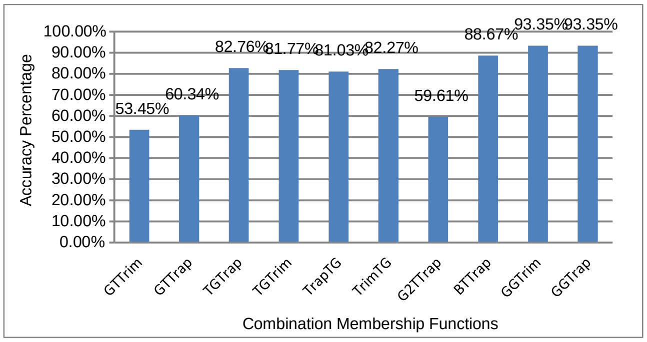


Figure 4 Accuracy Percentage Comparison Between Type-1 FIS Combination Membership Functions (Fuzzy Numbers)

Figure 5 shows the differences of the complaint based on classification categories using the real number for five fuzzy type-1 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. The classifications categories involve; (a) normal (b) serious and (c) critical. There are two observations can be made which are the trends for each classification category and the number of differences based on membership functions. In the first observation, it can be seen that the trend for each classification category is not similar. It shows that serious category has the nearest value to 0 for all membership functions compare to others.

The second observation is the Gaussian 2 Curve has the smallest number of differences compare to others with the total of 28 and follow by Gaussian Curve with the total of 32.

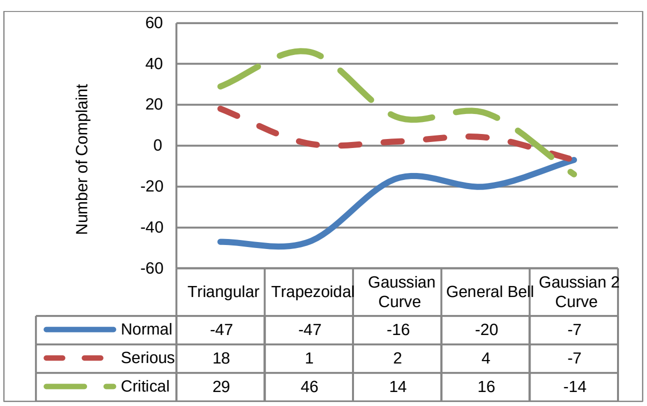


Figure 5 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-1 FIS Membership Functions (Real Numbers)

Figure 6 shows the differences of the complaint based on classification categories using the real number for ten combination fuzzy type-1 membership functions. It shows that BTTrap has the smallest number of differences compare to others with the total of 32. Then, it follows by GGTrim and GGTrap with the total of 44.

From these two results as shown in Figure 5 and Figure 6, Gaussian 2 Curve has the smallest number of differences using real numbers.

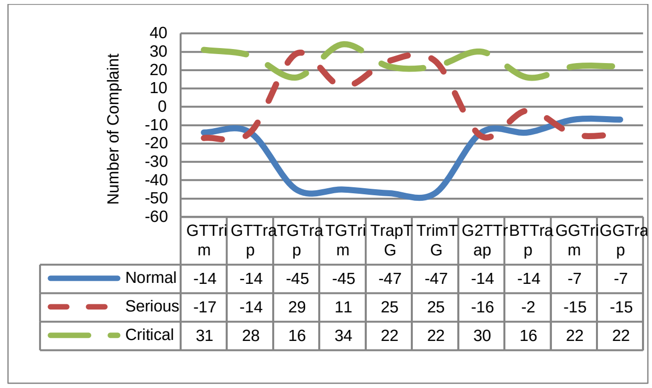
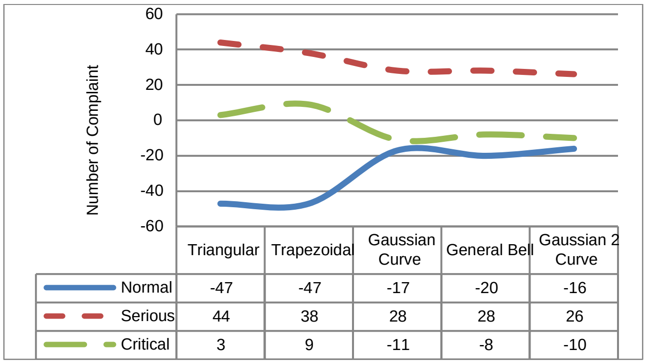


Figure 6 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-1 FIS Combination Membership Functions (Real Numbers)

Figure 7 shows the differences of the complaint based on classification categories using the fuzzy number for five fuzzy type-1 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. The classifications categories involve; (a) normal (b) serious and (c) critical. There are two observations can be made which are the trends for each classification category and the number of differences based on membership functions. In the first observation, it can be seen that the trend for each classification category is not similar. It shows that critical category has the nearest value to 0 for all membership functions compare to others.

The second observation is the Gaussian 2 Curve has the smallest number of differences compare to others with the total of 52.

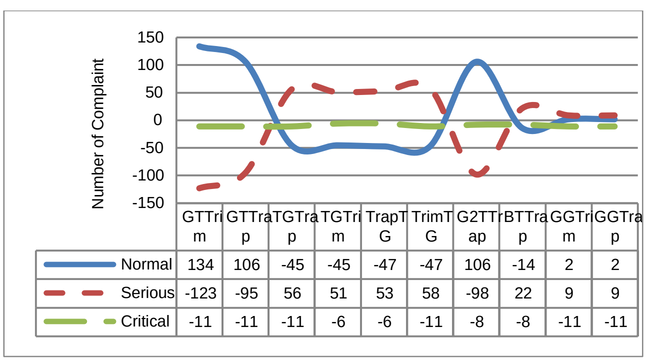


	Triangular	Trapezoidal	Gaussian Curve	General Bell	Gaussian 2 Curve
Normal	-47	-47	-17	-20	-16
Serious	44	38	28	28	26
Critical	3	9	-11	-8	-10

Figure 7 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-1 FIS Membership Functions (Fuzzy Numbers)

Figure 8 shows the differences of the complaint based on classification categories using the fuzzy number for ten combination fuzzy type-1 membership functions. As in Figure 7, the results also show that the trend for each classification category is not similar. It shows that critical category has the nearest value to 0 for all membership functions compare to others. The next thing the results show that GGTrim and GGTrap have the smallest number of differences compare to others with the total of 22.

From these four results, as shown in Figure 5, Figure 6, Figure 7 and Figure 8, GGTRim and GGTrap membership functions using fuzzy numbers have the smallest number of differences for fuzzy type-1 membership functions.



	GTTrim	GTTrap	TGTrap	TGTrim	TrapTG	TrimTG	G2TTrap	BTTrap	GGTrim	GGTrap
Normal	134	106	-45	-45	-47	-47	106	-14	2	2
Serious	-123	-95	56	51	53	58	-98	22	9	9
Critical	-11	-11	-11	-6	-6	-11	-8	-8	-11	-11

Figure 8 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-1 FIS Combination Membership Functions (Fuzzy Numbers)

Figure 9 shows the processing time taken using real numbers for fuzzy type-1 membership functions. The results show five fastest membership functions in sequence starting with the fastest are; (i) Trapezoidal with 0.429 seconds (ii) TGTrap with 0.439 seconds (iii) BTTrap and GGTrap with 0.440 seconds (iv) GTTrap with 0.441 seconds and (v) GTTrim with 0.444 seconds.

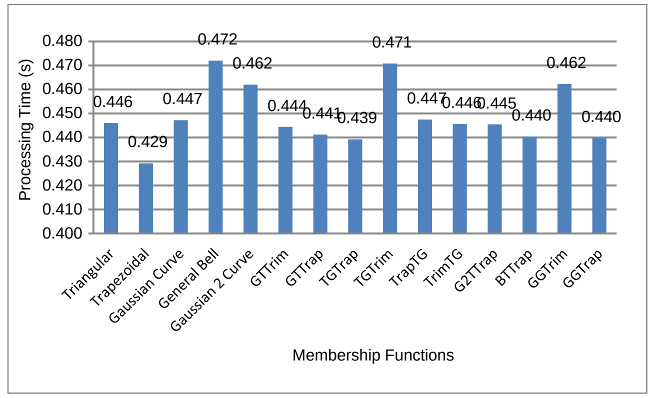


Figure 9 Processing Time for Type-1 Single & Combination Membership Functions (Real Numbers)

Figure 10 shows the processing time taken using fuzzy numbers for fuzzy type-1 membership functions. The results show five fastest membership functions in sequence starting with the fastest are; (i) TGTrap and GGTrap with 0.438 seconds (ii) Triangular with 0.439 seconds (iii) BTTrap with 0.440 seconds (iv) GTTrap, TGTrim and GGTrim with 0.441 seconds and (v) Trapezoidal with 0.442 seconds.

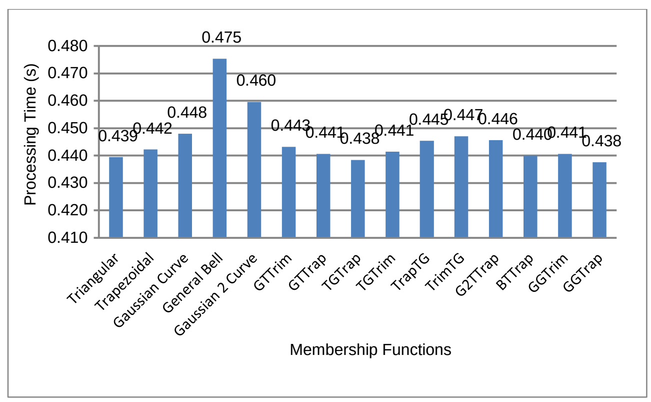


Figure 10 Processing Time for Type-1 Single & Combination Membership Functions (Fuzzy Numbers)

Based on these two results as show in Figure 9 and Figure 10, Trapezoidal membership functions using real numbers has the fastest processing for fuzzy type-1 membership functions.

3.2 Fuzzy Type-2

Figure 11 shows the accuracy using real numbers for five fuzzy type-2 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. It can see that Trapezoidal has the highest accuracy of 93.35%, follow by Triangular with 92.86% accuracy. The third one is Gaussian 2 Curve with 91.87% accuracy follow by Gaussian Curve for the fourth with 90.64% accuracy and last follow by General Bell with 85.71% accuracy.

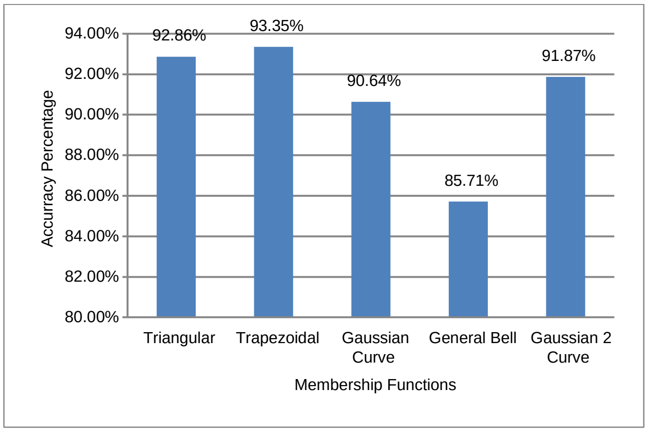


Figure 11 Accuracy Percentage Comparison Between Type-2 FIS Membership Functions (Real Numbers)

Figure 12 shows the accuracy using real numbers for ten combination fuzzy type-2 membership functions. The results show that GTTrap has the highest accuracy of 92.86% compare to others.

From these two results as shown in Figure 11 and Figure 12, Trapezoidal membership functions have the highest accuracy using real numbers.

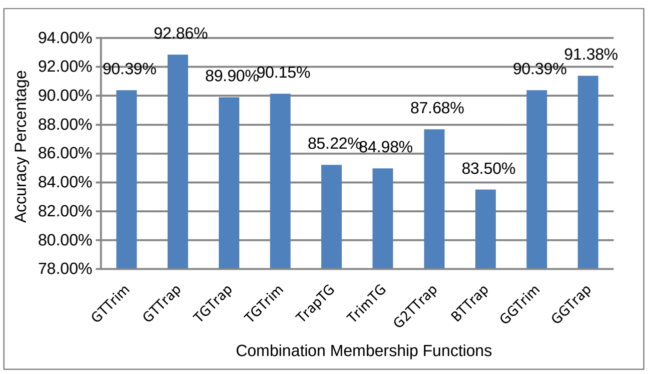


Figure 12 Accuracy Percentage Comparison Between Type-2 FIS Combination Membership Functions (Real Numbers)

Figure 13 shows the accuracy using fuzzy numbers for five fuzzy type-2 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. It shows that Triangular has the highest accuracy of 94.58%, follow by Trapezoidal with 91.38% accuracy, the third follow by Gaussian 2 Curve with 91.13% accuracy, the fourth follow by Gaussian Curve with 88.92% accuracy and last is General Bell with 86.45% accuracy.

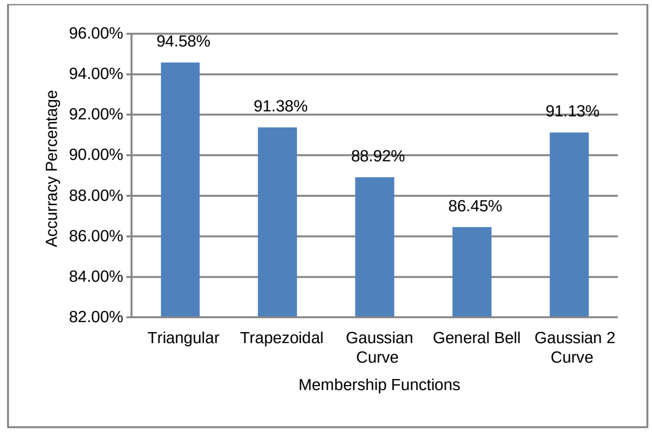


Figure 13 Accuracy Percentage Comparison Between Type-2 FIS Membership Functions (Fuzzy Numbers)

Figure 14 shows the accuracy using fuzzy numbers for ten combination fuzzy type-2 membership functions. The results show that GTTrap, GGTrim and GGTrap have the highest accuracy with 91.13% compare to others.

From these four results as shown in Figure 11, Figure 12, Figure 13 and Figure 14, Triangular membership functions using fuzzy numbers have the highest accuracy for fuzzy type-2 membership functions.

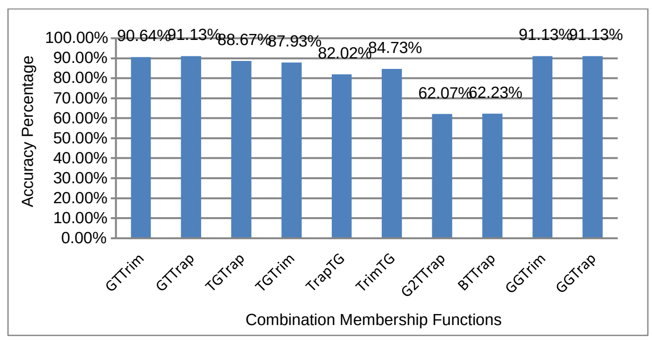
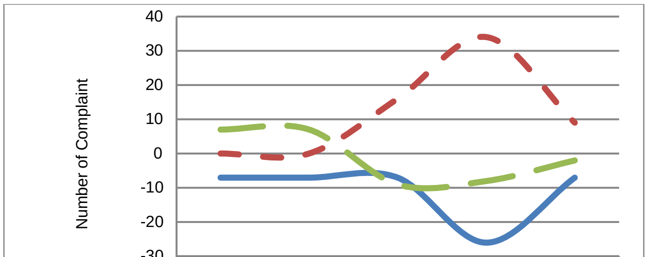


Figure 14 Accuracy Percentage Comparison Between Type-2 FIS Combination Membership Functions (Fuzzy Numbers)

Figure 15 shows the differences of the complaint based on classification categories using the real number for five fuzzy type-2 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. The classifications categories involve; (a) normal (b) serious and (c) critical. There are two observations can be made which are the trends for each classification category and the number of differences based on membership functions. In the first observation, it can be seen that the trend for each classification category is not similar. It shows that critical category has the nearest value to 0 for all membership functions compare to others.

The second observation is the Triangular and Trapezoidal have the smallest number of differences compare to others with the total of 14.

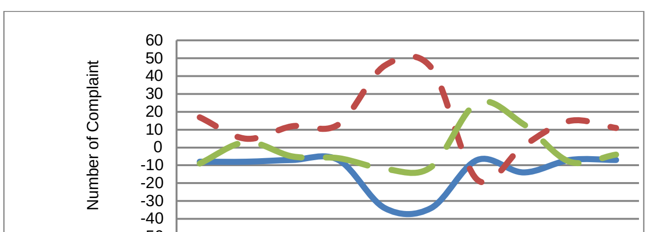


	Triangular	Trapezoidal	Gaussian Curve	General Bell	Gaussian 2 Curve
Normal	-7	-7	-7	-26	-7
Serious	0	0	16	34	9
Critical	7	7	-9	-8	-2

Figure 15 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-2 FIS Membership Functions (Real Numbers)

Figure 16 shows the differences of the complaint based on classification categories using the real number for ten combination fuzzy type-2 membership functions. It shows that GTTrap has the smallest number of differences compare to others with the total of 16. Then, it follows by GGTrap with the total of 22.

From these two results as shown in Figure 15 and Figure 16, Triangular and Trapezoidal have the smallest number of differences using real numbers.

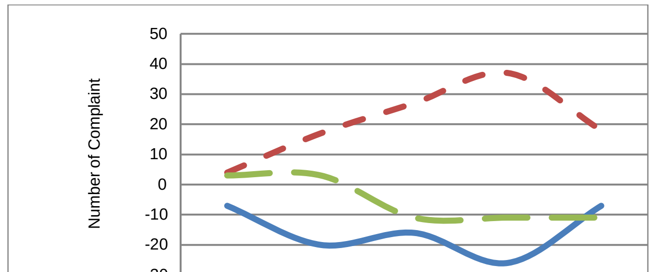


	GTTrim	GTTrap	TGTrap	TGTrim	TrapTG	TrimTG	G2TTrap	BTTrap	GGTrim	GGTrap
Normal	-8	-8	-7	-7	-34	-34	-7	-14	-7	-7
Serious	17	5	12	13	46	45	-18	1	15	11
Critical	-9	3	-5	-6	-12	-11	25	13	-8	-4

Figure 16 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-2 FIS Combination Membership Functions (Real Numbers)

Figure 17 shows the differences of the complaint based on classification categories using the fuzzy number for five fuzzy type-2 membership functions; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve have implemented. The classifications categories involve; (a) normal (b) serious and (c) critical. There are two observations can be made which are the trends for each classification category and the number of differences based on membership functions. In the first observation, it can be seen that the trend for each classification category is not similar. It shows that critical category has the nearest value to 0 for all membership functions compare to others.

The second observation is Triangular has the smallest number of differences compare to others with the total of 14.

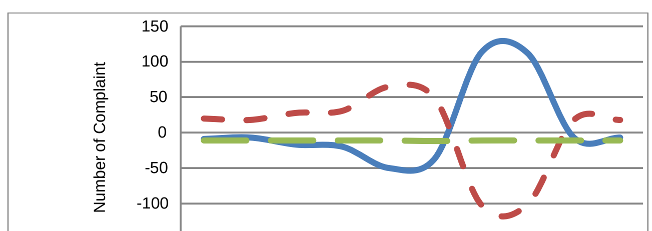


	Triangular	Trapezoidal	Gaussian Curve	General Bell	Gaussian 2 Curve
Normal	-7	-20	-16	-26	-7
Serious	4	17	27	37	18
Critical	3	3	-11	-11	-11

Figure 17 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-2 FIS Membership Functions (Fuzzy Numbers)

Figure 18 shows the differences of the complaint based on classification categories using the fuzzy number for ten combination fuzzy type-1 membership functions. As in Figure 17, the results also show that the trend for each classification category is not similar. It shows that critical category has the nearest value to 0 for all membership functions compare to others. The next thing the results show that GTTrap, GGTrim and GGTrap have the smallest number of differences compare to others with the total of 36.

From these four results, as shown in Figure 15, Figure 16, Figure 17 and Figure 18, Triangular membership functions using fuzzy numbers has the smallest number of differences for fuzzy type-2 membership functions.



	GTTrim	GTTrap	TGTrap	TGTrim	TrapTG	TrimTG	G2TTrap	BTTrap	GGTrim	GGTrap
Normal	-9	-7	-17	-20	-50	-36	113	112	-7	-7
Serious	20	18	28	31	65	48	-102	-101	18	18
Critical	-11	-11	-11	-11	-11	-12	-11	-11	-11	-11

Figure 18 Differences Number of Complaint Comparison Based on Categories Between Experts and Type-2 FIS Combination Membership Functions (Fuzzy Numbers)

Figure 19 shows the processing time taken using real numbers for fuzzy type-2 membership functions. The results show five fastest membership functions in sequence starting with the fastest are; (i) Gaussian Curve with 1.642 seconds (ii) General Bell with 1.690 seconds (iii) GGTrim with 1.793 seconds (iv) TrimTG with 1.794 seconds and (v) TrapTG with 1.834 seconds.

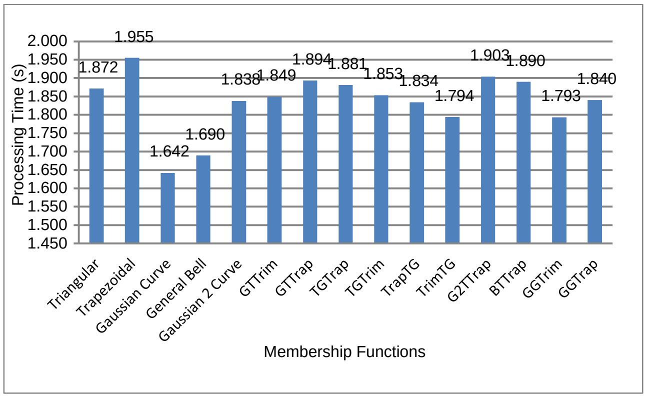


Figure 19 Processing Time for Type-2 Single & Combination Membership Functions (Real Numbers)

Figure 20 shows the processing time taken using fuzzy numbers for fuzzy type-2 membership functions. The results show five fastest membership functions in sequence starting with the fastest are; (i) Gaussian Curve with 1.636 seconds (ii) General Bell with 1.686 seconds (iii) TrapTG with 1.799 seconds (iv) TrimTG with 1.805 seconds and (v) Gaussian 2 Curve with 1.842 seconds.

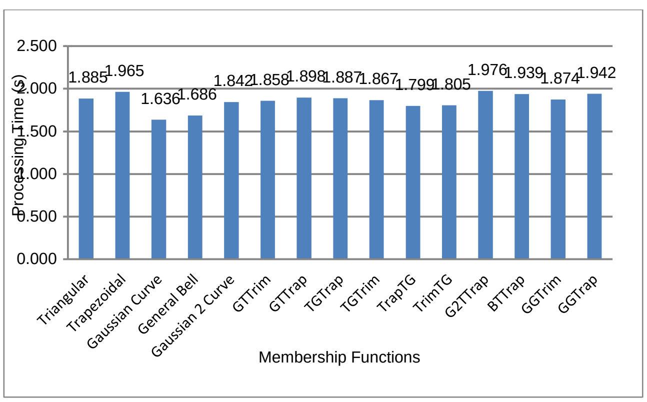


Figure 20 Processing Time for Type-2 Single & Combination Membership Functions (Fuzzy Numbers)

Based on these two results as show in Figure 19, and Figure 20, Gaussian Curve membership functions using fuzzy numbers has the fastest processing for fuzzy type-2 membership functions.

3.3 Summary

In summary, customer complaint classification using fuzzy approach has been successfully implemented. The results show the proposed approach has high accuracy, small differences number on categories and faster processing time. Table 6 shows the best performance of membership function based on; (i) Accuracy (ii) Differences number based on categories and (iii) Time processing.

It shows that Triangular (fuzzy type-2) membership function using fuzzy number is the most accurate compared to human benchmark with 94.58%. Next, for small differences number on categories, three membership functions have the smallest differences number. The membership functions are Triangular (fuzzy number), Trapezoidal (real number) and Triangular (real number). All are fuzzy type-2 membership functions. Then, for last category Trapezoidal (fuzzy type-1) membership function using real number has the fastest processing time. Overall, based on these three categories identified that GGTrap (fuzzy type-1) membership function using fuzzy number is the best membership function for customer handling process.

Table 6 Membership Function Result Comparison

Membership function	Accuracy (%)	Differences Number on Categories	Time Processing (s)
Type-1			
GGTrim (Fuzzy)	93.35	22	0.441
GGTrap (Fuzzy)	93.35	22	0.438
Trapezoidal (Real)	75.62	94	0.429
Type-2			
Triangular (Fuzzy)	94.58	14	1.885
Trapezoidal (Real)	93.35	14	1.955
Triangular (Real)	92.86	14	1.872
Gaussian Curve (Fuzzy)	88.92	54	1.636

4.0 CONCLUSION

The study on complaint handling process using fuzzy approach for classification and ranking methodology has successfully implemented. Issues on uncertainties that exist in the complaint handling process between customer complaint and experts input have properly handled by implementing fuzzy type-1 and fuzzy type-2. This paper proposes Fuzzy Logic Complaint Handling Algorithm (FLCHA) to handle the complaint handling process. The FLCHA used fuzzy logic approach to classifying real complaint, and non-real complaint, improve time processing and automate the complaint handling process. The five steps method to process the complaint handling was presented. Real customer complaint from local government has been used to simulate the proposed algorithm. Seven experts from the local government are also working together to help to produce the complaint specification. Selective membership function was chosen to identify the performance of the algorithm. The results show that FLCHA produces a reliable result and has high accuracy compare to human experts decision. Overall GGTrap (fuzzy type-1) membership function using fuzzy number is the best membership function for customer handling process with accuracy 93.35% and processing time 0.441 seconds.

Further simulation and testing for the proposed approach still can be done by using a different type of domain, sets of customer complaint data and a different number of data. The objective is to identify the performance consistency of the proposed approach. Besides, details study also can be done on the improvement of the complaint characteristics process to produce final scoring value for the complaint.

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