STATUS OF THESIS

Title of thesis	Interval Type-2 Fuzzy Model for Customer Complaint Handling

I RAZULAIMI RAZALI

hereby allow my thesis to be placed at the Information Resource Center (IRC) of Universiti Teknologi PETRONAS (UTP) with the following conditions:

1. The thesis becomes the property of UTP
2. The IRC of UTP may make copies of the thesis for academic purposes only.
3. This thesis is classified as

[ ] Confidential

[√] Non-confidential

If this thesis is confidential, please state the reason:

____

The contents of the thesis will remain confidential for ___________ years.

Remarks on disclosure:

____

Endorsed by

______________________	______________________
Signature of Author	Signature of Supervisor
Permanent address: Universiti Teknologi MARA Cawangan Pahang Kampus Raub 27600 Raub Pahang.	Name of Supervisor Assoc. Prof. Dr Jafreezal Jaafar
Date : ______________	Date : ______________

UNIVERSITI TEKNOLOGI PETRONAS

INTERVAL TYPE-2 FUZZY MODEL FOR CUSTOMER COMPLAINT HANDLING

by

RAZULAIMI RAZALI

The undersigned certify that they have read, and recommend to the Postgraduate Studies Programme for acceptance this thesis for the fulfillment of the requirements for the degree stated.

Signature: ______________________

Main Supervisor: Assoc. Prof. Dr Jafreezal Jaafar

Signature: ______________________

Co-Supervisor: ______________________

Signature: ______________________

Head of Department: Assoc. Prof. Dr Wan Fatimah Wan

Date: ______________________

INTERVAL TYPE-2 FUZZY MODEL FOR CUSTOMER COMPLAINT HANDLING

by

RAZULAIMI RAZALI

A Thesis

Submitted to the Postgraduate Studies Programme

as a Requirement for the Degree of

DOCTOR OF PHILOSOPHY

INFORMATION TECHNOLOGY

UNIVERSITI TEKNOLOGI PETRONAS

BANDAR SERI ISKANDAR,

PERAK

SEPTEMBER 2018

DECLARATION OF THESIS

Title of thesis	Interval Type-2 Fuzzy Model for Customer Complaint Handling

I RAZULAIMI RAZALI

hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTP or other institutions.

Witnessed by

Signature of Author

Signature of Supervisor

Permanent address: Universiti Teknologi MARA Cawangan Pahang Kampus Raub 27600 Raub Pahang.

Name of Supervisor
Assoc. Prof. Dr Jafreezal Jaafar

Date :

Date :

DEDICATION

To my parents, *Abah* and *Mama*, thanks for your continuous care and prayers. To *Wan Isni Sofiah Binti Wan Din*, my amazing wife, thanks for your care and love for me. Your support and understanding have made it possible for me to complete this work.

ACKNOWLEDGEMENTS

Alhamdulillah, all praise belongs to Allah, we praise Him, seek His help, and ask for his forgiveness. We seek refuge in God from evils of our souls and our bad deeds. A person, who is guided by God, will never be misguided by anyone and a person who is misguided by God can never be guided by anyone. I bear witness that there is no God except Allah, Who has no partner. That which Allah wills (will come to pass). There is no power but with Allah. All praises are due to Allah the Almighty, the Merciful.

Many people have provided me with much help and assistance during this study. It is a great pleasure to acknowledge with sincere gratitude to my main supervisor, Associate Professor Dr. Jafreezal Bin Jaafar for his valuable advice and precious insights. For the excellent support and guidance provided in the completion of this work, as well as for his incomparable dedication to mentoring. He is very helpful and understanding. I am very fortunate to have him to guide consistently and encourage me throughout this research journey.

Most important of all, my deepest gratitude goes to my lovely and supportive father, Haji Razali Bin Haji Mat Talib, my mother Hajah Zubaidah Binti Haji Hasan for her prayer, my lovely wife Wan Isni Sofiah Binti Wan Din for her encouragement throughout the years. Special thanks also to all my family.

ABSTRACT

Complaint management system (CMS) has become increasingly important for organizations, businesses, and government in Malaysia. The interaction between customers and business provider based on complaints which referring to perceptions and wording involves uncertainties and not an easy task in complaint handling process to rank the complaint. The main problem in carrying out this complaint handling process contains uncertainties due to the perceptions and wording from the complainants and input from experts based on their opinions and experiences towards classifying and ranking the customer complaint. Existing models perform the complaint handling process based on crisp requirements specification. These crisp-based requirements specification cannot represent the uncertainties effectively. Moreover, existing models also use the crisp computation method to perform the complaint handling process, which is less accurate and precise to handle the uncertainties. Therefore, in this research, fuzzy approach comprises of fuzzy type-1 (FT1), and interval fuzzy type-2 (IT2) is used for the complaint handling process. This research aims to minimize the effect of uncertainties in existing crisp-based complaint handling models. Also, another aim of this research is to derive fundamental reference by creating complaint specification references in the Malay language. The exercise to create the specification involving experts and Fuzzy Delphi Method (FDM) used to resolve and extract the experts' input. The deployment of Interval Type-2 Fuzzy Model (IT2FM) is using fuzzy logic approach which emphasized on the combination of principal and detail complaints characteristics that are specified using fuzzy linguistic values. The reliability of IT2FM was being evaluated and affirmed. Its validity is compared to three sets of complaints data that provided by local government and also with conventional fuzzy model. The fuzzy method successfully identifies the real complaint and rank the complaint. The technique also overcomes the uncertainty that exists between experts in producing characteristics value in each domain. Overall, the proposed model is successful in producing highly consistent results with the human experts.

ABSTRAK

Sistem Pengurusan Aduan (CMS) telah menjadi semakin penting untuk organisasi, perniagaan dan kerajaan di Malaysia. Interaksi antara pelanggan dan penyedia servis berdasarkan aduan yang merujuk kepada persepsi adalah sukar untuk dikenalpasti dan ianya bukan tugas yang mudah dalam proses pengendalian aduan. Masalah utama dalam menjalankan proses pengendalian aduan ini ialah wujudnya ketidakpastian disebabkan persepsi dan pendapat daripada pelanggan dan maklumbalas daripada pakar-pakar berdasarkan pendapat dan pengalaman mereka dalam menentukan keutamaan aduan pelanggan. Model-model sedia ada bagi perlaksanaan proses mengenalpasti keutamaan aduan adalah berdasarkan kepada kriteria-kriteria *crisp-based*. Syarat-syarat tersebut berasaskan *crisp-based* tidak mempunyai keupayaan untuk mewakili kriteria-kriteria yang ketidaktentuan. Selain itu, model-model sedia ada juga menggunakan kaedah berdasarkan nilai *crisp-based* untuk menjalankan pengendalian proses, yang kurang tepat untuk menangani ketidakpastian dalam aduan. Oleh yang demikian, dalam kajian ini, pendekatan *fuzzy type-1 (FT1) dan interval fuzzy type-2 (IT2)* digunakan dalam eksperimen yang menggunakan model pengendalian aduan. Kajian ini bertujuan untuk mengurangkan kesan daripada ketidaktentuan dalam model pengendalian aduan sedia ada. Di samping itu, satu lagi matlamat penyelidikan ini adalah untuk mewujudkan asas rujukan utama berdasarkan kepada spesifikasi rujukan utama aduan dalam Bahasa Melayu. Perlaksanaan proses mewujudkan spesifikasi ini melibatkan pakar-pakar dan penggunaan *Fuzzy Delphi Method* (FDM) untuk memproses maklumat-maklumat yang diberikan oleh pakar-pakar. Penggunaan *Interval Type-2 Fuzzy Model* (IT2FM) adalah berdasarkan kepada penggunaan pendekatan *fuzzy logic* yang menggunakan kombinasi ciri-ciri utama dan terperinci aduan yang dinyatakan dengan menggunakan nilai-nilai *fuzzy linguistics*. Kebolehpercayaan IT2FM dinilai dan telah disahkan. Proses penilaiannya dilaksanakan dengan menggunakan tiga set data aduan yang disediakan oleh kerajaan tempatan dan dengan model pengendalian aduan yang sedia ada. Kaedah *fuzzy* yang digunakan berjaya mengenal pasti yang aduan sebenar dan mengklasifikasikan aduan

tersebut. Teknik ini juga mengatasi ketidaktentuan yang wujud di antara pakar-pakar dalam menghasilkan nilai bagi ciri-ciri yang dikenalpasti dalam domain aduan yang tertentu. Secara keseluruhannya, algoritma yang dicadangkan adalah berjaya dalam menghasilkan keputusan yang amat konsisten dengan keputusan pakar-pakar manusia.

TABLE OF CONTENT

ABSTRACT vii

ABSTRAK viii

TABLE OF CONTENT xi

LIST OF TABLES xvi

LIST OF FIGURES xviii

LIST OF ABBREVIATIONS xx

LIST OF NOMENCLATURES xxiii

Chapter 1 1

INTRODUCTION 1

- 1.1 Background 1
- 1.2 Background of the Problem 3
- 1.3 Problem Statement 5
- 1.4 Research Questions 7
- 1.5 Research Aims and Objectives 7
- 1.6 Scope of the Research 8
- 1.7 Significance of the Research 8
- 1.8 Organization of the Thesis 9

Chapter 2 11

LITERATURE REVIEW 11

2.1 Overview of Literature Review 11

2.2 Complaint Management System 11

2.3 Selection of Intelligent Soft Computing Method 14

2.4 Handling Uncertain Information with Fuzzy Logic 17

2.5 Comparison between Fuzzy Type-1 and Fuzzy Type-2 24

2.6 Related Works 29

2.7 Fuzzy Limitation 45

2.8 Fuzzy Delphi Method 47

2.9 Summary 49

Chapter 3 50

METHODOLOGY 50

3.1 Overview of the Research Phase 50

3.2 Conventional Complaint Handling Model 53

3.3 Proposed Methods 55

3.4 Details Process of the Proposed Methods 58

3.4.1 Customer Complaint Information Extraction 59

3.4.2 Selection of Experts 60

3.4.3 Complaint Specification References 62

3.4.4 Fuzzy Rules for Complaint Classification and Ranking 66

3.4.5 Complaint Weighted Characteristics Calculation 71

3.4.6 Complaint Scoring and Classification 72

3.5 Design and Development of FIS Models..74

3.6 Evaluation Method..79

3.7 Summary..81

Chapter 4..82

RESULTS AND DISCUSSION..82

4.1 Complaint Specification Reference for IT2FM..82

4.1.1 Fundamental References for Domain Landscape and Recreation.......83

4.1.2 Fundamental References for Domain Enforcement..87

4.1.3 Fundamental References for Domain Mechanical and Electrical Engineering..95

4.2 Experiment I: Classification and Ranking using Fuzzy Type-1 99

4.2.1 Experimental Setup..104

4.2.2 Results..105

4.2.3 Discussion..111

4.3 Experiment II: Classification and Ranking using Interval Type-2 Fuzzy114

4.3.1 Experimental Setup..115

4.3.2 Results..115

4.3.3 Discussion..121

4.4 Verification of IT2FM..124

4.4.1 IT2FM and Conventional Fuzzy..124

4.4.2 IT2FM and Human Experts' Benchmark 128

4.5 Discussion 131

4.6 Summary 132

Chapter 5 133

CONCLUSION 133

5.1 Summary of the Thesis 133

5.2 Research Contributions 135

5.3 Future Work 137

REFERENCES 138

APPENDICES 158

APPENDIX A (APPROVAL APPLICATION LETTER FOR DATA EXTRACTION ON E-ADUAN (ISPAAA) FROM DBKL) 158

APPENDIX B (APPROVAL LETTER FOR DATA EXTRACTION ON E-ADUAN (ISPAAA) FROM DBKL) 159

APPENDIX C (DATA EXTRACTION DETAILS REQUIREMENT ON E-ADUAN (ISPAAA) FROM DBKL) 160

APPENDIX D (MEMO LETTER FOR DISCUSSION ON E-ADUAN (ISPAAA) WITH THE EXPERTS FROM DBKL) 161

APPENDIX E (SAMPLE DATA FOR DOMAIN LANDSCAPE AND RECREATION) 162

APPENDIX F (SAMPLE DATA FOR DOMAIN ENFORCEMENT) 163

APPENDIX G (SAMPLE DATA FOR DOMAIN MECHANICAL AND ELECTRICAL ENGINEERING) 164

APPENDIX H (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – FIRST EVALUATER) 165

APPENDIX I (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – SECOND EVALUATER) 167

APPENDIX J (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – THIRD EVALUATER) 169

LIST OF TABLES

Table 2.1: Comparison between Fuzzy Logic and Probability Methods 16
Table 2.2: The Reviewed Articles on Related Works...41
Table 2.3: Mapping of Research Gaps and Research Objectives 44
Table 2.4: Comparison of the Traditional Delphi and the Fuzzy Delphi Methods......48
Table 3.1: Experts Basic Information 61
Table 3.2: Predefined Scale 63
Table 3.3: The Mapping Scheme for Fuzzy Number 66
Table 3.4: Mapping Scheme for Complaint Classification..74
Table 3.5: Fuzzy Inference System Rules...78
Table 4.1: *Tajuk* (principal complaint) weightage (Landscape & Recreation: real number)...84
Table 4.2: *Tajuk* (principal complaint) weightage (Landscape & Recreation: fuzzy number)...85
Table 4.3: *Butir* (complaint details) weightage (Landscape & Recreation: real number)...86
Table 4.4: *Butir* (complaint details) weightage (Landscape & Recreation: fuzzy number)...88
Table 4.5: *Tajuk* (principal complaint) weightage (Enforcement: real number) 89
Table 4.6: *Tajuk* (principal complaint) weightage (Enforcement: fuzzy number) 91
Table 4.7: *Butir* (complaint details) weightage (Enforcement: real number)..............93
Table 4.8: *Butir* (complaint details) weightage (Enforcement: fuzzy number)...........96
Table 4.9: *Tajuk* (principal complaint) weightage (Mechanical and Electrical Engineering: real number) 98
Table 4.10: *Tajuk* (principal complaint) weightage (Mechanical and Electrical Engineering: fuzzy number) 98
Table 4.11: *Butir* (complaint details) weightage (Mechanical and Electrical Engineering: real number) 100
Table 4.12: *Butir* (complaint details) weightage (Mechanical and Electrical Engineering: fuzzy number) 102
Table 4.13: Membership Function Result Comparison for Domain Landscape and Recreation (FT1) 112

Table 4.14: Membership Function Result Comparison for Domain Enforcement (FT1) 113
Table 4.15: Membership Function Result Comparison for Domain Mechanical & Electrical Engineering (FT1) 114
Table 4.16: Membership Function Result Comparison for Domain Landscape and Recreation (IT2) 122
Table 4.17: Membership Function Result Comparison for Domain Enforcement (IT2) 123
Table 4.18: Membership Function Result Comparison for Domain Mechanical & Electrical Engineering (IT2) 123
Table 4.19: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using FT1 Approach (Real Number) 125
Table 4.20: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using FT1 Approach (Fuzzy Number) 126
Table 4.21: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using IT2 Approach (Real Number) 127
Table 4.22: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using IT2 Approach (Fuzzy Number) 128
Table 4.23: Accuracy Percentage between Domains Using FT1 Approach 129
Table 4.24: Accuracy Percentage between Domains Using IT2 Approach 130

LIST OF FIGURES

Figure 2.1: Definition of Soft Computing (Zadeh, 1994) 15
Figure 3.1: Research Methodology 52
Figure 3.2: Conventional Customer Handling Fuzzy Model 54
Figure 3.3: Interval Type-2 Fuzzy Model for Complaint Handling Process 58
Figure 3.4: Data Extraction Pre-Processing 60
Figure 3.5: Complaint Specification References Pre-Processing 62
Figure 3.6: Complaint Categories Weights 65
Figure 3.7: FIS for FT1 Real Number 76
Figure 3.8: FIS for FT1 Fuzzy Number 76
Figure 3.9: FIS for IT2 Real Number 76
Figure 3.10: FIS for IT2 Fuzzy Number 76
Figure 3.11: Complaint Ranking Program Pseudo code 78
Figure 4.1: Accuracy Percentage Comparison between FIS Membership Functions (LR: FT1 Real Numbers) 106
Figure 4.2: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: FT1 Real Numbers) 107
Figure 4.3: Accuracy Percentage Comparison between FIS Membership Functions (LR: FT1 Fuzzy Numbers) 107
Figure 4.4: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: FT1 Fuzzy Numbers) 108
Figure 4.5: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: FT1 Real Numbers) 109
Figure 4.6: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: FT1 Fuzzy Numbers) 109
Figure 4.7: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: FT1 Real Numbers) 110
Figure 4.8: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: FT1 Fuzzy Numbers) 111
Figure 4.9: Accuracy Percentage Comparison between FIS Membership Functions (LR: IT2 Real Numbers) 116

Figure 4.10: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: IT2 Real Numbers)................................116
Figure 4.11: Accuracy Percentage Comparison between FIS Membership Functions (LR: IT2 Fuzzy Numbers)..117
Figure 4.12: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: IT2 Fuzzy Numbers) 117
Figure 4.13: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: IT2 Real Numbers).............................118
Figure 4.14: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: IT2 Fuzzy Numbers) 119
Figure 4.15: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: IT2 Real Numbers) 120
Figure 4.16: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: IT2 Fuzzy Numbers).......................121
Figure 4.17: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using FT1 Approach (Real Number).....................................124
Figure 4.18: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using FT1 Approach (Fuzzy Number)...................................125
Figure 4.19: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using IT2 Approach (Real Number).......................................126
Figure 4.20: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using IT2 Approach (Fuzzy Number) 127

LIST OF ABBREVIATIONS

3PL	Third Party Logistics
AHP	Analytical Hierarchy Process
ANN	Artificial Neural Network
BSC	Balanced Scorecard
BTTrap	Bell-Triangular-Trapezoidal
CAC	Call Admission Control
CCMS	Customer Complaint Management System
CMS	Complaint Management System
CPM	Critical Path Method
CRM	Customer Relationship Management
CRs	Cognitive Radios
DMs	Decision Makers
FAHP	Fuzzy Analytic Hierarchy Process
FDM	Fuzzy Delphi Method
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Controller
FLS	Fuzzy Logic System
FMEA	Failure Modes and Effects Analysis
FOU	Footprint of Uncertainty
FPGA	Field Programmable Gate Array

FT1	Fuzzy Type-1
FT1MF	Fuzzy Type-1 Membership Function
FT2	Fuzzy Type-2
G2TTrap	Gaussian2-Triangular-Trapezoidal
GA	Genetic Algorithm
GGTrap	Gaussian-Gaussian-Trapezoidal
GGTrim	Gaussian-Gaussian-Triangular
GIS	Geographical Information System
GTTrap	Gaussian-Triangular-Trapezoidal
GTTrim	Gaussian-Trapezoidal-Triangular
ICSI	Integrated Customer Satisfaction Index
IT2	Interval Type-2 Fuzzy
IT2MF	Interval Type-2 Membership Function
IT2FM	Interval Type-2 Fuzzy Model
KM	Karnik-Mendel
MCDM	Multi Criteria Decision Making
MFs	Membership Functions
OR	Operating Room
OUM	Open University of Malaysia
QoS	Quality of Service
SOA	Service Oriented Architecture

TGTrap	Triangular-Gaussian-Trapezoidal
TGTrim	Trapezoidal-Gaussian-Triangular
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TrapTG	Trapezoidal-Triangular-Gaussian
TrimTG	Triangular-Trapezoidal-Gaussian
UCEs	Ubiquitous Computing Environments
VOC	Voice of Customer
WMNs	Wireless Mesh Networks

LIST OF NOMENCLATURES

E_k	Expert
c_i	Characteristic
C_j	Category
Q_{jk}	Unique Characteristic
r_{mjk}	Important Rating
r_{pk}	Required Characteristic
FW_i	Aggregated Weighted Value
AVr_x	Average Rating Score Among all the Experts

CHAPTER 1

INTRODUCTION

1.1 Background

Complaint is a kind of feedback that customers or users to show dissatisfactory against their expectation (Faed, 2010; Stevens et al., 2018; Trappey et al., 2010). Feedback from the customers is an effective method to identify the quality of services (Ismail, 2017; Razali et al., 2011). The customer communicates with the business provider on their dissatisfaction towards services, facilities or goods through the customer complaints. Customer complaint is a raw data and needs to be processed to retrieve the valuable information. The activity to process the complaint is call complaint handling. Complaint handling is known as a process to distinguish the real complaints with the unreal complaints (Aguwa et al., 2017; Gonzalez & Tamayo, 2005). According to El-Helaly et al. (2015), Gronroos (1988), Najar et al. (2010) and Najjar et al. (2010) complaint handling is to resolve the dissatisfaction and to take appropriate action to enhance customers' satisfactory levels. Furthermore Vos et al. (2008) and Waqas et al. (2014) stated complaint handling related to operational activities focus on helping customers resolve their complaints.

Nowadays, most of the organizations that provide services are aware of the importance getting feedback from the customer regarding their services (Hipp & Grupp, 2005; Kim et al., 2018). They realize that feedback from the customer is one of the effective and fastest approaches to improve the quality of their services (Chen & Chieh, 2011; Coussement & Poel, 2008; Cui et al., 2017; East, 2000; Fornell & Wernerfelt, 1988). The complaint is a unique behavior that delivers essential information regarding services (Gyung et al., 2010). This kind of information if appropriately managed will provide benefits to organizations, especially those that provide services and products. Organizations must design, build, operate and continuously upgrade systems for managing complaints to exploit this information (Gonzalez & Tamayo, 2005).

Complaint management system (CMS) has become increasingly important for organizations, businesses, and government in Malaysia. The interaction between customers and business provider based on complaints which referring to perceptions and wording involves uncertainties and not an easy task to develop a reliable and efficient application to classify the priority of the complaint. Furthermore, immediately responded to the complainants has become one of the major driving forces behind the development of CMS and as such, efficient complaint handling process needs to establish in the application (Latifah et al., 2010).

In this fast evolving online application environment, CMS requires a new efficient method that automates part of the complaint handling process. By using such method, the complaint handling process becomes faster and more efficient. However, to establish the new method, it remains time-consuming and challenging task, where human expert plays a critical role.

On the complaint handling front, automating the complaint process is one of the significant issues in knowledge management technologies. Today, customers are very particular about the response that they receive from their complaints. Time to respond must be reasonable, and the answers to the complaints must satisfy and solve the problem arise. Hence, to achieve this, it has involved automated complaint handling process. The automated process integrates human experience in understanding complaints. In this context, the primary challenge in complaint handling process involves assessing the validity of a customer complaint. Customer complaints need to classified as complaints or non-complaints. Next, the customer complaints need to be specified the importance which will allow prioritizing the complaints automatically and ranking them based on importance. From this description, the automated process needs to introduce by using an appropriate method that can successfully solve the issues.

In a CMS, the most critical aspect of its applications is the design of the complaint system (Faed, 2010). Poorly managed or designed complaint system will impact the company's reputation (Faed, 2010; Najar et al., 2010; Stephens & Gwinner, 1998; Trappey et al., 2010). Complaints are costly because most knowledge regarding services exists in the customer complaints based on their experience (Faed, 2010; Trappey et al., 2012; Gonzalez & Tamayo, 2005). Another aspect needs to take care is responsive towards the complaint. Within reasonable timeframes, the complaint must be entertained, responded and resolved immediately for excellent customer satisfaction (Coussement & Poel, 2008; Sultan et al., 2008). So, to properly handle complaints, an automated complaint system is the best solution.

Automated CMS is essential for complaint processing, integrating human experience in understanding complaints and the application of machine learning techniques. The primary challenge in complaint handling processing involves assessing the validity of a customer complaint by the communication between a customer and a company representative (Galitsky, 2006; Galitsky et al., 2009). Currently, most of CMS solutions are limited to the use of keyword processing to relate the complaint to the specific domain of the complaint. Most of the complaints handling functionalities are still perform manually to avoid slower performance, quality assurance and sustainability costs if using natural language processing or machine learning techniques (Galitsky et al., 2009). Typically, customers express their complaints by using plain text approach. However, analysis of textual complaints is not an easy task to retrieve the valuable information (Galitsky et al., 2009). Hence, fundamental reference needs to derive by creating complaint specification references to classify real complaint automatically.

In summary, reliable complaint handling process is important to retrieve accurate interpretation of the customers' complaint. A proper method need to explore and identify for handling and extracting the suitable keyword from the complaint dataset. Additionally, from the related works discussed in the next chapter of this thesis and from other non-cited similar literature reviewed, the authors observe that to date, no similar work on complaint handling method has conducted in the Malay language. All complaint handling method in Malay would require the involvement of the experts, the basic text-processing tools and the most important is the suitable fundamental reference for the identified domain of complaint.

1.2 Background of the Problem

Typically complaint handling process for the specific complaint involves experts with experiences and uncertain, difficult and complex customer complaint (Lee et al., 2015). 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 (John & Coupland, 2009). 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 (John & Coupland, 2009).

Based on previous studies, researchers proposed several complaints handling method to solve the uncertainties issues. Basically, the issues focused on the process to extract the related keyword from the textual data. However, most of the previous method works used exact numeric values as reference to the keyword. This is known as crisp-based requirements. This type of approach has become the option most of the previous researcher because crisp-based requirements is simplicity, non-complicated algorithm as well as fast computation. However, most of works implement crisp-based requirements, which have been proven to not having tolerance to handle uncertainties. Besides, it is argued that in complaint management system, the accuracy and precision are crucial parameters to use in ranking the priority of the customer complaint, to properly handle customer complaint and to improve services provided to the customer.

Furthermore, as mentioned previously the dataset of the complaint is in Malay language. As for information in Malaysia environment, most of the interaction for the people is in Malay language. The service providers including the government sector are using Malay language as the main communication and interaction with the customer. Hence, this study used complaint dataset in Malay language for the experiments. Besides, Malay language has been one of the less resourced languages as English is well-studied with satisfactory achievements in much computational linguistic research. Less-resourced languages refer to languages that are lack of the basic resources that are fundamental to computational linguistics and have a relatively small corpus of texts (Gasser, 2010). Less-resourced language is a term interchangeably used with resource-poor language. However, with the advent of computing power today, the digital information of Malay must be treasured to allow not only Malaysians to access this information widely but also to other interested linguists in the world. In addition, Malay language is different with English language related with the use of adjective. Also, both Malay language and English language are not similar on the conversion of root words to other words and currently there are no acceptable standard for conversions (Hong, 2013). Additionally, there is no existing research applying fuzzy approach that used the Malay text to define the ranking function for the Malay language (Rodzman et al., 2017).

Moreover, this study focused on the complaint handling process in Malaysia environment. Since year 2010 until year 2018, only 19 studies related to complaint handling in Malaysia published officially in ISI, Scopus and IEEE publication databases. These number are too far behind compared to others country in doing research in the same area. Hence, it is a good opportunity to do research related to complaint handling and focus on Malaysia perspective. Furthermore the research finding would benefit on the improvement and enhancement of complaint handling process in Malaysia. Later, government and private sector also would benefit the important role of the complaint handling in improving their services.

1.3 Problem Statement

Complaint handling process contains uncertainties that resulted from perceptions and wording of complainants (John & Coupland, 2009). Also, the process to identify the status of the complaint which involves a group of experts also implicates uncertainties (John & Coupland, 2009). On the other hand, most of the complaints handling requirements in the existing complaint handling model are using crisp specifications. This crisp requirements specification has become the mainstream in complaint handling process due to its simplicity, fast computation and the unavailability of the linguistic values-based model to carry out the complaint handling tasks. However, this crisp complaint handling requirements specification has a problem in adapting the uncertainties. This problem occurred because complaint handling requirement values based on complainants' data are less efficient if defined in the crisp form. Crisp requirements do not have high tolerance towards the uncertain complaint values. These uncertainties, if not handled efficiently, will negatively affect complaint handling process regarding accuracy and precision.

Another problem to establish complaint specification reference is that involvement of experts is essential to ensure the reliability of the complaint specification reference. In this situation, the issues arise when the process involving opinions and suggestion from different experts with different knowledge and experience. The uncertainties occur caused by the subjective opinion of experts towards complaint characteristics values. Different experts may perceive value differently upon the same characteristic. The uncertainties between these experts are also known as fuzziness of common understanding of expert opinions (Bouzonet al., 2016; Chao et al., 2017; Hsu et al., 2010; Tseng et al., 2018). Thus, this fuzziness needs to solve and to test the consistency of the expert's opinions in producing reliable complaint characteristics values, which eventually if not resolve correctly will affect the accuracy and precision of the complaint handling process results.

Other than the requirements specification, existing models also perform their complaint handling process based on crisp computation. Crisp computation has a low capability in minimizing the accuracy and precision effects that result from the uncertainties in complaint environment. These effects occurred because it does not have the degree of freedom to tolerate the dynamically changing data on the perceptions and wording from the complainants.

As conclusion, the research problem can be summarized:

1) Complaint handling process involves high level of uncertainties issues.
2) Using crisp-based requirements by implement exact numeric number for criteria / characteristic.
3) Inputs from experts are consolidating using crisp-based method.
4) Using crisp-based method in complaint handling process which not appropriate to handle uncertainties issue.

1.4 Research Questions

This research proposes a fuzzy approach to solve the problems mentioned above. Hence, this study has devised problems into research questions as follows:

1. Can existing fuzzy methods determine the uncertainties issues between experts to develop fundamental reference based on the Malay language?
2. How can fuzzy approach evaluate the vagueness in complaint handling process to classify real complaint?
3. How could fuzzy approach in other languages with different structures be leveraged into the Malay language?
4. How can fuzzy approach be efficiently integrated into the development of the proposed complaint handling method?
5. How reliable the fundamental reference in the complaint handling process to produce highly consistent results with the human experts?
6. How can the proposed complaint handling method generate highly consistent results with the human experts?

1.5 Research Aims and Objectives

This thesis will focus on designing and developing Interval Type-2 Fuzzy Model (IT2FM) which can improve complaint handling process efficiency and less time-consuming. IT2FM will focus on classifying and ranking the complaints. The objectives of this research are as follows:

(i) To derive fundamental reference for classifying and ranking complaints by creating complaint specification references in the Malay language using Fuzzy Delphi Method (FDM).

(ii) To develop an approach for constructing fuzzy type-1 (FT1) and interval type-2 fuzzy (IT2) membership functions and rules based on real complaint data.

(iii) To design a fuzzy inference system (FIS) model based on the expert's input.

(iv) To experiment and evaluate the performance of the proposed models against the human-generated benchmark.

1.6 Scope of the Research

The research concentrates on improving complaint handling process on classifying and ranking the complaints. Complaint specification references need to be established based on the Malay language for IT2FM which also referred to as a fundamental reference. Three sets of complaints data that provided by the local government were used to develop the fundamental reference. The provided data is focusing on servicing towards the local population. Besides, seven of experts were involved to help to identify the characteristics of the complaints data. The experts also worked together to validate the efficiency of the proposed model. The same set of data was used to test the proposed models. The experimentations are done through simulations using Matlab version 2013.

1.7 Significance of the Research

Complaint management process comprises two main processes, which are receiving complaints and providing solutions. Both processes involve a high level of uncertainties due to the variations and inconsistency of the experts' opinions. As a result time-consuming and challenging to coordinate the opinions occur during the process. As regards, the primary purpose of the complaint management is to deliver a good solution for any complaints that arise. Effectiveness and immediate response to the complaints are essential to increase the level of satisfaction of the complainants. The achievement of this objective depends on a reliable process that can resolve the uncertainties issue. Even though the prior research was carried out, this research wants to introduce a new method that can solve the uncertainties issue. Hence, this study explores the fuzzy approach to solving the uncertainties issue that occurs in the complaint management process. The result of the study will be used to resolve the uncertainties issue and fulfills the main purpose of the complaint management.

The study proposed a new classification and ranking mechanism in complaint handling process which focuses on two combination parameters that are principal and details characteristics for the efficiency of identifying real complaints. These models provide a solution for the improvement of the complaint handling process, and Fuzzy Logic approach will be used as a medium to blend the selected parameters and produce one output chance to classify real complaint. This study will develop a new model called Interval Type-2 Fuzzy Model (IT2FM) to improve the complaint classifying and ranking process. This model has the potential of not only increasing the efficiency of complaint classifying and ranking but also minimizing the cost of its implementations.

1.8 Organization of the Thesis

This thesis comprises of six chapters which organized as follows:

Chapter 1 presents the background of the thesis focusing on classification and ranking mechanism in complaint handling process, problems statements, research objectives, scopes of the research, significances of the research and the thesis layout.

Chapter 2 discusses the literature reviews on published works in the related fields of complaint handling process, complaint management, intelligent techniques which are Fuzzy Logic, complaints characteristics analysis metrics and lastly the summary of the chapter which highlights the proposed methodology used in this thesis.

Chapter 3 describes in detail the research methodology. It presents the theoretical aspects which used in the thesis. It consists of the basic concepts of fuzzy sets which include fuzzy union and fuzzy intersection. Then, the chapter discussed the theoretical background of FLC architecture. Next, on the methodology part, it covers the data extraction from the local government and focuses on the selection of parameters by the experts. Next, establish the fundamental reference by creating complaint specification references based on the Malay language. Then, the chapter followed by the IT2FM which includes the generating of fuzzy rules. Next, calculated the complaint characteristics weighted. After that, assigned the complaint scoring and classification using Fuzzy Logic and followed by ranking the complaint. The efficiency of this method is tested by using the sets of complaint data that provided by the local government. The validations of the proposed method are compared against the human-generated benchmark. Lastly, the chapter highlights the overalls steps introduced for the IT2FM.

Chapter 4 presents the finding of classification and ranking model. Prior to that, the segregation of parameters into the combinations of principal and details are elaborated. Next, the analysis of five membership function and ten combinations membership function. The proposed method is compared to the human benchmark and the discussion of results.

Chapter 5 discusses the whole research work that was accomplished in completing this thesis. It discusses the limitations faced at all stages of development, and the ideas to be retained in future work. The thesis conclusion restates the contributions and summarizes the results of the experiments.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview of Literature Review

This chapter begins with the discussions on the significance of the problems that have been identified in Chapter 1. These are covered in sections 2.2 – 2.5. Then section 2.6 discusses the related works with the aims to summarize and evaluate past researchers, as well as to discover the research gaps. Sections that follow, which are 2.7 – 2.8 contain discussions on the proposed methods. These discussions aim at placing the proposed research into its context so that it becomes the foundation for the methodology framework presented in Chapter 3.

2.2 Complaint Management System

Customer complaint is not a new topic to discuss when relating to the service-oriented company or government sector. In Malaysia, customer complaint has become one of the essential 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 (Linder & Schmitt, 2015; Phatak & Nisar, 2017). 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 is 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 more extended period from the actual working hours. It is an excellent 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 (Rampersad, 2001). The complaint is natural human behavior on responding towards something that not satisfied their expectation. Trappey et al. (2010) 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 (Trappey et al., 2010). 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 (Filip, 2013). 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 (Sander et al., 2010). This process is also known as service recovery which has a significant impact on customer retention and the beneficial usage of complaint information for quality improvements (Stauss & Schoeler, 2004). Service provider acknowledges the importance 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 (Ladwein & Crie, 2002; Davidow & Dacin, 1997; Faed et al., 2016).

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 (Shahin, 1997). Priceless information of complaint is vital for the service provider to use it to plan a proper strategy to increase the performance of service (Anders, 2009; Trappey et al., 2010). 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 (Tax et al., 1998). Complaint management is also known as a process to disseminate information at identifying and correcting customer dissatisfaction (Filip, 2013). Thus, a reliable information system needs to handle the complaint, which can profit the business and support the customers to increase their satisfaction level (Gonzalez & Tamayo, 2005). This kind of system is usually known as customer complaint management system (CCMS). The fundamental of developing a successful CCMS is depended 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 (Lee et al., 2015). 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 (John & Coupland, 2009). 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 (John & Coupland, 2009).

With various approaches to complaint handling process, Park and Lee (2011) presented a framework to establish product specification by transforming customer opinions from websites. The process is using text-mining to transform customer opinions were 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 (Park & Lee, 2011).

Pyon et al. (2011) proposed a web-based decision support system namely Voice of the Customer (VOC) to handle customer complaints about business process management, and improve the service based on the data extraction. The received data will go through the process of comparison, exception, and summarization for data enrichment (Pyon et al., 2011).

Trappey et al. (2010) analyzed and developed a 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 will increase the efficiency of the response towards customer complaints (Trappey et al., 2010). Therefore, the proposed framework will improve the service quality of the restaurant.

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, and create significant dialogue clusters. From these clusters, derive meaningful trends, baselines, and interpretations of consumer satisfaction and dissatisfaction (Jarrar et al., 2003). Later, the authors improved the method by present the intelligent complaint handling based on interoperable ontology and case-based reasoning to offers an informative and knowledge-based methodology to resolve customer complaints systematically with self-learning feature (Lee et al., 2015; Trappey et al., 2012). Thus, all the existing work is focused on increasing the effectiveness of solving the customer complaint to improve services and products quality.

2.3 Selection of Intelligent Soft Computing Method

Section 2.2 discusses the problem in managing the imprecision that exists in complaint handling process. Another problem identified in this thesis is that the involvement of the experts to solve the complaint which facing different opinions for identifying ranking and solution of the complaint. Both issues are related to the uncertainties in handling a customer complaint. The appropriate approach to managing these uncertainty and imprecision problems is through soft computing method.

Soft computing mimics the ability of the human mind to perform approximate reasoning through tolerance towards imprecision and uncertainty (Zadeh, 1994). Soft computing has been classified by Zadeh (1994) into four types, namely probabilistic, fuzzy logic, neurocomputing and genetic algorithm. Each of these soft computing methods has a specific purpose; probabilistic and fuzzy logic address imprecision and uncertainty problems, while neurocomputing and genetic algorithm are for learning. This definition of soft computing is also supported by Choudhary (2014), Potey & Sinha (2015), Saridakis & Dentsoras (2008) and Ko et al. (2010), and it is summarized in Figure 2.1 below.

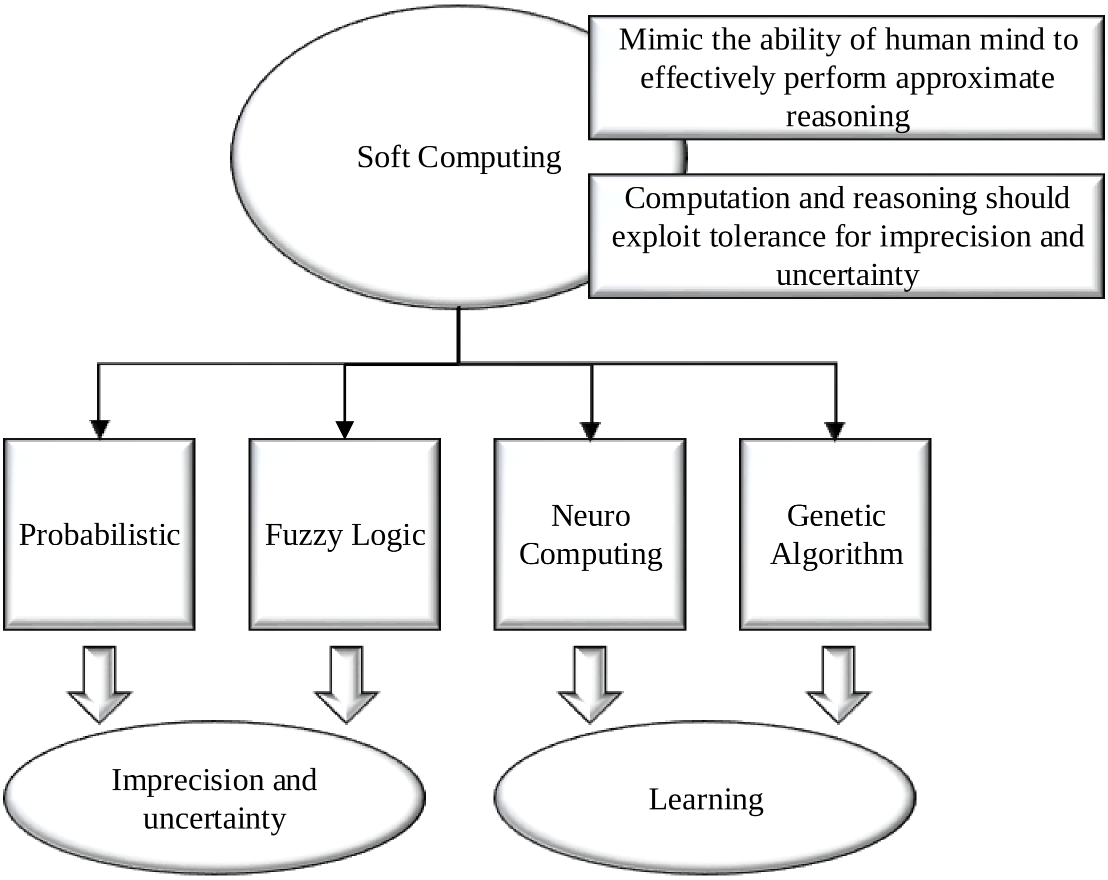

Figure 2.1: Definition of Soft Computing (Zadeh, 1994)

The objective of this research is to answer the questions related to managing the vagueness in complaint handling process to classify real complaint and handling of the uncertainties issues between experts to develop fundamental reference based on the Malay language. However, the learning process in the model is not covered under the scope of this research. Hence, the selection of the soft computing method is focused on the comparison between fuzzy logic and probability methods, as described in Table 2.1.

Table 2.1 compares fuzzy logic and probability methods regarding the contexts of this research, which include how the model behaves and what kind of input the model takes for computation. In this research, the proposed model performs the complaint classification and ranking based on the fundamental reference. Moreover, the context of this research requires the fundamental reference to be specified using linguistic values; instead of crisp values as used in the probability method. Hence, fuzzy logic is a more appropriate soft computing method than the probability for the proposed IT2FM.

Table 2.1: Comparison between Fuzzy Logic and Probability Methods

Criterion	Fuzzy Logic	Probability	References
Behavior	Deterministic - imposing granular membership to the linguistic values	Probabilistic - the likelihood of the occurrence of an event	Ko et al. (2010) Raina and Thomas (2012)
Input	Linguistic values - e.g., response time is moderate-high	Crisp values - e.g., response time is 50 ms in 98% of the time	Dubois and Prade (1993) and Rosario et al. (2008)

In a different perspective, neurocomputing and genetic algorithms were also found to be used for uncertainty and imprecision management, as well as multi-valued decision making, despite being categorized as the learning soft computing methods (Ko et al., 2010; Saridakis & Dentsoras, 2008). However, previous research showed that the two methods are less competent than fuzzy logic to represent imprecise knowledge, and to manage both uncertainty and cognitive uncertainty (Ghalia & Alouani, 1995; Gupta & Rao, 1994; Kejík & Hanus, 2010; Saridakis & Dentsoras, 2008; Saxena & Saxena, 2013). Furthermore, neuro computing's functionality representation is also difficult to be understood as compared to fuzzy logic representation. This functionality representation criterion is important when the procedures of how complaint handling process to classify real complaint (Saridakis & Dentsoras, 2008; Vieira et al., 2004). Meanwhile, the genetic algorithm has been widely deployed to gain advantages in optimization and learning (Back et al., 1997; Ko et al., 2010; Saxena & Saxena, 2013; Tahmasebi & Hezarkhani, 2012).

Another well-known Artificial Intelligent (AI) method which can be used is Artificial Neural Network (ANN) (Guo et al., 2010; Jassi & Wraich, 2014; Kaur & Rai, 2014; Kaur & Rai, 2013; Nimbalkar, 2012; Shao, 2011). In the 1940s, the ANN was proposed and derived by McCulloch and Pitts' (1990) pioneering work. The previous study applied ANN method to solve issues related to forecasting. Furthermore, ANN is flexible computing frameworks that can flexible computing frameworks and universal. However, to produce accurate results, ANN needs a huge amount of historical data for the learning process. In this situation, financial data is full of uncertainties which ANN method is having a problem to handle this uncertainty. Therefore, to resolve this issue, this study proposed a new hybrid method which combines ANN method and fuzzy regression model (Khashei, Reza Hejazi, & Bijari, 2008). Furthermore, in other research that applied ANN method facing the same issues when related with uncertainties (Efendigil et al., 2009; Kartal et al., 2016; Tavana et al., 2016; Yazgan et al., 2009). Thus, other approaches must combine with ANN such as feature selection to overcome the uncertainties issues. To summarize, fuzzy logic has a better capability in managing uncertainty and imprecision issues than neurocomputing, genetic algorithm methods, and ANN, hence making it more relevant to the scope of this study.

2.4 Handling Uncertain Information with Fuzzy Logic

As discussed in Section 2.3, fuzzy logic has been proposed in this study because it is appropriate for addressing the contexts of the problems to be solved which involve uncertainties and imprecision. The method has been applied to handle uncertainty issue such as in the health monitoring system of offshore wind-farms (Qian, 2006). The research claimed that existing monitoring systems implement constant threshold in recording data regardless of the time of the day or month. This kind of fixed or crisp threshold scheme, however, does not give satisfactory performances as the environment is always changing. This uncertainty is influenced by various factors, such as natural factors like the difference in temperature during daytime and nighttime, and during winter and summer. Hence, it is unlikely that crisp threshold produces optimized monitoring results. Besides, if the threshold is set to too high, it will lead to the increase of missed detections. On the other hand, if it is set to too low, it will increase false positives. Therefore, the research proposed a novel fuzzy-based method that can produce flexible thresholds in monitoring the health of offshore wind-farms. The results showed that the proposed method had produced better performance than the existing method.

Similarly, Martin et al. (2014) investigated uncertainty issue in an information delivery model for the banking sector. The sector’s environment comprises various levels of users with the requirement of various levels of information. The model receives information from business analysis and determines the best users for the particular information. This process involves multi-criteria decision making. The main challenge is that users may come out with different levels of information which lead to inconsistent situations. Furthermore, users' interests may change from time to time or from person to person. The interests may also change according to the situation. This condition leads to uncertainty. Therefore, to solve these uncertainty and inconsistency issues, the model proposed in the research was implemented using fuzzy analytical hierarchy process (AHP). This fuzzy-based method can outperform the crisp-based multi-criteria decision-making model.

A similar fuzzy-based model was also implemented to manage the uncertainty in forest fire detection (Dutta et al., 2014). The model comprises some sensors being deployed in a forest. These sensors detect various data such as temperature and humidity and send them to the central node. The variations of data create the uncertainty of information. Fuzzy logic was proposed in the study as a method for handling this uncertainty because it can deal with controlling variables in a natural way using linguistic terms. Furthermore, fuzzy logic is more suitable for managing them to generate the detection results.

Fuzzy logic has also provided advantages to a CPM-based method for scheduling construction projects. The main motivation for adopting fuzzy logic was the uncertain conditions of construction activities. The project risks primarily caused this uncertainty. The study presented in Wilrich (2007) suggested that fuzzy sets represent the activity duration. Meanwhile, the study also proposed a fuzzy operation method to carry out the CPM network calculations. The results showed that the developed fuzzy method produced a good performance in modeling the uncertainty in CPM calculations.

Likewise, it was found that cognitive radios (CRs) face difficulties to properly determine the usability of unoccupied channels due to intrinsic asymmetry and traffic uncertainty. As a result, the study presented in Prenesti & Gosmaro (2015) proposed a channel ranking algorithm which was implemented using the fuzzy logic theory. The results showed that the proposed method outperformed the traditional crisp-based approach.

The advantages of fuzzy logic over crisp-based approach have also been discovered in decision making and ranking situation. In a recent study conducted by Alias et al. (2009) indicated that the degree of preference of the decision makers (DMs) and the degree of risk tolerance that the DMs are ready to take is vital on river ranking process. However, the study found out that previous research using point value to represent the subjective data which are not appropriate to represent the DMs preferences. Moreover, this point value cannot represent the DMs preference adequately in a real situation. Besides, it is convenient for the DMs to express interval judgments than fixed value judgments due to the fuzzy nature of the comparison process. Therefore, the study proposed the use of fuzzy set theory in multi-criteria decision making (MCDM) to handle uncertainties in the river ranking process. Furthermore, this study using Fuzzy Analytic Hierarchy Process (FAHP) technique to rank alternatives to find the most reasonable and efficient use of river system. Likewise, Panagiotis and Ioannis (2009) stated that selection of human resources is a complex process that involves a significant amount of uncertainties and subjectivity. Consequently, the study discovered it is not suitable for the selection process referred to statistical analyses of test scores that are treated as accurate reflections of reality. Hence, the study proposed the use of fuzzy multi-criteria decision making (MCDM) methodology for selecting employees under the occurrence of uncertainties.

Similarly, the service performance analyses involved stakeholders' judgments which are basically comprised of possible uncertainties judgments value related to incompleteness for partial ignorance, imprecision for subjectivity and vagueness. As a result, Lupo (2013) proposed the fuzzy set theory and the analytic hierarchy process (AHP) method on a recent extension of the SERVQUAL model to effectively handle uncertainty in service performance analyses. In particular, the use of the fuzzy set theory is to handle the uncertainties and the AHP method is applied as a tool to estimate the importance weights of the strategic service attributes.

Additionally, Lin et al. (2013) mentioned that healthcare organizations could control, monitor and improve their service quality focus on operating room (OR) performance using an effective performance evaluation system. The reason is the evaluation process involve managers to assess the OR performance based on the opinion and expertise. This kind of approach contains uncertainties value related to subjective data from the managers. Therefore, the study explored the use of balanced scorecard (BSC) to facilitate the managers and proposed the use of the fuzzy linguistic method for evaluating OR performance. The advantage of the fuzzy linguistic method is to manage the uncertainties in the performance evaluation process. In addition, input from experts is important to build a performance indicators system based on BSC theory.

In another domain of study which relates to fashion, Lin (2013) presented fashion design scheme evaluation system for fashion design scheme proposal process. The study determines appropriate criteria weight with the involvement of experts. The degree of acceptance of the decision maker is comprised of the complex decision-making process of selecting appropriate preferences. This study applied fuzzy set theory to handle the uncertainties in the decision-making process.

Furthermore, the previous study related to hotel business highlighted method to identify top managers' competencies in hotel unit leaders for career development improvement. The competencies evaluation process is based on perceptions of the importance of various competencies in different dimensions. Consequently, this study proposed the use of fuzzy set theory, specifically using the Fuzzy Delphi and Analytic Hierarchy Process to handle the existence of uncertainties issue that related to perceptions determination process. (Shyan et al., 2011)

Moreover, a study in logistics domain Soh (2010) indicated that the selection process for the identification of a third party logistics (3PL) provider that best fits user requirements involves multiple criteria and alternatives and may be one of the most complex decisions facing logistics users. In this regard, this study proposes an evaluation framework and methodology for selecting a suitable 3PL provider. The decision-making problem for selecting the best 3PL provider has been receiving much attention recently among scholars as well as business practitioners. In many practical cases, decision-makers can be imprecise about their level of preference because of incomplete information or knowledge, the vagueness of the human thought process, and the inherent complexity and uncertainty of the decision environment. Thus, it is difficult for a decision maker to express pairwise comparison judgments as exact numerical values on a ratio scale. Moreover, to go beyond this limitation, it is more natural to express the comparison ratios as interval numbers or fuzzy sets because they are suitable for representing uncertain human judgments. For this reason, this study applies a fuzzy modification of AHP (that is, fuzzy AHP) to determine the relative importance of selection criteria. Next, to construct the criteria framework, a preliminary list of 21 criteria was prepared from relevant literature and subsequently presented to three academic experts for their review to determine the final set of candidate criteria.

Similarly, Chen (2002) proposed an algorithm for external performance evaluation in the area of logistics from retailers' viewpoint under fuzzy environment. The process always has to find precise data when applying the conventional crisp decision method. However, under many conditions, it is difficult to get precise data because the data are from the experience and the judgment of decision makers. Therefore, this study proposed the use of the fuzzy set theory on the decision algorithm to solve the distribution center selection problem.

Furthermore, Hsu et al. (2010) indicated that due to the funding scale and complexity of lubricant regenerative technology, the selection of recycling technology and policy for waste lubricant oil can be viewed as a multiple attribute decision process that is normally made by a review committee with experts from academia, industry, and the government. This study aims to provide a systematic approach towards the technology selection. Hence, this study proposed two-phase procedures which involve the use of fuzzy set theory to solve the existence of uncertainties in the technology selection process. The first stage utilizes Fuzzy Delphi Method to obtain the critical factors of the regenerative technologies by interviewing the preceding experts. In the second stage, the study applied Fuzzy Analytic Hierarchy Process to find the importance degree of each criterion as the measurable indices of the regenerative technologies. This study considers eight kinds of regenerative technologies which have already been widely used and establishes a ranking model that provides decision-makers to assess the prior order of regenerative technologies.

Hongxia et al. (2009) also proposed a fuzzy evaluation approach for services selection based on the extended QoS model to manage the uncertainties value within the process. This study aims to define an extended QoS model to accurately describe the quality of web service in the open distributed environment. With the increasing popularity of web services, a wide variety of web services with similar functions are offered, which brings the problem of selecting the most appropriate one from a group of web services that can satisfy the functional requirements for a special task. To optimize services selection, one of the premises is to describe the QoS for web service accurately. Thus, this study presented an extended tree-like QoS web service with the use of the fuzzy set theory to measure the quality criteria.

As well, Gu and Zhang (2007) identified that finding a product with high quality and reasonable price online is a difficult task due to the uncertainty of Web data and queries. To handle the uncertainty problem, this study proposed the Web Shopping Expert, a new type-2 fuzzy online decision support system. This study aims at promoting the integration of type-2 fuzzy logic into a decision support system for Web decision makers. The focus is to develop a Web-based decision support system (Web Shopping Expert) using the interval type-2 FLS to handle fuzzy multi-criteria and deal with vague and imprecise Web data.

Moreover, Quek et al. (2009) described a novel approach to traffic flow analysis and modeling using a specific class of self-organizing fuzzy rule-based system known as the Pseudo Outer-Product Fuzzy-Neural Network using the Truth-Value-Restriction method (POPFNN-TVR). Although many statistical regression models of road traffic relationships have been formulated, the models have proven to be unsuitable due to multiple and ill-defined traffic characteristics. Alternative methods such as neural networks have thus been sought but, despite some promising results, the design remains problematic, and implementation is equally difficult.

Also, Makropoulos et al. (2003) stated that urban water management is a demanding decision-making environment where optimal planning presupposes a synthesis of heterogeneous information of high spatial resolution to ensure site-specific implementation. Georeferenced information in the urban environment is becoming increasingly available, although uncertainty remains an issue for the information's value in any deterministic analytical framework. The decision support approach developed in this research to overcome the domain-specific spatial analysis problem is the loose coupling of a commercial GIS. The mathematical framework adopted to overcome the problems of information heterogeneity and linguistic ambiguity. This paper discussed a mathematical framework for the development of a domain-specific SDSS that can easily be adapted to some urban water management contexts. The use of approximate reasoning through the use of type-1 and type-2 FISs as well as ordered weighted averaging techniques is justified by the extent to which linguistic variables have to be used in the planning process when necessary information includes engineering, social, and economic constraints. The potential to improve and refine the framework presented here is substantial and can lead to a more accurate, site-specific implementation of water management practices.

Bailey et al. (2003) also stated that site selection for large-scale facilities is often a group multi-criteria decision-making problem under uncertainty. Existing algorithms for site selection have little or handling a non-consensus group no capability for the environment, or to factor quantitative uncertainty into an analysis. This study presented a new fuzzy algorithm that is practical to implement in raster GIS and suitable for multiple decision maker site selection problems under uncertainty. Differing linguistic assessments from decision makers are combined using a relevance matrix, and quantitative uncertainty is modeled using a method based on type-2 fuzzy sets. Outputs from the algorithm have a high information value as they include measures of conflict, risk, and uncertainty, as well as compensatory and non-compensatory aggregated suitability. This study proposed a computationally efficient algorithm for multi-criteria, multi-decision maker site quantitative selection problems under linguistic and uncertainty, and outlined its implementation in ArcView GIS.

In conclusion, there are number of evidence found in the literature that shows the importance of handling vague and uncertain properties using the fuzzy technique. The first motivation is related to human perception and opinion that is uncertain. It is evident that fuzzy-based mechanism performs better than crisp-based mechanism, particularly in the condition where the inference is constructed based on data from a human. The second motivation is that decision making, and ranking applications may need to deal with vague information as it has become the users' preference, especially to the service provider. It is evident that this kind of vague information is more suitable to be processed using fuzzy technique than crisp technique. Overall, this subtopic has shown that the problem of handling uncertainties using fuzzy logic is worth exploring. Most existing decision making and ranking models were developed based on the crisp concept. Numerous works in the literature, however, have discovered that uncertain and vague information is handled better using fuzzy technique than crisp technique.

2.5 Comparison between Fuzzy Type-1 and Fuzzy Type-2

Section 2.4 shall present numerous studies that promoted the advantages of fuzzy logic over crisp technique in handling vagueness and uncertainty in decision making and ranking environment. In the family of fuzzy logic, different types may also offer different levels of performance. This research proposes the implementation of FT1 and FT2 (IT2) in the IT2FM. Furthermore, fuzzy approach theoretical framework has more capability in handling vagueness and uncertainties. This issue of performance comparison between FT1 and FT2 has been investigated in numerous previous works. They are presented and discussed in this section.

The main works that theoretically support FT2 implementation are the studies that had been carried out by Mendel (2003) and Mendel (2007). The studies claimed that though FT1 can handle vagueness and uncertainty, its implementation is based on certain or precise MFs. Hence, the accuracy and precision may diminish in the process. The studies concluded that the use of FT1 in handling a high degree of vagueness, such as in the field of computing with words, is scientifically incorrect. They found that FT2 has a greater ability than FT1 to handle uncertainty and vagueness problems.

These findings have been further supported by John & Coupland (2007), who also stated that the introduction of FT2 provides an opportunity to produce better handling of uncertainty than FT1. Although FT1 has been proven to manage problems that involve uncertainty, vagueness, and imprecision, FT2 is believed to be more powerful, particularly in handling higher level of uncertainty such as human perception. The main reason is that, unlike FT1, FT2 runs its inference based on non-crisp MFs. Hence, the study proposed that FT2 be used when the computation problems involve a lot of uncertainty and vagueness. Furthermore, when a problem is more uncertain and vague, its handling can be significantly improved with FT2 implementation.

Similar problems on uncertainty and vagueness had also been investigated in the area of nonlinear plants control. To manage these problems, Melin & Castillo (2002) have proposed an adaptive-based control model. The model was implemented based on a hybrid concept using FT2 and neural networks. The study used non-linear plants that are similar to the two-link robot arm as its case study. The control of non-linear plants was tested in different conditions using FT1 and the hybrid approach as proposed by the study. The results demonstrated that the hybrid approach is better regarding accuracy and efficiency. This proposed hybrid model has leveraged on the advantages of both neural networks and FT2 algorithms. The study concluded that the main advantage provided by FT2 in the case of this non-linear plant is it's greater ability to model uncertainties as compared to FT1.

This uncertainty management ability of FT2 has inspired more research to be conducted, which included its use in improving mobile robots navigation. This type of navigation involves a huge amount of uncertainties (Hagras, 2004). This is due to the ever-changing and dynamic nature of unstructured conditions and outdoor environments. Hagras (2004) argued that FT1 cannot fully handle these uncertainties due to its crisp fuzzy sets. Therefore, the study proposed the use of FT2 in the implementation of autonomous mobile robot navigations. In the experiments, the FT2-based and FT1-based implementations were tested in unstructured and challenging indoor and outdoor environments. The results showed that FT2-based implementation outperformed FT1-based implementation.

Similarly, Wu & Tan (2004) described the implementation of FT2 fuzzy logic controllers (FLC) in controlling liquid-level process. The FT2 FLC was developed according to a two-step approach. The first step was FT1 FLC parameters generation and optimization using a genetic algorithm (GA). The second step was blurring the footprint of uncertainty that finally has led to the construction of FT2 FLC model. The experiment results showed that the proposed FT2 FLC was able to cope well with the complexity of the plant. Furthermore, the FT2 FLC also outperformed FT1 FLC in handling uncertainty in the modeling process.

A similar comparison between FT1 and FT2 has also been carried out by Figueroa et al. (2005). The study focused on tracking mobile objects in robotic soccer games. The robotic soccer games context involves a player who has to track a mobile object accurately, which is a ball. The positions of the player and the ball are measured using image processing method. This process normally involves a huge amount of uncertainties. Due to this, FT1 FLC is used in the existing solutions. However, it is evident that several sources of uncertainty have degraded the performance of FT1 FLC-based solutions. The study, therefore, proposed FT2 FLC implementation. The FT2 FLC was constructed by imposing uncertainty in the crisp MFs of FT1. The conducted experiments demonstrated that the proposed FT2 FLC implementation was able to handle uncertainties in a better way. The results also showed that the implementation of FT2 FLC had improved the performance without increasing the computational cost of the controller.

Another similar performance comparison between types of fuzzy logic was studied by Doctor et al. (2004). The study proposed a novel system for intelligent agents in ubiquitous computing environments (UCEs). The system has functionalities to learn and adapt user behaviors, where their implementations were using FT2-based controllers. The experiments showed that the system was able to learn and adapt user behaviors, which allowed the agents to control the UCE on behalf of the user. These intelligent agents, however, need to deal with an enormous amount of uncertainties which are caused by noise from sensors and the dynamically changing environment. In this study, it was proven that the proposed FT2-based agents were able to outperform the FT1-based agents in the occurrence of uncertainty and imprecision. In addition, Lynch et al. (2005) stated that the environment for operating marine propulsion and traction diesel engines is highly dynamic and uncertain. However, current speed controllers are developed based on FT1 FLC, which means that they are not able to fully manage these uncertainties. The study, therefore, proposed FT2 FLC implementation. The proposed model has shown that its capability of handling these uncertainties is better than FT1 FLC.

This kind of uncertainty management ability is also required for hardware implementation. The research presented in a study by Melgarejo et al. (2004) described this issue by elaborating on how the FT2 inference system called Pro-Two was applied for hardware implementation. This implementation was employed over field programmable gate array (FPGA). The study compared the proposed implementation with FT1 implementation regarding equalization of a non-linear and time-varying communication channel. The experiment results showed that the proposed FT2 implementation was more robust than the FT1 implementation regarding the internal operations linked to arithmetic resolution.

Robustness is also highly required for the network, especially in dealing with congestion issue that result from the ever-increasing amount of resources per user. In this network environment, a mechanism called Call Admission Control (CAC) plays important roles in allocating the resources according to their availability. The CAC avoids network congestions partly by taking into account the network's QoS properties as well as the users' requirements in its process. Therefore, this process has to model network behaviors that contain a huge amount of uncertainty and imprecise properties. As a result, Boumella & Djouani (2010) claimed that fuzzy logic is the best solution to handle this kind of conditions. In the study, FT1 and FT2 implementations in the CAC were comparatively discussed. The results showed that both FT1 and FT2 implementations have managed to reduce congestion. However, FT2 provided better performance than FT1 regarding meeting users' expectations on QoS delivery.

Furthermore, Pangsub & Lekcharoen (2010) also discussed the issue related to network, i.e., traffic policy scheme to manage congestion. As the network behaviors become more and more complicated to be managed, this kind of traffic policy scheme should be able to adapt, hence ensure the delivery of the expected users' QoS. In the study, FT2 control was proposed due to its traits of having the abilities to handle uncertainties, especially in the environment of alternated burst and silence. The study compared the FT2, FT1 and conventional Leaky Bucket mechanisms. The results demonstrated that the FT2-based mechanism outperformed the others in the events of alternated burst and silence network conditions.

Parallel findings have also been found in the area of wireless mesh networks (WMNs). This study was conducted by Masri (2014), where a novel scheme for traffic regulation in WMNs was proposed. The scheme regulates the traffic by considering buffer evolution at routers and the traffic priority properties. The scheme hence can predict problems such as network congestion and the violation of QoS. The purposes of the scheme are to avoid congestion and to smooth out the real-time and interactive services of WMNs. In the study, the scheme was implemented using IT2 so that it could adapt to the uncertainty of the WMNs. The experiments showed that the proposed scheme produced a good performance in different network and traffic conditions.

In a different area of research, a recent study by Moharrer et al. (2015) proposed an IT2-based two-phase methodology to represent human perceptions. The perceptions describe users' satisfaction towards online services and are expressed using linguistic terms. The perceptions are expressed linguistically because humans naturally describe their feelings using words and expressions from natural language. It is also believed that through natural language, the perceptions are better communicated to people. However, this kind of linguistic-based perception is vague and imprecise. Different people may interpret the same term differently. Therefore, despite having an ability to deal with uncertainty and vagueness, FT1 is prone to performance degradation due to its crisp MFs. Hence, in the study, IT2- based implementation was proposed. The results showed that the proposed implementation yielded a good performance and exhibited reasonable interpretability.

A few other studies like Dereli et al. (2011) and Sepulveda et al. (2007) have also presented the superiority of FT2 implementation over FT1. Despite this advantage, FT2, however, has just gained its popularity recently, though it was introduced way back in 1975 (Zadeh, 1975). A question was raised: why didn't FT2 become popular immediately after its introduction? John & Coupland (2007) delved into this thoroughly and concluded that fuzzy logic has been receiving attention in research in a natural way. This means, more studies were initially conducted to understand the true benefits of FT1. To prematurely bypass the learning and research in FT1 is considered uncharacteristic. Only after a certain period, the research on FT2 implementation has been gradually carried out. The main factors are the fact that FT1 may have closely reached its maturity level as nowadays, there are more challenging problems involving a huge amount of vagueness and uncertainties which requires FT2 solutions.

This trend can be observed from the number of articles and proceedings according to the publication year. The number of published researches on FT2 recorded a significant increase from the year 2000 to 2015. For SCOPUS database, the number of publications increased 3560% in 15 years, from 10 publications (in 2000) to 366 publications (in 2015). A similar pattern is also evident in ISI database, where a steady upward trend was recorded from 2002 to 2015. A significant increase of 14250% occurred in 13 years, where two publications were recorded in 2002 while 287studies were published in 2015.

In summary, this subtopic discusses two important issues that formed the motivation behind this research. Firstly, the presented and discussed studies had shown the significant benefits of FT2 implementation over FT1. The main factor that promotes this fact is the ability of FT2 to handle vagueness and uncertainty better than FT1. Therefore, this subtopic covers one of the problems identified in this research, which is to determine the more accurate and precise way to perform complaint handling process. Secondly, this section also reveals that FT2 implementation has gained more popularity in the recent years. It is believed that two reasons support this upward trend of FT2-based researchers. The first reason is that the current research problems are facing more challenging problems especially in dealing with uncertainties and vagueness. One of the influencing factors is that more network resources and properties are available nowadays, which leads to more uncertainty. Another influencing factor is that more works are done to deal with human perceptions. This kind of problems involves a greater level of vagueness, requiring the introduction of FT2 implementation. The second reason is that research on FT1 has been conducted vastly in the last few decades. Although this may not have reached a saturated state yet, numerous researchers are now geared towards exploring the extended version of FT1 that offers more significant benefits, namely FT2. Hence, the research on fuzzy-based complaint handling process as proposed by this thesis will offer a significant contribution to the body of knowledge.

2.6 Related Works

This section discusses studies related to the research proposed by this thesis. These related works are collected through two different approaches, namely restrictive and unrestrictive search criteria.

In the restrictive search, only journal articles are selected for review. These articles are collected from the three main publication databases namely ISI, SCOPUS and Google Scholar. The main advantage of restrictive search is that it offers precise search results where only the previous works that are related to complaint management system and complaint handling process are collected and discussed. Two search keywords are used when searching in ISI and SCOPUS databases, which are "*complaint management system*" and "*complaint handling process*." Meanwhile, the same keywords are used in Google Scholar search. The search covers articles published in all years. The results of the search comprise a huge number of articles, of which not all of them are related to this research. In general, these collected articles could be divided into three broad categories namely complaint handling process, complaint management system and customer complaint framework which focus more on business domain. Only articles from the first and second category are chosen for review, which comprises a total of 23 journal articles.

Meanwhile, the unrestrictive search involves articles collection from the same three sources namely ISI, SCOPUS, and Google Scholar but with more relaxed search criteria. The main reason is to broaden up the search so that more related works could be identified. Four other search keywords are introduced, namely "*complaint*," "*customer complaint*," "*multi-criteria decision*" and "*fuzzy AND automated*." Furthermore, under this unrestrictive search, refereed articles from conference proceedings are also reviewed. Moreover, the related sources that are cited in the collected articles are also reviewed. The criterion of publication year remains the same which is for all years. As a result, 60 more articles are found, which can be divided into two categories, namely service monitoring, and service selection and composition. The subsequent paragraphs discuss some of these reviewed works.

Firstly, the work presented in Aguwa et al. (2017) developed a new approach for properly interpreting and analyzing the fuzzy voice of the customer using association rule learning and text mining. This unique methodology converts textual and qualitative data into a common quantitative format which is then used to develop a mapped Integrated Customer Satisfaction Index (ICSI). ICSI is a framework for measuring customer satisfaction. Previous measures of customer satisfaction ratio failed to incorporate the cost implications of resolving customer complaints/issues and the fuzzy impact of those complaints/issues on the system. In most of the studies, researchers used qualitative techniques and tried to use numerical data analysis since direct usage of the raw textual data to extract customers’ true opinions is a challenging task. Among the studies mentioned above, some of them focus on text mining which is an essential technique to interpret the customer requirements, due to the nature of VOC datasets which are mostly textual data. Moreover, since VOC reflects the customers’ feelings and feedbacks, interpreting ambiguous data to identify the customers’ true point is of high importance. This issue gives rise to the use of fuzzy logic to model these real-life datasets properly. The primary objective of this study is to provide an accurate interpretation of the customers’ dynamic textual and quantitative data by consolidating the data into a common crisp value using fuzzy logic. As well, as a feedback mining method, and then to develop a formula to achieve an Integrated Customer Satisfaction Index (ICSI) by considering warranty costs. However, the study did not focus on classifying and ranking the complaint based on priority as proposed by this thesis. Besides, the study did not consider the use of fundamental reference based on specific complaint domain. As well, the study does not focus on Malay language textual data.

Furthermore, there was a research conducted by Li et al. (2017) that proposed a hybrid approach based on fuzzy AHP and 2-tuple fuzzy linguistic method to evaluate in-flight service quality. The proposed approach provides significant benefit in term of better understand the passengers' preference and obtain their perception of service quality. This study is comprised of three stages. In the first stage, the study proposed the use of the modified version of SERVQUAL instrument and constructed a hierarchy of the evaluation index system for in-flight service quality. In the second stage, the study proposed the use of fuzzy AHP to analyze the structure of the in-flight service evaluation problem. Pairwise comparisons for evaluation criteria and sub-criteria are made to determine the weights of criteria and sub-criteria by using linguistic variables. In the third stage, the study assesses the ratings of sub-criteria in linguistic values to express the qualitative evaluation of passengers' subjective opinions, and transforms the linguistic values into 2-tuples and utilizes the 2-tuple linguistic arithmetic mean operator to obtain the average ratings of 100 respondents. Humans and preference judgments are often vague and cannot estimate their preference with an exact numerical value. Conventional measurement makes use of cardinal or ordinal scales to measure the quality of service; this scale used crisp number is difficult to represent the customer's preference. Hence, the fuzzy set theory is an appropriate method for dealing with uncertainty. However, the research is focused on evaluating in-flight service quality and did not focus on classifying and rank the complaint based on priority as proposed by this thesis.

Moreover, Yilmaz et al. (2016) explored the effects of two sets of factors relating to complaint management on firm performance, namely, (1) customer response factors and (2) organizational learning factors, thereby integrating organizational learning into the conceptualization of complaint management. Symmetric testing using hierarchical regression analysis of data obtained from complainants and firm managers revealed the joint effects of the two main paths on firm performance, independently from one another. Another distinctive nature of the study is that multiple source data are obtained and used in the analyses, both from firms in the sample and from their complaining customers. An online complaint website provided data regarding real complainants' fairness perceptions of the complaint handling processes of respective firms and their after complaint loyalty. In addition, multiple correspondents from the firms in the sample provided data regarding the complaint handling approaches, fairness perceptions of complaint handling practices, learning, and immediate and long-term performance assessments of firms. To identify and explore these causal recipes, the study proposed the use of fuzzy set comparative qualitative analyses using the fsQCA software. This study is different from the research proposed by this thesis as they aimed at the effects of two sets of factors relating to complaint management on firm performance.

Next, Dasgupta et al. (2016) indicated that automatic multi-label classification of customer complaints is becoming critical for online customer service solutions and electronic customer relationship management systems. This study focused towards the analysis and classification of customer complaint logs related to the telecommunication domain. Most of the existing approaches have treated the problem as a crisp and single-label classification task. This study also observed that most of the customer complaints belong to multiple domains. Thus, it becomes important to device a fuzzy multi-label classification framework for such a task. Therefore, the study proposed the use of fuzzy KNN classification technique to classify customer complaint logs into their respective problem domain. The study annotated the collected dataset through a fuzzy multi-label annotation framework and explored different feature sets. However, the study did not focus on classifying and rank the complaint based on priority as proposed by this thesis. Besides, the study did not consider the use of fundamental reference based on specific complaint domain. As well, the study does not focus on Malay language textual data.

Similarly, Faed et al. (2014) analyzed the relationships between the main components of customer relationship management (CRM) and customer complaints in the domain of logistics and transport. This research indicated that companies are reluctant to admit that they have difficulties with customers' complaints, but as yet there appears to be no complete solution to this issue. Customer complaints must be comprehensively collected and analyzed to remedy this situation. Issues must be classified, and timely solutions must be developed. The framework will address the relationship between customer satisfaction issues, loyalty, and customer acquisition and estimate customer satisfaction and loyalty. Thus, the research defined fuzzy rules, using which we ascertain the relationship between customer satisfaction and the main relevant variables based on nonlinear modeling and using a fuzzy inference system, namely the Takagi–Sugeno-type approach.

Again in 2016, Faed et al. (2016) investigated and developed various techniques to address customer complaints. Although many frameworks and approaches have been proposed to evaluate and address customer complaints, most of the research work fails to address the fact that companies today are facing an immeasurable quantity of complaints, and due to customers' high expectations, companies cannot effectively address the complaints. Issues related to complaint management system:

1) Since many issues emerge every day within work environments, more operators and experts must be recruited by companies to solve customer problems. In none of the studies in the literature have authors provided a solution to prevent negative feedback from customers.
2) Hypotheses are analyzed using descriptive and qualitative methods, whereas the use of quantitative data would yield more precise results.
3) No innovative approach has been proposed for the evaluation and measurement of customer satisfaction and customer complaints.

4) The CRM and complaint management systems (CMS) literature fail to provide a framework and a complete methodology to deal with all types of customer complaints tailored to all types of companies.

The research stated that customer relationship management (CRM) is an exclusive strategy and a business paradigm that assists companies to improve the customers' perception of value. An effective CRM can meet customer expectations. However, the research identified that there had been no CRM system and strategy available that can assist in surpassing customer expectations. Hence, this research categorized and analyzed the data gathered from drivers at the port who are considered to be the customers through an interview and questionnaire. The two studies are different from the research proposed by this thesis as they aimed at analysis for the relationships between the main components of customer relationship management (CRM) and customer complaints in the domain of logistics and transport. While the study proposed by this thesis is focusing on classifying and rank the complaint based on priority by referring to specific complaint domains.

Furthermore, a study in healthcare domain aimed to evaluate causal effects of different healthcare quality aspects of quality of services perceived by patients in hospitals. Several methods have been proposed to measure the quality of health services which often face uncertainty. Therefore, Khanjankhani et al. (2016) proposed the use of multiple criteria decision-making models (MCDM) and fuzzy theories to overcome such ambiguities due to human judgments. Furthermore, this study proposed the use of DEMATEL technique and TOPSIS method to evaluate hospital services' quality. However, the study did not focus on classifying and rank the complaint based on priority as proposed by this thesis. Besides, the study did not consider the use of fundamental reference based on specific complaint domain. As well, the study does not focus on Malay language textual data.

Another study related with a customer complaint, Shahin et al. (2015) proposed an integrative approach of failure modes and effects analysis (FMEA) and technique for order preference by similarity to ideal solution (TOPSIS) for prioritizing electronic customer complaints. This study tried to propose an integrated approach for analyzing and improving complaints of customers of Isfahan Province Gas Company, respectively by starting the process and calculating the data related to modes of customers dissatisfaction and failures causes were complaints and using FMEA and TOPSIS techniques, the investigated and prioritized. Data were collected and classified. After forming the team of experts, the FMEA forms were filled, and required data for using in TOPSIS technique was extracted from them. As it was observed, the results obtained by two techniques were different. TOPSIS technique, because of considering numbers weight, and because organizational experts determined this weight, can be more effective in analyzing and improving customers' complaints. Then, to improve organizational activities continuously and forever, and to prevent failure creation and consequently customers dissatisfaction and complaints, updating FMEA and determining higher priority for improvement by TOPSIS technique, were performed. Findings imply that lack of meter reading and lack of issuance and delay in sending bill are the highest ranked complaints. However, the study did not focus on classifying the complaint based on priority as proposed by this thesis. Furthermore, the study did not consider the use of fundamental reference based on specific complaint domain. Moreover, the study does not focus on Malay language textual data.

Additionally, the research on complaint handling using the different method introduced by Lee et al. (2015). This study developed an informative and intelligent complaint handling system that applied the concept of customer complaint ontology serves as an interoperable knowledge representation. The approach, used to calculate case similarity for case retrieval, is also developed and empirically evaluated in the Intelligent and interoperable handling system for customer complaints (i-CCH) platform. Handling complaints successfully can resolve crises and help maintain customer loyalty. Hence, from a customer relationship management (CRM) perspective, it is well worth collecting and analyzing complaint-related knowledge. Constructing ontology of customer complaints is the first crucial step in CRM. However, the system proposed by the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. Furthermore, the study also did not consider fuzzy logic technique in their proposed system.

Furthermore, Pyon et al. (2011) stated in the financial service industry, service improvement should be considered from process viewpoint and customer viewpoint, because the value creation is ultimately linked with internal business processes on the back office and customers, are involved as a co-producer of value. In this perspective, customer complaints through call centers are adequate to support the analysis of service improvement in the financial service industry. In this study, the authors proposed a web-based decision support system for business process management employing customer complaints, namely Voice of the Customer (VOC), and it is handling data for service improvement. It involves VOC conversion for data enrichment and includes analysis of summarization, exception, and comparison. For the service improvement, it should be considered not only performance data for each business process but also non-measurable contents such as customer responses. In this VOC conversion and analysis, the study employed traditional concepts of quality management. The study identified the characteristics of VOC by applying Failure Modes and Effect Analysis (FMEA) to differentiate the necessity or urgency of process improvement. However, this study did not consider uncertainties, which differs from the aims of the research presented in this thesis. Besides, the study also did not propose the employment of fuzzy logic in their proposed system.

In addition, Chen and Chieh (2011) proposed the theory of reasoned action (TRA) and the theory of planned behavior (TPB) to predict which factors can determine consumers' intentions to complain when they meet an online or offline service failure. The findings of the study will help marketers to address the key factor which influences consumers' intention to the complaint and to improve firm performances to meet consumer needs. However, the study did not focus on classifying and ranking the complaint based on priority as proposed by this thesis. Furthermore, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not consider fuzzy logic technique in their proposed method.

Similarly, this study presented a concept learning approach to relate a human behavior pattern to classes (Galitsky & Rosa, 2011). The study used a representation language of labeled directed acyclic graph labels with vertices for communicative actions and arcs for temporal relations, causal links and attack relations on them. For machine learning, the scenarios are represented as a sequence of communicative actions attached to agents; the communicative actions are grouped by subjects, and the order of communicative actions is retained using binary predicates after. The study also considered the concept lattice of communicative actions and showed how Nearest Neighbor and JSM learning machinery could implement the procedure of relating a complaint to a class. This study applied concept learning techniques to solve some problems in the customer relationship management (CRM) domain. The study presented a concept learning technique to tackle common scenarios of interaction between conflicting human agents (such as customers and customer support representatives). However, the study did not focus on classifying and ranking the complaint based on priority as proposed by this thesis. Furthermore, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not consider fuzzy logic technique in their proposed method.

Moreover, Park and Lee (2011) presented a framework for extracting customer opinions from websites and transforming them into product specification data. The suggested framework enables to incorporate customer opinions efficiently with new product development processes and to design online customer centers to collect better and analyze useful information. This study also did not focus on classifying and ranking the complaint based on priority as proposed by this thesis. Furthermore, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not consider fuzzy logic technique in their proposed method.

In the research conducted by Homburg et al. (2010) stated that the large investments required for high-quality complaint handling design, managers need practical guidance in understanding its actual importance for their particular company. However, while prior research emphasizes the general relevance of complaint handling design, it fails to provide a more differentiated perspective on this interesting issue. This study, which is based on an integrative multi-level framework and a dyadic dataset, addresses this important gap in research. Results indicate that the impact of a company's complaint handling design varies significantly depending on the characteristics of the complaining customers with which the firm has to deal. Further, this paper shows that contingent on these characteristics, a company's complaint handling design can shape complainants' fairness perceptions either considerably or only slightly. This study did not have an emphasis on classifying and ranked the complaint based on priority as proposed by this thesis. Additionally, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not propose the employment of fuzzy logic in their proposed method.

Furthermore, Trappey et al. (2010) indicated that an effective and efficient response to the complaints from the customer is an essential indicator of a service-oriented company's performance, especially for a high-end restaurant chain group. This study overcomes the deficient approach of current (as-is) complaint handling through process re-engineering. Due to that this study developed and analyzed a (to-be) framework of complaint handling system for a Japanese restaurant chain. In the first phase, the study depicted the as-is complaint reporting process. In the second phase, the to-be complaint handling model and its process are defined using a formal integrated process modeling (INCOME) approach. The new framework includes complaint reporting, compensation diagnosis, and complaint analysis. Furthermore, this paper also discusses the decision supports of complaint resolution automatically by the system and its benefit comparing to the current practices. On the other hand, this research did not highlight specifically on classify and ranking the complaint based on specific complaint domain as proposed by this thesis. Moreover, the study did not examine the uncertainties issue in the customer complaint, which differs from the aims of the research presented in this thesis. The study also did not consider the employment of fuzzy logic in the complaint handling model.

Similarly, Latifah et al. (2010) examined complaints management of Open University of Malaysia (OUM) about accessibility and responsiveness. The study is carried out using a survey method utilizing questionnaires of 12 items grouped into two dimensions namely accessibility and responsiveness, involving 100 OUM staff as respondents. The findings suggest that there is a low level of accessibility and responsiveness in OUM's complaints management system. This implies that there is a need to have in place easily accessible and well-publicized mechanisms for resolving complaints. In addition, a responsive complaints management system should allow staff to handle complaints quickly and should include established time limits for action that reflect the complexity of the problems. This study did not focus on classifying and ranking the complaint based on specific complaint domain as proposed by this thesis. Moreover, the study did not examine the uncertainties issue and also did not consider the use of fuzzy logic in the study.

Additionally, Najar et al. (2010) tried to improve the relation between citizens and government by presenting a new model based on Service Oriented Architecture (SOA). The study indicated that governments' complaint handling websites do not encourage citizens to submit their complaints online as users were confused in interacting with different departments' websites to make a simple complaint. The researcher explored that in traditional complaint systems, a variety of complaints types in governments' sector is the most important barrier for implementing of complaint system based on Service Oriented Architecture (SOA).With utilizing the presented model in government body, on one hand, citizens' governments will have the ability to minimize dissatisfaction, and on the other hand, it can encourage citizens as controlling government body such to participate in governments' staffs and organizations. Results of this study can be a good reference to find out users' needs from e-complaint and the importance of complaint in the body of government. However, this study did not discuss specifics on classifying and ranked the complaint based on specific complaint domain as proposed by this thesis. In addition, the study did not examine the uncertainties issue and also did not consider the employment of fuzzy logic theory in the proposed model.

Furthermore, Bidgoli and Akhondzadeh (2010) presented a new approach to using data mining tools for customer complaint management. The study applied the association rule mining technique to discover the relationship between different groups of citizens and different kinds of complainers. Analyzing these rules, make it possible for the municipality managers to find out the causes of complaints, so, it leads to facilitate engineering changes accordingly. The idea of contrast identifies the attributes of association rules are also applied characterizing patterns of complaints occurrence among various groups of citizens. The results would enable the municipality to optimize its services. Again, this study did not seem interested in classifying and ranked the complaint based on specific complaint domain as proposed by this thesis. Besides, the study did not examine the uncertainties issue and also did not consider the employment of fuzzy logic theory in the proposed model.

Moreover, Galitsky et al. (2009) stated that automating customer complaints processing is a major issue in the context of knowledge management technologies for most companies nowadays. Automated decision-support systems are important for complaint processing, integrating human experience in understanding complaints and the application of machine learning techniques. In this context, a major challenge in complaint processing involves assessing the validity of a customer complaint by the emerging dialogue between a customer and a company representative. This study presented a novel approach for modeling and classifying complaint scenarios associated with customer-company dialogues. Such dialogues are formalized as labeled graphs, in which both company and customer interactions through communicative actions, providing arguments that support their points. However, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not propose the employment of fuzzy logic in their proposed approach. Moreover, the study did not reflect the use of fundamental reference based on specific complaint domain. As well, the study does not focus on Malay language textual data.

Similarly, Coussement and Poel (2008) introduced a methodology to improve complaint-handling strategies through an automatic email-classification system that distinguishes complaints from non-complaints. As such, complaint handling becomes less time-consuming and more successful. The classification system combines traditional text information with new information about the linguistic style of an email. The empirical results show that adding linguistic style information into a classification model with conventional text-classification variables results in a significant increase in predictive performance. In addition, this study reveals linguistic style differences between complaint emails and others. However, the study did not examine the uncertainties issue, which differs from the aims of the research presented in this thesis. Additionally, the study did not propose the use of fuzzy logic theory in their proposed approach. Moreover, the study did not reflect the use of fundamental reference based on specific complaint domain. As well, the study does not focus on Malay language textual data.

Likewise, Sultan et al. (2008) stated that Complaint Management System is a system to enable customers to channel the issues about the organization for immediate action. Thus, responsive complaint system is essential for the organization to ensure customers satisfaction in managing complaints. This study introduced the agent-based Complaint Management System (ACM). The objective of the system has autonomously accepted the complaints and forward to the respective responsibility. Initial result shows the system can entertain users complaint with minimal intervention by a human. Keyword recognition was proposed as an intelligent element for the system. Future efforts are looking for a complete agent-based complaint management system with more intelligent features. However, the study did not consider uncertainties, which differs from the aims of the research presented in this thesis. The study also did not propose the employment of fuzzy logic in their proposed approach. Moreover, the study did not reflect the use of fundamental reference based on specific complaint domain.

Overall, it can be summarized that the search for related works has gone through two phases. Firstly, the usages of restrictive search, where the set criteria are limited and narrow. Secondly, unrestrictive search, where the criteria used in the exploration process are broadened up. The restrictive and unrestrictive searches involved the review of 23 and 60 publications respectively. This review of 83 publications reveals that there has been no similar research presented thus far. Table 2.2 summarizes some of these reviewed works based on the collected publications.

Table 2.2: The Reviewed Articles on Related Works

No.	Article	Ranking complaint?	Fuzzy implementation?	Fundamental reference?	IT2 implementation?
1	Aguwa et al. (2017)	No	Yes	No	No
2	Li et al. (2017)	No	Yes	No	No
3	Yilmaz et al. (2016)	No	Yes	No	No
4	Dasgupta et al. (2016)	No	Yes	No	No
5	Faed et al. (2014)	No	Yes	No	No
6	Faed et al. (2016)	No	Yes	No	No
7	Khanjankhani et al. (2016)	No	Yes	No	No
8	Shahin et al. (2015)	No	Yes	No	No
9	Lee et al. (2015)	Yes	Yes	No	No
10	Pyon et al. (2011)	Yes	No	No	No
11	Chen and Chieh (2011)	No	No	No	No
12	(Galitsky & Rosa, 2011)	No	No	No	No

No.	Article	Ranking complaint?	Fuzzy implementation?	Fundamental reference?	IT2 implementation?
13	Park and Lee (2011)	No	No	No	No
14	Homburg et al. (2010)	No	No	No	No
15	Trappey et al. (2010)	No	No	No	No
16	Latifah et al. (2010)	No	No	No	No
17	Najar et al. (2010)	No	No	No	No
18	Bidgoli and Akhondzadeh (2010)	No	No	No	No
19	Galitsky et al. (2009)	Yes	No	No	No
20	Coussement and Poel (2008)	Yes	No	No	No
21	Sultan et al. (2008)	Yes	No	No	No

This study identified research gaps based on all of these collected related works, comprising three important areas. Firstly, the study focus on the ability to handle linguistic values-based in the complaint handling process due to the customer perceptions and the opinions towards certain issues related to the complaint. This is because complaint handling process that comprises of an input from the customers which based on perceptions and wording involve high level of uncertainties (Dereli et al., 2010; Dongrui & Mendel, 2007). Most of the above related works implement crisp-based requirements, which have been proven to not having tolerance to handle uncertainties. The crisp-based requirements are related with the process to extract the specific keyword from the textual data (complaint dataset). The previous method works used exact numeric values as reference to the keyword. The crisp-based requirement cannot interpret correctly the customer perceptions and wordings. Hence, it will affect the complaint handling process regarding accuracy and precision. The potential reasons crisp-based requirements specification has become the option of many researchers because its simplicity, non-complicated algorithm as well as fast computation. However, it is argued that in complaint management system, the accuracy and precision are crucial parameters and used for classifying and ranking the customer complaint, properly handling customer complaint and improving services provided to the customer. Therefore, the linguistic value-based requirements can fulfilled the purpose for complaint handling process as proposed in this thesis.

Furthermore, the task to identify complaint's characteristic need the involvement of experts. The experts' participation is important to make sure the characteristics selection based on valid experience and knowledge of the people that directly involve with the complaint handling process. Even though part of the previous study involving experts to the needs criteria for the existing method but the process to establish the criteria or characteristics weightage is depend on the crisp-based method. Hence, the identified criteria's weightage will affect the accuracy of the complaint final results. As well, the involvement of the number of experts to identify proper characteristic based on expertise and opinions also cause a high level of uncertainties (Dereli et al., 2010; Dongrui & Mendel, 2007). On the other hand, these issues can solve with applying fuzzy logic approach to fulfill the research gap.

Moreover, the next research gap that can identify from the previous study is regarding the usage of the fundamental reference. As mentioned earlier in the previous chapter, the fundamental reference contains specific information that used to extract related characteristics or criteria from the textual dataset. The related works showed that existing approach is not use the fundamental reference. Hence, this will affect the performance of the complaint handling process and the accuracy of the complaint final results. However, this issue can solve by establish the fundamental reference to contain information of complaint characteristics and accurate weightage value with the helped from the experts. Additionally, the fundamental reference will have identified characteristics based on specific domains.

Secondly, most of the reviewed related works also implemented the crisp method in complaint handling process. This crisp method has a less ability to handle uncertainties as compared to FT1 and IT2 methods. Also, the fuzzy methods contain extra degrees of freedom to tolerate the uncertainties values. As discussed above, the crisp method has become the method of choice because it is less complicated, simple and offers fast computational time. However, the accuracy and precision of complaint handling results are degraded, due to the behavior of crisp method that performs monitoring using hard computation. Thirdly, the reviewed related works also found that FT2 or IT2 can outperform the crisp solutions regarding accuracy and persistence. The proposed approach will offer significant improvements to complaint handling process.

Overall, this section of related works identifies the research gaps in the complaint handling process. This research fills in the research gaps by proposing to establish the fundamental reference based on specific complaint domain. The process is involving experts who have experience and knowledge related to complaint handling process. Furthermore, linguistic value-based requirements will be used for the experts for characteristics selection and rating process. Next, the identified rating from the experts will be consolidated using Fuzzy Delphi Method to produce the final characteristics weightage for the fundamental reference. Moreover, this study propose to use fuzzy logic approach (FT1 and IT2) for solving the uncertainties issue. Besides, the research involved the use of Malay language textual dataset which give a good opportunity for contributing to the body of knowledge because the existing research in complaint handling process, fuzzy approach never being used to define the ranking function for the Malay language (Rodzman et al., 2017). This concludes that the proposed research will provide significant findings and contributions to the body of knowledge. Refer to Table 2.3 for the summary and mapping between research gaps and research objectives of this study.

Table 2.3: Mapping of Research Gaps and Research Objectives

Research Gaps	Research Objectives
1) Fundamental reference is not used for characteristic extraction from textual dataset. 2) Using crisp-based requirements by implement exact numeric number for criteria / characteristic. 3) Inputs from experts are consolidating using crisp-based method. 4) Complaint textual dataset is not Malay language.	1) To derive fundamental reference for classifying and ranking complaints by creating complaint specification references in the Malay language using Fuzzy Delphi Method (FDM).
5) Using crisp-based method in complaint handling process which not appropriate to handle uncertainties issue.	2) To develop an approach for constructing fuzzy type-1 (FT1) and interval type-2 fuzzy (IT2) membership functions and rules based on real complaint data. 3) To design a fuzzy inference system (FIS) model based on the expert's input.
6) To proof the concept of complaint handling and ranking process using fuzzy logic as proposed in this thesis.	4) To experiment and evaluate the performance of the proposed models against the human-generated benchmark.

2.7 Fuzzy Limitation

Fuzzy logic systems have achieved dramatic success in practice. The main advantage of a fuzzy logic approach is that fuzzy logic approaches are non-linear and can approximate complex dynamical systems. However, fuzzy logic systems are not the most appropriate choice inaccurate computing. There are limitations in fuzzy logic systems as follows:

Memberships transformations: technologies of partitioning the universe of discourse in fuzzy logic systems have become very complicated to achieve more accurate results. In general cases, the more parameters and intervals identified, the more accuracy can be achieved. However, too many intervals could result in the fewer fluctuations in the process modeling and complicate the defuzzification process (Jana et al., 2017; Y. Wang, 2016; T. Wu, Liu, & Qin, 2018).

IF-THEN Rules: in a fuzzy logic system, the IF-THEN rules are determined by experts' knowledge or learned from historical data. In data-intensive application, to improve accuracy in modeling, too many rules are required to be implemented at once in a fuzzy logic system; sometimes this is not possible in practice. Due to practical data being uncertain with noise, dramatically numerous unnecessary fuzzy logical relationships will emerge from sudden changes (anomalies) and transient variation in data that may trigger irrelevant rules. With data-intensive applications, it is very difficult to resolve the conflict between partitioned fuzzy sets, high computational cost and high computational complexity (Almaraashi et al., 2016; Baykasoğlu & Gölcük, 2017; D'Urso, 2017; Majeed et al., 2018; Salaken et al., 2017; Sharifian et al., 2018; Wang, 2016).

Approximate reasoning: the reasoning of fuzzy logic systems is approximate reasoning, which is different from statistical models. For example, the reasoning in arithmetic is exact and accurate. According to the fixed inputs given, the outputs of an arithmetical model are unique (Wang, 2016). In addition, using interval type-2 FL with IF-THEN rules has an important limitation related to the computational cost demanded by the defuzzification operation, mainly considering the large number of data in typical clustering and classification problems (Bobillo & Straccia, 2017; Comas et al., 2017).

Basically, all above highlighted limitation in fuzzy approach can control by identify appropriate number of parameters. Research that need to use fuzzy approach has to select only important parameters to make sure the fuzzy approach can work at optimum level. There are related studies that using fuzzy approach with right number of parameter which produce good result and success in their study. Firstly, Gupta et al. (2018) proposed a novel hybrid model for forecasting low dimensional numerical data which is named as ClusFuDE. The proposed method uses an improved automatic clustering approach for clustering the historical numerical data. Furthermore, this study used two parameters as the control parameter and the research findings showed that the proposed method outperforms all the existing methods in the literature.

Secondly, Abaei et al. (2018) developed a fuzzy logic expert system for predicting the fault proneness of software modules. This study used six parameters to achieve optimal prediction result. The final results of this study showing improvement result to compare with the existing method. Furthermore, Tarasyev (2018) analyzed a set of economic factors that related with decision on educational path for students. This study applied four parameters to estimate the possibility of the students on optimizing the decision making process on personal education path. Moreover, Tomar et al. (2018) developed an intelligent system to decide the route preference based on real time traffic information. This study used the combination of logistic regression with fuzzy logic approach to compute the possibility path. The proposed method use five parameters for the decision making process. Also, Phoemphon (2018) investigated a method that uses soft computing approaches in a hybrid model for improving a traditional range-free-based localization method (centroid). This method integrates an extreme learning machine (ELM) optimization technique and uses fuzzy logic system into centroid with four parameters to produce an outstanding result.

In summary, the understanding of fuzzy approach is a must before researcher decided to choose fuzzy approach as a method for solving their issues. From a few previous works proved that with proper number of parameters used for fuzzy approach, the result will be outstanding.

2.8 Fuzzy Delphi Method

Delphi method is an iterative method used to survey and collect most reliable consensus of a group of experts on a particular subject (Dalkey & Helmer, 1963). This method was originally developed in the 50s by the RAND Corporation in Santa Monica, California. It has been widely applied in various areas such as project planning, needs assessment, public policy analysis, and health research. The main advantage of the Delphi is subject anonymity which can effectively reduce the influences of dominant views which often is a concern when using group-based processes to gather and synthesize information (Dalkey & Rourke, 1971). Furthermore, the issue of confidentiality is enhanced by the geographic dispersion of the participants and the use of electronic communication such as email to solicit and exchange information. As such, certain shortcomings associated with group dynamics such as manipulation or pressure to conform or adopt a certain viewpoint can be minimized.

Despite its advantage, the Delphi method has also been criticized for several issues. One of the issues is that the survey procedure would often need to be repeated several times until the acceptable result is reached. Furthermore, experts sometimes are required to modify their opinions to meet the mean value of all the experts' opinions. Thus, it can be difficult to maintain the active participation by experts, the whole way through and so the response rate may be lower than the one of meetings (Kardaras et al., 2013; Kardaras et al., 2013). The multiple feedback processes also might result in other difficulties such as misinterpretation of the experts' opinions due to the failure to take fuzziness into account (Bouzon et al., 2016) and high expenses of the capital and time to collect the opinions (Chao et al., 2017; Kannan, 2018). Additionally, the traditional Delphi method has obvious weaknesses, including its subjectivity and time-consuming features.

In order to overcome the above limitations, to properly capture the vagueness, uncertainty, and imprecise nature that often exist in experts' subjective opinions and to increase the efficiency of the conventional Delphi method, a fuzzy set theory proposed by Zadeh (1965) has been integrated along with the traditional Delphi technique (Kannan, 2018). In the fuzzy Delphi method, the experts' judgments are represented by fuzzy numbers. Then, the subjective opinions are transformed into objective data through a fuzzy operation. Compared with the traditional method, Zhang (2017) identified the main advantages of the fuzzy Delphi method include: (a) the fuzzy Delphi method comprehensively considers the uncertainty and ambiguity of the experts' subjective thinking, so that each expert's opinion can be fully reflected in the decision. Thus, the results obtained are objective and reasonable. (b) Obtaining the final decision through only one round of a survey avoids the several rounds of survey employed in the traditional Delphi method. Thus, the research time and costs are reduced. Table 2.4 summarizes comparison of the traditional Delphi and the fuzzy Delphi methods as explained above.

Table 2.4: Comparison of the Traditional Delphi and the Fuzzy Delphi Methods

Different Characteristics	Traditional Delphi	The Fuzzy Delphi Method
Number of rounds (Ouyang & Guo, 2017; Wang & Yeo, 2016)	Usually more than two rounds	One round
Mode of interaction type of question (Tseng, 2017; Wang & Yeo, 2016)	Could be semi-structured question	Must be structured question
Time and cost consumption (Mahjouri et al., 2017)	High possibilities	Low possibilities
Decline in response rate (Wang & Yeo, 2016)	High possibilities	Low possibilities
Achievable of stability or consensus result (Bouzon et al., 2016; Hsu et al., 2017)	Easy	Easier

The most representative of which is the fuzzy Delphi method developed by Murray et al. (1985). The fuzzy Delphi method integrated the traditional Delphi Method with a fuzzy theory to improve the vagueness of the method. A fuzzy set $\tilde{A}$ in the universe of discourse X is characterized by the membership function $\mu_A \sim (x)$ that assigns to each element x in X a real number in the interval [0, 1]. The numerical value of $\mu_A \sim (x)$ represents the membership grade of x in $\tilde{A}$.

Basically, the triangular fuzzy number (TFN) is based on a three value judgment: the minimum possible value l_1, the mean possible value m_2, and the maximum possible value u_3. These values depend on the linguistic preferences. Assume that the significance value of a number of j elements given by a number of i experts is

$\tilde{x} = (l_{ij},\ m_{ij},\ u_{ij})$, then I = 1, 2, 3, …n and j = 1, 2, 3, …m. The weighting $\widetilde{a_J}$ of *j* elements is $\widetilde{x_J} = (l_j,\ m_j,\ u_j)$, wherein $\widetilde{l_J} = min\{l_{ij}\}, m_j = \frac{1}{n}\sum_1^n m_{ij}$ and $u_j = \min\{u_{ij}\}$. The definite value $\widetilde{R_J}$ is obtained using the simple center of gravity method to defuzzify the fuzzy weight $\widetilde{x_J}$.. The proper criteria can be screened from numerous criteria by setting the threshold. The principles of screening are described as follows: If $\widetilde{R_J} \geq \alpha$, the *j* criterion is accepted for the evaluation criteria; if $\widetilde{R_J} < \alpha$, then the criterion not accepted (Tseng & Bui, 2017; Tseng et al., 2018; Tseng et al., 2018).

2.9 Summary

Firstly, this chapter justified that the problems identified in this research are significant to be studied. The reviewed literature showed that complaint handling process gains noteworthy benefits by allowing the process to define complaint specification requirements using linguistic values vaguely. Other than that, this chapter also revealed that crisp technique is less capable of handling uncertainties than fuzzy logic. This issue of handling the effects of uncertainties is one of the problems identified in this research. Secondly, this chapter summarized and evaluated past research. The aim is to find similarities and differences in this previous research. The discussions in this chapter showed that the research gaps do exist and the proposed research carries significance in filling these gaps. Thirdly, this chapter also discussed the methods of the research as well as the implementation of the proposed complaint handling process. The objective of these reviews and discussions is to place the proposed research into its context. The discussions involved the complaint management system, selection of intelligent soft computing method, handling uncertain information with Fuzzy Logic, comparison between FT1 and IT2, related works with complaint handling process, fuzzy limitation and Fuzzy Delphi Method.

CHAPTER 3

METHODOLOGY

This chapter begins with overviews and discussion general steps of experimentations using Fuzzy Logic approach. Next, Section 3.2 gives a general view of the conventional model. Then, Section 3.3 explained a general information on the proposed method process. Next, the chapter continues with Section 3.4 for the details process of the proposed method. This section starts with Subsection 3.4.1. which explained the extraction of the complaint dataset. Then, the section followed by Subsection 3.4.2 which covers the second step of the model that is the selection of the experts. Next, Subsection 3.4.3 described the details process to form complaint specification references for the third step. The forth step is to determine the fuzzy rules for complaint classification and ranking in Subsection 3.4.4. Subsection 3.4.5 discusses the complaint weighted characteristics calculation. Then, complaint scoring and classification are discussed in Subsection 3.4.6. Section 3.5 discusses the design and development of FIS models. The evaluation method of IT2FM is mentioned in Section 3.6. Finally, Section 3.7 concludes the methodology, development, and implementation of IT2FM.

3.1 Overview of the Research Phase

This research is carried out based on experimental research approach, which aims at formulating Interval Type-2 Fuzzy Model (IT2FM) for complaint handling process. The research methodology consists of 6 phases that include literature review, the study of the ranking method using fuzzy approach, data collection, the formation of complaint specification references, development of classifying and ranking algorithm and performance measurements and validation and analysis of findings. This is summarized in Figure 3.1.

The study started with the literature review phase, which involves the investigation of existing and past research through critical evaluation of books, articles, proceedings, research reports and other academic resources. This investigation comprised of understanding on the current issues in linguistic values-based requirements specification, method selection, handling uncertainties with the fuzzy method, the comparison between FT1 and IT2 approach, related works, and complaint handling process as well as their system architecture. The objectives of this investigation are to identify research gaps and existing problems in the previous research. The reviews are summarized and presented appropriately so that the contributions of this research can be highlighted. The results from this literature review phase are the identified problems and research gaps, as well as the proposed methods, which have been described in Chapter 1 and 2 of this thesis.

Next phase, to investigate the capabilities of fuzzy approach in classifying and ranking Malay wording based on specific complaint domain. The outcome of this phase is the appropriate method for classifying and ranking complaint using Malay word based on specific domain with the involvement of a group of experts. The details of this phase are presented in Chapter 3 of this thesis.

The next phase involves conducting data collection which involves real complaint data from customer complaint management system (CCMS) of local government in Kuala Lumpur. A specific range of date and domains are identified for the extraction purposes. The details of this phase are explained in Chapter 3 of this thesis.

The following phase is to form complaint specification references. This exercise involves a group of experts that will help to extract suitable characteristic from the complaint data. The result of this phase is the complaint specification references which also known as fundamental references. All details of this phase are presented in Chapter 3 of this thesis.

Then, the development of classification and ranking model comprises of few tasks and part of the process involves the experts. The task is to investigate on how to create FT1 and IT2 membership function based on real complaint data with feedback from the experts. Next, the study continues to establish fuzzy rules on classifying and ranking the complaint. Once the specific requirement is identified, the following task is to establish a complete working model to handle the complaint handling process from data extraction until the final outcome. This phase represents the second and third objectives of the thesis and details are explained in Chapter 3 of this thesis.

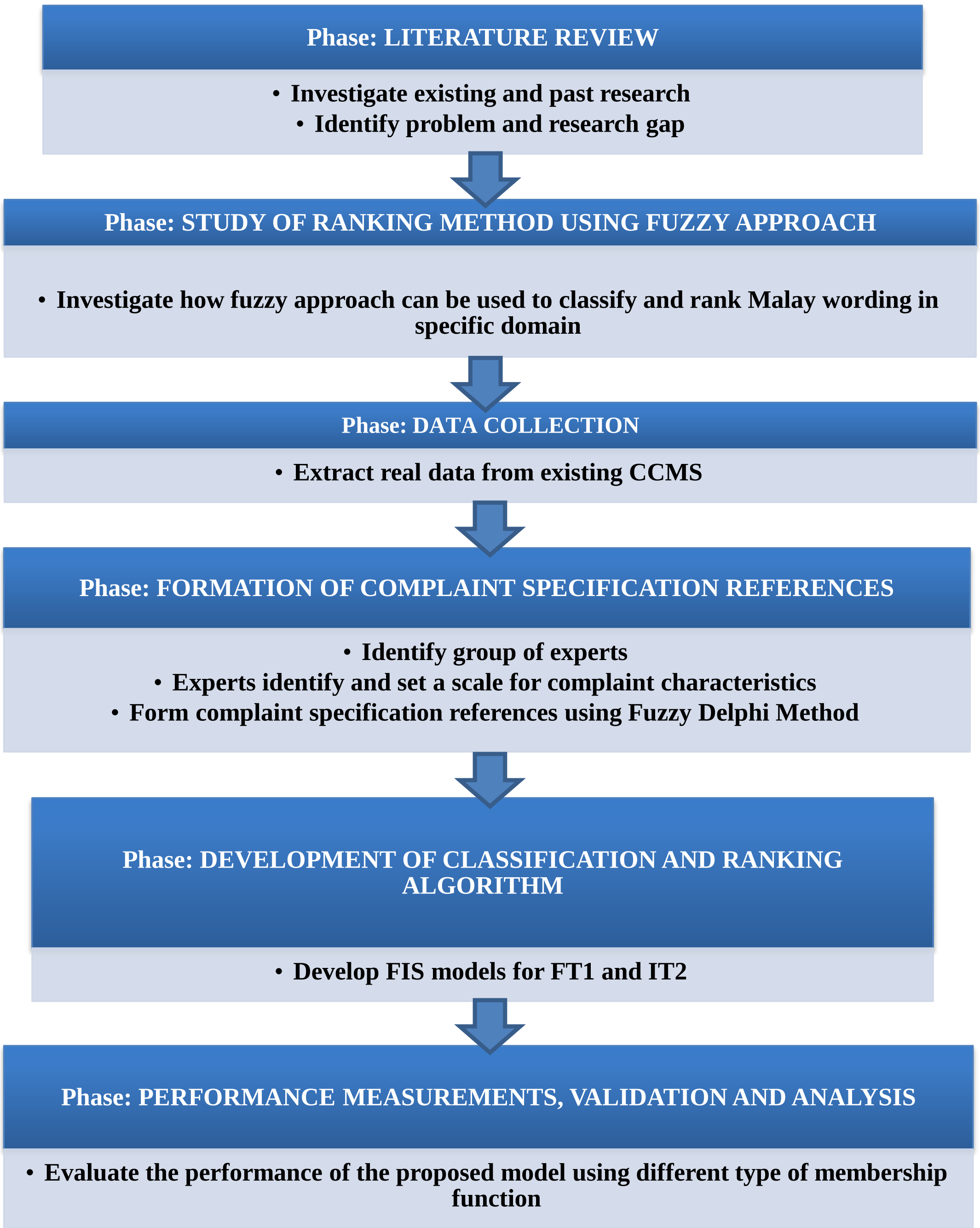

Figure 3.1: Research Methodology

Performance measurements, validation, and analysis of the model and approach constructed in the prior phases are explained in this phase. This phase involves some testing where the proposed method is evaluated through a comparative study with experts' human benchmark result and conventional complaint handling model result. The experimental setups, the detail explanation of the activities involved and the findings of these testing are analyzed and presented in Chapter 4 of this thesis.

3.2 Conventional Complaint Handling Model

The proposed study is trying to improve the existing complaint handling model. The existing model introduced by Doctor et al. (2008, 2009a, 2009b) using neuro fuzzy, FT1 and IT2 approach. Firstly, the conventional model starts with the extraction of the customer complaint data. Then, the author identified numbers of experts who have related knowledge and experience in handling the customer complaint to involve with the next process. Next, the experts are selected specific characteristic based on the customer complaint data and identified the category for each selected characteristic referring to the important scale. After that the experts will continue to rate each selected characteristic based on predefined scale. Once the experts' tasks are complete, each characteristic value from the experts calculated to get the average value for the characteristic. This value is used as the reference value for the selected characteristic. Next, these characteristics value are used to produce the fuzzy rules.

Then, using the same customer complaint data, complaint characteristic value is extracted and evaluated based on identified characteristic value on the previous process. All identified characteristic value identified from each customer complaint is calculated and aggregated to produce final complaint scoring. Lastly, the final scoring is mapped to produce complaint ranking. The above explained process is summarized in Figure 3.2.

Based on this explanation, the proposed study introduced new approach and step to improve the categorizing process which related in producing final customer complaint characteristic value. The improvement involved, firstly on the characteristic selected process based on two levels of complaint data which are principal and details. The next improvement is during the process to finalize the characteristic value. The proposed study introduced Fuzzy Delphi Method to calculate different value that produced from different expert. Besides, this study introduced the use of real number and fuzzy number for the characteristic value. The purpose for introducing these two types of number is to identify the best type of number that can be implemented in the characteristic extraction and calculation process to produce the complaint scoring.

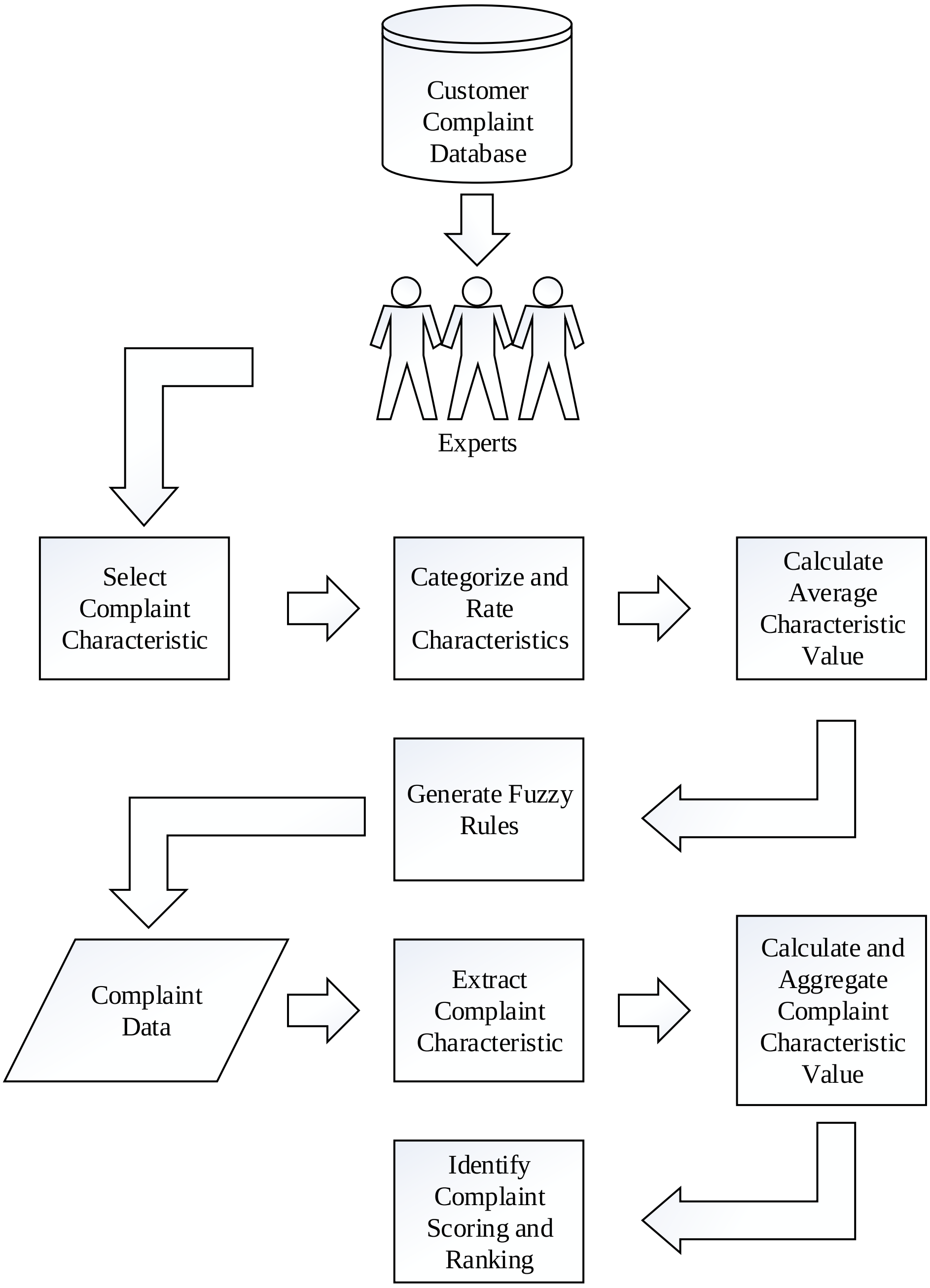

Figure 3.2: Conventional Customer Handling Fuzzy Model

Furthermore, this study developed the fuzzy rules based on two level of new complaint characteristic value. Thus, the purpose of this study to deal with uncertainties issue, increase the process efficiency and improve the accuracy of the complaint handling process can be fulfilled. The study also identified the best MFs can be used with the proposed model and which type of numbering format can produced accurate result for complaint handling process.

3.3 Proposed Methods

In this research, fuzzy logic approach (FT1 and IT2) is proposed for classifying real complaint and non-real complaint, rank the real complaint, increase the accuracy of the complaint handling process and improve the complaint handling time processing. This research selects FT1 and IT2 due to its ability to handle vague information that is specified using linguistic values. Furthermore, FT1 and IT2 are capable of producing better performance than crisp techniques in the event of uncertainties. IT2 specifically, and fuzzy logic generally, is a precise logic of imprecision and approximate reasoning that falls into two types; the capability to reason and make decisions in an environment of imprecision, uncertainty, partial truth and incompleteness of information; and the capability to perform physical or mental tasks without measurement or computations. This study falls into the first category where the input is crisp numbers but it is used to make reasoning or decision upon uncertain conditions and imprecise definitions of complaint specifications.

The proposed models are developed by FT1-based and IT2-based mathematical formulations. Then, the GUI-based forms of the models, known as IT2FM, are developed with Matlab’s FT1 and IT2 Toolbox. This research proposes that this development is carried out based on Mamdani FIS. Mamdani FIS is selected because of the following reasons; 1) it is more intuitive than Sugeno-type FIS (Dhimish et al., 2018); 2) it produces outputs through defuzzification process, hence, it is more expressive and interpretable than the Sugeno-type FIS’s weighted average process (Ilbahar et al., 2018); 3) its fuzzy rules are more interpretable than Sugeno-type FIS’s rules (Cózar et al., 2018; Sa’ad et al., 2018). The details of IT2FM development are discussed in sections 3.4.3 and 3.4.4 respectively.

Next, selection of membership functions (MFs) for this study involved number of MFs. Three major types of MFs that commonly used in fuzzy theories are Triangular, Trapezoidal and Gaussian Curve (Li et al., 2018). These three MFs and include another two types of MFs is used in this study. Besides, this study also applied ten combinations of MFs from the five main selected MFs. The purpose of this selection is to identify the optimum MFs in producing good result for complaint handling process. The selected membership functions are; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve. Next, 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).

Furthermore, Fuzzy Delphi Method (FDM) is used to finalize the complaint characteristic value for complaint specification reference. The implementation of FDM in this study because the process involves a group of experts which influence the uncertainties issues related to experts’ opinion and perception. FDM has an advantage in considering the uncertainty and ambiguity of the experts' subjective opinion, so that each expert’s judgment and opinion can produced objectively and reasonably results (Tseng et al., 2018; Zhang, 2017).

Figure 3.3 shows IT2FM which comprise of six main steps. The steps are (i) Customer Complaint Information Extraction (ii) Selection of Experts (iii) Establish Complaints Specification References (iv) Develop Fuzzy Rules (v) Create Complaint Weighted Characteristics Calculation and (vi) Generate Complaint Scoring and Ranking Calculation.

In step 1 of the proposed model, the customer complaint information is received from one of local government in Kuala Lumpur. The information is extracted from production data in CCMS which being used to receive feedback from the user around Kuala Lumpur area. The involvement of this local government in the study is formally request through a formal letter and accepted by the local government. Hence, the local government prepared the complaint information based on the details requirement that being highlighted to them.

In step 2, the proposed study needs involvement of the experts from the local government to participate in step 3 which involve with the process to form the complaint specification reference. The experts must be the person who has valid knowledge and experience also directly involve with the current process of the complaint handling. The number of the experts must not less than three experts to make sure the validity of the process (Soh, 2010). Number of experience years also is important because the factor will influence the process in producing accurate results.

In step 3, the experts will participate to establish complaint specification references which one of the main contribution in this study and improvement of the conventional method. The accomplishment of this step will fulfill the first objective for this study. Firstly, the experts need to select suitable characteristic from the complaint data based on specific domain to form the complaint specification reference. The selection of the characteristic is done for two level of complaint information which is principal and details information. Next, the selected characteristics need to be categorized by the experts based on three categories which are ‘Very Important,' ‘Important’ and ‘Normal.' Later, based on predefined scale the experts will rate each of the characteristic. Lastly, all identified rating score from each expert will be consolidated using FDM to produce final value for each of the characteristics. The final value will be formed in two types of format which is real number and fuzzy number. The purpose of implementing two types of numbering format in this study is to identify which numbering format will produce accurate and better complaint scoring and ranking results.

In step 4, the fuzzy rules are generated based on characteristic value from complaint specification references. Two types of input are identified for FIS reflected from step 3. The identified inputs are principal and details information. Then, FT1 and IT2 fuzzy sets are generated and will be used to produce the complaint score. All selected MFs that will be used as stated previously in this chapter will be generated. FIS rules will be generated referring to the suitable situation for the complaint handling process.

In step 5, all identified characteristic score in the complaint data will be aggregated to produce final complaint score. Lastly, in step 6, the final score will be mapped using mapping scheme to rank the complaint either the complaint is normal, serious or critical.

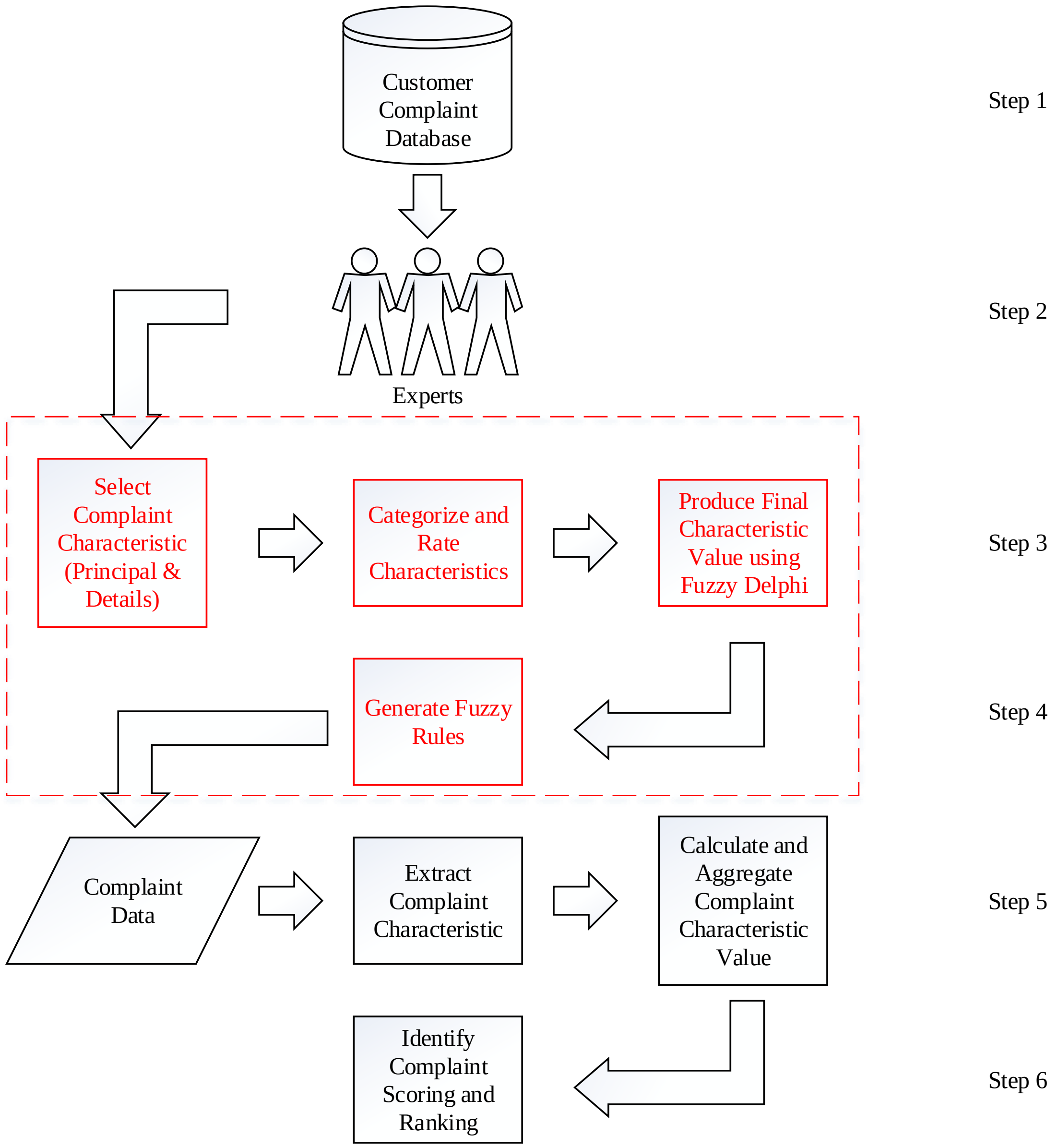

Figure 3.3: Interval Type-2 Fuzzy Model for Complaint Handling Process

3.4 Details Process of the Proposed Methods

In this sub-section, details process of the proposed methods that being explained above will be described properly for better understanding on the actual sequence of process. Related mathematical formula and model designed is presented for other researcher to duplicate the process or to improve the proposed model. The most important information to be highlighted in this sub-section is complaint specification reference and fuzzy rules process. These two processes are the main contribution in improving the conventional complaint handling model.

3.4.1 Customer Complaint Information Extraction

The data used in this research are obtained from real CCMS of local government in Kuala Lumpur. This study involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The data provided for each domain is 406 data for domain landscape and recreation, 487 data for domain enforcement and 557 data for domain mechanical and electrical engineering. The most important thing, the data is valid and good to use in this simulation. For this reason, the requirement of the data is; (i) three months duration (ii) completed complaint handling process (iii) Total of data must be more than 200 data. The decision on the number of data used in the study is based on the previous study that conduct experiment such as Arnold et al. used 225 data (2011), Faed et al. used 60 data (2016, 2014), Jonatahan and Turhan used 50 data (2007), Au et al. used 453 data (2009), Smith et al. used 375 data (1999), Wang et al. used 221 data (2011) and Galitsky and De La Rosa used 280 data (2011). Basically, the local government processes the customer complaint manually involving a group of people that work in a call center unit under Corporate Planning Department. The local government used CCMS as an IT platform to manage the complaint data.

Figure 3.4 shows data extraction pre-processing for the complaint handling process. The process started with domain landscape and recreation until process to form complaint specification references that involve identified experts. Once the complaint specification references for domain landscape and recreation is completed, the same process will be done for domain enforcement and domain mechanical and electrical engineering. Later, these three complaint specification references for each domain will be used for the experiment to find out either the complaint handling process will produce accurate result.

The details of the selection of experts and process to form the complaint specification references are discussed in 3.4.2 and 3.4.3 respectively.

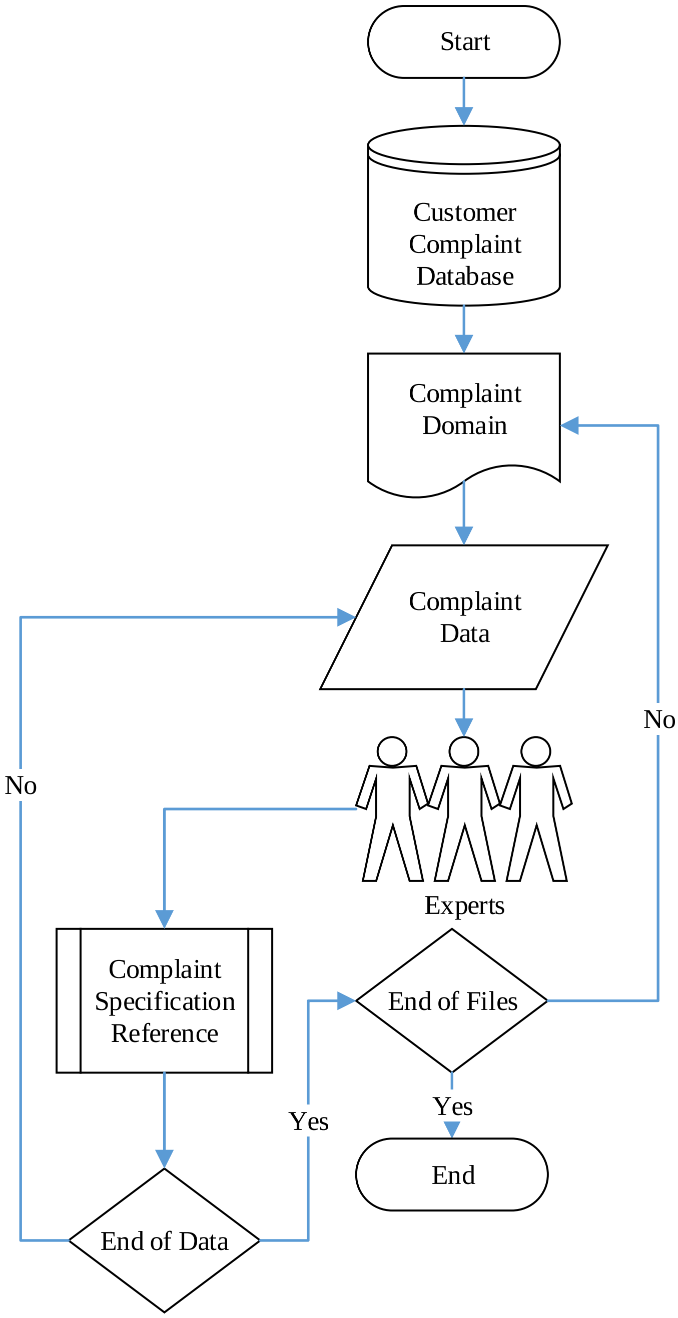

Figure 3.4: Data Extraction Pre-Processing

3.4.2 Selection of Experts

Next, this study needs to identify a reliable group of experts to help the construction of IT2FM with interpreting the complaint data. It is important for the IT2FM to capture the experts' opinion and decision during the process of complaint handling. The following things need to consider is the suitable number of expert that needs to involve in the study. This is important to make sure the foundation structure of the model is reliable to process the complaint data. Referring to the previous study that involved an expert, some experts participating in the study are between three to six experts. For example, Doctor et al. (2008), Dymova and Sevastjanov (2008), Panagiotis and Ioannis (2009) and Soh (2010) involved three experts in their work (2008). Then, another work done by Doctor et al. (2009a, 2009b) involved five experts. Furthermore, Jonathan and Turhan (2007), and Ozen et al. (2004) doing their study by using six experts. Hence, this study identified seven experts from the local government to help on the construction of IT2FM. The experts work in call center unit under Corporate Planning Department. This unit is responsible for receiving all complaints related to the local government and manage the complaint through the local government CCMS. Specific job of the experts is to classify and categorize the complaint and propose proper action to solve the complaint based on specific establish procedure. The experts have good experience and knowledge related to their jobs and responsibility towards customer complaint. Table 3.1 shows basic information about the experts.

Table 3.1: Experts Basic Information

No	Title	Working Experience (years)	Roles
1.	Assistant Manager	8	Categorize the complaint, update complaint status and forward the complaint to respective department for solving the issues
2.	Assistant Manager	4	
3.	Administrative Assistant	10	
4.	Clerk	7	
5.	Mechanical Technician	8	
6.	Assistant Enforcement	10	
7.	Administrative Assistant	4	

3.4.3 Complaint Specification References

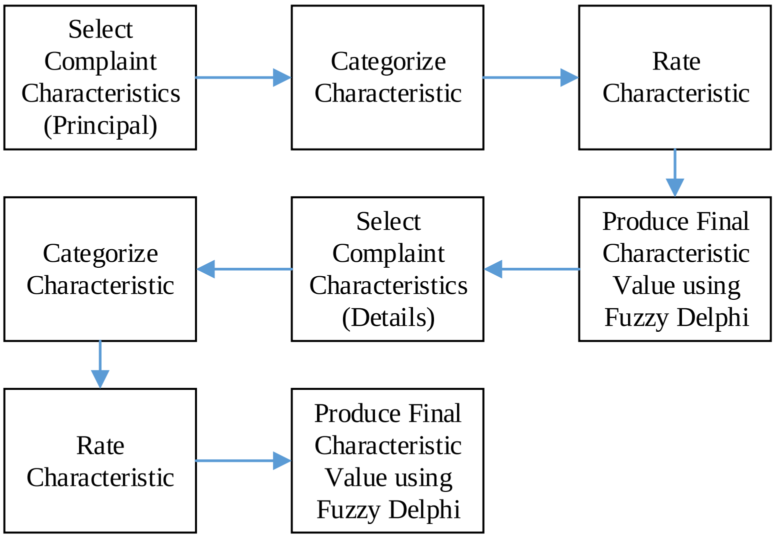

Figure 3.5: Complaint Specification References Pre-Processing

Figure 3.5 shows the complaint specification references pre-processing. In this third main process, the experts will select the characteristics of complaints to form the requirement's criteria that will be used to form complaint specification reference. 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 rate the significance of the selected characteristics using a predefined scale (Doctor et al., 2009a; Dongrui & Mendel, 2007; Mendel, 2013; Mendel, 2009; Wu & Mendel, 2009). Refer to Table 3.2 for the details of the linear scale and known as the best scale to represent weightage value and also used in most of the applications (Ishizaka & Labib, 2011).

Table 3.2: Predefined Scale

Importance Scale	Definition
1	Weakly importance
2	Values between weakly and equally
3	Equally importance
4	Values between equally and moderately
5	Moderately importance
6	Values between moderately and strongly
7	Strongly importance
8	Values between strongly and very strongly
9	Very strongly importance
10	Extremely importance

Hence, the process starts with a selection panel of R experts. Each expert denote as E_k where *k*=1 to R. L is the set of complaints specific characteristics which contains *N* characteristics c_i where *i*=1 to *N*. From the set *L* each expert E_k is asked to select choices of the characteristics for the three requirements categories ('Very Important,' 'Important' and 'Normal.') in the categorizing scheme. Each category formally denote as C_j where *j*=1 to 3 is the index for the categories: 'Very Important,' 'Important' and 'Normal.' respectively. The expert selects Q_{jk} unique characteristics c_{mjk} (from the set *L*) for each category C_{jk} where 0 < Q_{jk} < *N* and *m*=1 to Q_{jk}. The expert numerically rates the importance of each selected characteristic c_{mjk} using a predefined rating scale. The importance rating for each characteristic c_{mjk} is denoted as r_{mjk}. Most complaint area also have a 'Minimum' or ***'must have'*** set of characteristics without which complaint will be ignored. This is fixed for the complaint domain and defined in advance.

We denote this as a subset Minimum characteristics $L_{(minimum)}$ of L comprising of *U* characteristics c_p where 1 < *p* < *U*. The importance ratings for the characteristics in $L_{(minimum)}$ can also be set by each expert where the importance ratings of each 'Minimum' required characteristic c_p is denoted as r_{pk}.

From the process described above each expert E_k produces a completed complaint specification that categories and rates the importance of their preferences on the 'Minimum', 'Very Important,' 'Important' and 'Normal.' characteristics.

As mentioned in step 1 (3.4.1) this study involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. Each domain has two level information about the customer complaint which is *Tajuk* (principal complaint) and *Butir* (complaint details). Participated experts need to select the characteristics of this two-level information and give a proper value based on experts' opinion and experience. Therefore, two-level complaint specification references derived for each of respected domains. These complaint specification references used to handle complaint data in the next step for classification and ranking process. There are two types of characteristics value used for this study; (i) real number and (ii) fuzzy number. The real number is a set of numbers that can be mapped on a number line which are a negative value, positive value and value the zero in between. The set of real numbers is measurable, have a concrete value and can be manipulated. A fuzzy number is a simplification of a real number to a connected set of possible values which known as a weightage in between 0 and 1.

Involvement group of experts for this study produce differences opinions towards valuing the characteristics (Shing et al., 2010). This is a normal situation when a group of people decides on same criteria (Shahraki & Paghaleh, 2011). The uncertainties between these experts (Yang et al., 2013) are also known as fuzziness of common understanding of expert opinions (Hsu et al., 2010). Therefore, the Fuzzy Delphi method (FDM) is used to solve fuzziness between these experts and to test the consistency of the experts' judgment for the characteristics in constructing the complaint specification references (Shyan et al., 2011; Lin, 2013; Lupo, 2013).

3.4.3.1 Fuzzy Delphi Method

The identified complaint categories have different weights based on the meaning of the word itself, so the weights have been assigned to the categories on this basis and shows in Figure 3.6. Then, each characteristic weighted average is calculated by multiply each characteristic value that has been assigned by the experts with categories weights. As mentioned previously, there is two types characteristics value is used for this study; (i) real number and (ii) fuzzy number.

Categories	Normal	Important	Very Important
Weight	0.3	0.6	0.9

Figure 3.6: Complaint Categories Weights

The calculation characteristic weighted average for real number is shown as follows (Gupta et al., 2010):

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

(1)

Where c_i = the i^{th} evaluation characteristic and i = 1,2,…,n. E_j = the j^{th} expert, j = 1,2,…,m and L_{ij} = the linguistic evaluation of characteristic i by the expert j. Each element in the decision matrix is represented as a triangular fuzzy number (a_{ji}, b_{ji}, c_{ji}).

$$W_i = [(C_k L_{11})(C_k L_{12})(C_k L_{ij})]^{1/j}$$

(2)

Where W_i = weighted average of i^{th} characteristic. C_k = categories and k = 1,2,3,. Whereas, the calculation characteristic weighted average for the fuzzy number is used the geometric mean model and show as follows (Chao et al., 2017; Hsu et al., 2010):

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

(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 the simple center of gravity method to defuzzify the fuzzy weight $\widetilde{w}_i$ of each alternate element to the 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. Before the calculation of the characteristic weighted average, each characteristic value identified by experts based on real number need to convert to a fuzzy number. The converting process is done by using mapping scheme as shown in Table 3.3. This mapping scheme is created based on the agreement of the experts to make sure the relationship of the criteria importance remains. The mapping scheme is established through discussion between the experts and researcher.

Table 3.3: The Mapping Scheme for Fuzzy Number

Category	Importance Scale	Linguistics Terms	Fuzzy Number
Normal	1-5	Very Low	(0, 0, 0.1)
Normal	6-10	Low	(0, 0.1, 0.3)
Important	1-5	Moderate Low	(0.1, 0.3, 0.5)
Important	6-10	Moderate	(0.3, 0.5, 0.7)
Very Important	1-4	Moderate High	(0.5, 0.7, 0.9)
Very Important	5-7	High	(0.7, 0.9, 1)
Very Important	8-10	Very High	(0.9, 1, 1)

3.4.4 Fuzzy Rules for Complaint Classification and Ranking

In this forth main process, 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.'

As explained in the previous step, the categorized and rated characteristics for each expert E_k are used to generate the parameters for type-1 MFs that represent the fuzzy sets associated with the linguistic labels 'Low', 'Moderate' and 'High' based on the expert's preferences. More formally A_s^k is a type-1 fuzzy sets associated with a linguistic label s where s=1 to 3 is the index for the labels: 'Low', 'Moderate' and

‘High’ respectively for each expert E_k. In our system, the shapes of the type-1 MFs for each type-1 fuzzy sets are based on left shoulder (for ‘Low’ complaint), non-symmetric triangular (for ‘Moderate’ complaint), and right shoulder (for ‘High’ complaint) MFs respectively where M is the maximum range of the MFs. The parameters $[a_{MF},\ b_{MF}]$ denote the left and right defining points of the support of a MF. In the case of the non-symmetric triangular type-1 membership function, the point for the MF equalling to 1 is denoted as e. The parameters $[a^k_{MF_{(s)}}, b^k_{MF_{(s)}}]$ and $e^k_{(2)}$ for each type-1 MF are derived directly from the categorized and rated requirement characteristics supplied by each expert E_k and are calculated as follows:

For Left shoulder MF:

$$a^k_{MF_{(1)}} = \sum_{p=1}^{U} r_{pk} \tag{5}$$

$$b^k_{MF_{(1)}} = \sum_{m=1}^{Q_{1k}} r_{m1k} \tag{6}$$

For the Triangular MF:

$$a^k_{MF_{(2)}} = a^k_{MF_{(1)}} \tag{7}$$

$$b^k_{MF_{(2)}} = b^k_{MF_{(1)}} + \sum_{m=1}^{Q_{2k}} r_{m2k} \tag{8}$$

$$e^k_{(2)} \quad = b^k_{MF_{(1)}} \tag{9}$$

For the Right shoulder MF:

$$a^{k}_{MF_{(3)}} = b^{k}_{MF_{(1)}} \tag{10}$$

$$b^{k}_{MF_{(3)}} = b^{k}_{MF_{(2)}} \tag{11}$$

Based on Equations (5), (6), (7), (8), (9), (10) and (11) the generated type-1 fuzzy sets for an expert E_k will conform with the required guidelines in CMS where complaint will receive a maximum membership in the type-1 fuzzy sets for **'High'** if it contains all the 'Very Important' rated characteristics and will only receive a maximum membership in the type-1 fuzzy sets for **'Moderate'** if it contains the combination of all the 'Very Important' and 'Important' plus some 'Normal' characteristics. It should be noted that having the combination of all the 'Very Important' characteristics and some of the 'Important' characteristics will lead to being on the boundary between the **'Moderate'** and **'Good'** sets.

The type-1 fuzzy sets that are generated for each expert E_k earlier are aggregated to create the FOU's for type-2 fuzzy sets. Using the Representation Theorem (J M Mendel & John, 2002), each interval type-2 fuzzy set $\tilde{A}_s$ is computed as:

$$\widetilde{A_s} = \bigcup_{k=1}^{R} A_s^k \tag{12}$$

Where A_s^k is referred to as the k^{th} embedded type-1 fuzzy set and ∪ is the union operation (Feilong & Mendel, 2007). The process of generating $\tilde{A}_s$ is based on approximating the upper MF $\left(\bar{\mu}_{\tilde{A}_s}(x)\right)$ and the lower MF $\left(\underline{\mu}_{\tilde{A}_s}(x)\right)$ of $\tilde{A}_s$. This will depend on shape of the embedded type-1 fuzzy sets and the FOU model which is to be generated for $\tilde{A}_s$. The propose system use interior FOU models for approximating the upper and lower MF parameters from all the embedded non-symmetric triangular type-1 MFs (thus representing the 'Moderate' category). The resulting interior interval type-2 fuzzy set is described by parameters: $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$, $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters: $\overline{a}_{MF}$, $\underline{b}_{MF}$ for a non-symmetric triangular lower MF, with an intersection point (d, μ_d) (Feilong & Mendel, 2007). Shoulder FOU models are used for approximating all the left and right shoulder embedded type-1 MFs. The resulting left and right shoulder interval type-2 fuzzy sets are described by the parameters: $\underline{a}_{MF}$, $\underline{b}_{MF}$, $\overline{a}_{MF}$ and $\overline{b}_{MF}$ to represent the upper and the lower shoulder MFs (Feilong & Mendel, 2007). The procedures for calculating these parameters are now described as follows:

1) *FOU models for interior FOUs:* Given the parameters for the symmetric triangular type-1 MFs generated for each of the *k* experts $\left[a^k_{MF_{(2)}}, b^k_{MF_{(2)}}\right]$ and $e^k_{(2)}$ the procedure for approximating the FOU model for interior FOUs is as follows (Feilong & Mendel, 2007):

   For the upper MF $\overline{\mu}_{\tilde{A}_{(2)}}(x)$ we need to follow the following steps:

   (1) For $\mu(x) = 0$, find $\underline{a}_{MF}$ to be equal to the minimum $a^{min}_{MF_{(2)}}$ of all left-end points $a^k_{MF_{(2)}}$ and $\overline{b}_{MF}$ to be equal to the maximum $b^{max}_{MF_{(2)}}$ of all right-end points $b^k_{MF_{(2)}}$ (Feilong & Mendel, 2007).

   (2) For $\mu(x) = 0$, find $\underline{c}_{MF}$ to be equal to the minimum $e^{min}_{(2)}$ of the centres $e^k_{(2)}$ and $\overline{c}_{MF}$ to be equal to, maximum $e^{max}_{(2)}$ of the centres $e^k_{(2)}$.

   (3) Approximate the upper MF $\overline{\mu}_{\tilde{A}_{(2)}}(x)$ by connecting the following points with straight lines: $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$ and $\overline{b}_{MF}$. The result is a trapezoidal upper MF.

   The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}_{(2)}}(x)$ are as follows:

   (1) For $\mu(x) = 0$, find $\underline{a}_{MF}$ to be equal to the maximum $a^{max}_{MF_{(2)}}$ of all left-end points $a^k_{MF_{(2)}}$ and $\overline{b}_{MF}$ to be equal to the minimum $b^{min}_{MF_{(2)}}$ of all right-end points $b^k_{MF_{(2)}}$ (Feilong & Mendel, 2007).

   (2) Compute the intersection point (d, μ_d) by the following equations (Feilong & Mendel, 2007):

$$d = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})}$$

(13)

$$\mu_d = (\underline{b}_{MF} - d)/(\underline{b}_{MF} - \underline{c}_{MF})$$

(14)

(3) Approximate the lower $\overline{\mu}_{\tilde{A}_{(2)}}(x)$ by connecting the following points with straight lines: $\overline{a}_{MF}$, d, and $\underline{b}_{MF}$. The results is a triangle lower MF.

2) *FOU models for shoulder FOUs:* Given the parameters $\left[a^k_{MF_{(1)}}, b^k_{MF_{(1)}}\right]$ and $\left[a^k_{MF_{(3)}}, b^k_{MF_{(3)}}\right]$ for the respective left and right shoulder type-1 MFs generated for each of the k experts, the following is the procedure to approximate the FOU model for left-shoulder FOUs (Feilong & Mendel, 2007).

(1) For $\mu(x) = 0$, find $\overline{b}_{MF}$ to be equal to the maximum $b^{max}_{MF_{(1)}}$ of all end points $b^k_{MF_{(1)}}$ (Feilong & Mendel, 2007).

(2) For $\mu(x) = 1$, find $\overline{a}_{MF}$ to be equal to the maximum $a^{max}_{MF_{(1)}}$ of all end points $a^k_{MF_{(1)}}$ (Feilong & Mendel, 2007).

(3) Approximate the upper MF $\overline{\mu}_{\tilde{A}_{(1)}}(x)$ by connecting the following points with straight lines: (0:1), $(\overline{a}_{MF}, 1)$ and $(\overline{b}_{MF}, 0)$. The results is a left shoulder upper MF.

The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}_{(1)}}(x)$ are as follows:

(1) For $\mu(x) = 0$, find $\underline{b}_{MF}$ to be equal to the minimum $b^{min}_{MF_{(1)}}$ of all end points $b^k_{MF_{(1)}}$ (Feilong & Mendel, 2007).

(2) For $\mu(x) = 1$, find $\underline{a}_{MF}$ to be equal to the minimum $a^{min}_{MF_{(1)}}$ of all end points $a^k_{MF_{(1)}}$ (Feilong & Mendel, 2007).

(3) Approximate the lower $\underline{\mu}_{\tilde{A}_{(1)}}(x)$ by connecting the following points with straight lines: (0:1), $(\underline{a}_{MF}, 1)$ and $(\underline{b}_{MF}, 0)$. The results is a left shoulder lower MF.

The procedure for approximating an FOU model for right-shoulder FOUs is similar to the one for left-shoulder FOUs. The upper MF $\overline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated as follows:

For $\mu(x) = 0$, $\underline{a}_{MF} = a^{min}_{MF_{(3)}}$ and for $(x) = 1$, $\underline{b}_{MF} = b^{min}_{MF_{(3)}}$. Therefore the resulting right shoulder upper MF $\overline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated by connecting the following points with straight lines: $(\overline{a}_{MF}, 0)$, $(\overline{b}_{MF}, 1)$, and (M,1). The lower $\overline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated as follow: For $\mu(x) = 0$, $\overline{a}_{MF} = a^{max}_{MF_{(3)}}$ and for $(x) = 1$, $\overline{b}_{MF} = b^{max}_{MF_{(3)}}$. Therefore the resulting right shoulder lower MF $\underline{\mu}_{\tilde{A}_{(3)}}(x)$ is approximated by connecting the following points with straight lines: $(\overline{a}_{MF}, 0)$, $(\overline{b}_{MF}, 1)$, and (M,1).

3.4.5 Complaint Weighted Characteristics Calculation

In this fifth main process, complaint's characteristics are extracted from the complaint data set based on complaint specifications that being derived in the third main process. 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 an aggregated value that will have used during classification process in the final step. The calculation of complaint characteristics aggregated value is shown as follows:

$$FW_i = \sum_{i=1}^{n} wc_i \tag{16}$$

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).

3.4.6 Complaint Scoring and Classification

The process of the ranking complaint is based on comparing the complaint characteristics extracted from the complaint with the rated, and categorized characteristics define by each expert. Complaint characteristics extracted from CMS using language processing and information extraction techniques. The extracted complaint characteristics are then scored using a scoring method.

A complaint can be formally defined as a set of *W* complaints characteristics c_h where *h*=1 to *W*. Each complaint characteristic c_h is compared to the characteristics c_{mjk} which have been selected by each expert E_k to see if there is a match $(c_h == c_{mjk})$. Each matching complaint characteristic is denoted as c_x where $c_x = c_h = c_{mjk}$ and *x*=1 to $W_x$where W_x is the number of matching characteristics. For each matching complaint characteristic c_x (belonging originally to characteristics *m* in category *j*), the average rating score among all the experts who selected it, is calculated as follows:

$$AVr_x = \frac{\sum_{k=1}^{V} r_{mjk}}{V} \tag{17}$$

Where *V* is the number of experts that selected and rated c_x. Not all the experts may categorise c_x with the same requirements category. The requirement category that AVr_x will be assigned to is therefore chosen as the most frequently occurring category C_j which the *V* experts had selected for categorizing c_x. For each requirements category C_j, the assigned average rating scores AVr_{xj} are aggregated to produce a total category score Cs_j which is weighted using predefined weighting factor w_j based on the significance that is given to the C_j category in the selection process. The final score for a complaint is then calculated as follows:

$$FRs = \sum_{j=1}^{3} (Cs_j w_j) \tag{18}$$

The final ranking score *FRs* will be mapped to each type-2 fuzzy set $\tilde{A}_s$ to determine the membership degree of the complaint to each type-2 fuzzy set. The membership degree is calculated as the centre of gravity of the interval membership of $\tilde{A}_s$ at *x* as follows (J M Mendel, 2001):

$$\mu_{\tilde{A}_s}^{cg}(x) = f_x^{cg}(\tilde{A}_s) = \frac{1}{2}\left[\overline{\mu}_{\tilde{A}_s}(x) + \underline{\mu}_{\tilde{A}_s}(x)\right] \tag{19}$$

Where *x=FRs.*

The type-2 fuzzy set with the highest interval membership is selected for ranking the complaint as follows:

$$\mu_{\tilde{A}_s^{q^*}}^{cg}(x) \geq \mu_{\tilde{A}_s^{q}}^{cg}(x) \tag{20}$$

Where $q \ast \in \{1, \dots 3\}$.

The type-2 fuzzy sets provide a methodology for representing the ranking decision for the complaint regarding linguistic labels which are easily understandable by the human user. The scoring scheme provides a transparent break down of how each complaint characteristic in the complaint is categorized and rated by the selection panel of experts. This can be used to justify the system selection and ranking decision.

In the sixth main process, 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 the forth main process. The final value is generated based on Mamdani FIS. Five fuzzy membership functions and ten combination membership functions are used. 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 of the complaint.

Table 3.4: Mapping Scheme for Complaint Classification

Category	Importance Scale
Normal	0.0 >= final_score <= 0.3
Serious	0.3 > final_score <= 0.7
Critical	0.7 > final_score < 1.0

Next, the final score need to identify the complaint classification. The classification need to produce by mapping the final score with mapping scheme as shown in Table 3.4. This mapping scheme is created based on the agreement and discussion between the experts and researcher.

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 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 justify 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.

3.5 Design and Development of FIS Models

As explained in Chapter 1, the proposed fuzzy-based IT2FM applied FT1 and IT2 for this study. FIS component for FT1 and IT2 approach constructed using FT1 and IT2 Toolbox of Matlab software. The setup of FIS is using Mamdani-type and five fuzzy type-1 membership function (FT1MF) and interval type-2 membership function

(IT2MF). The main idea of using Mamdani FIS is to describe the process states by linguistic variables and to use these variables as inputs to control rules (Alavi, 2013). Besides, Mamdani FIS has advantages on the intuitive, widespread acceptance and suitable to human input (Dhimish et al., 2018; Kisi, 2013; Muduli et al., 2018). Also, Mamdani FIS has the capability on processing high dimensional problems with limited data items (Sun & Liao, 2018; Wang et al., 2013). The selected membership functions are; (i) Triangular (ii) Trapezoidal (iii) Gaussian Curve (iv) General Bell and (v) Gaussian 2 Curve. This study also applied ten combinations of MF to identify the reliable and accurate result. 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). Referring to previous explanation in 3.4.1 there are three complaint domains extracted for this study which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. While, as mentioned in 3.4.3 there are two types of characteristics value used for this study which is a real number and fuzzy number. Hence, FIS models based on FT1 and IT2 created for each complaint domain using the real number and fuzzy number.

Figure 3.7, Figure 3.8, Figure 3.9, and Figure 3.10 shows the models apply the fundamental components of FT1 and IT2 FIS that comprise input, implication, aggregation, defuzzification, and output. In this research, the AND method is set as MIN operation, while the OR method is set as MAX operation. Meanwhile, the implication and aggregation processes involve MIN and MAX operations respectively. Finally, the type reduction process uses CENTROID operation. All of these operations have been thoroughly discussed in Chapter 2.

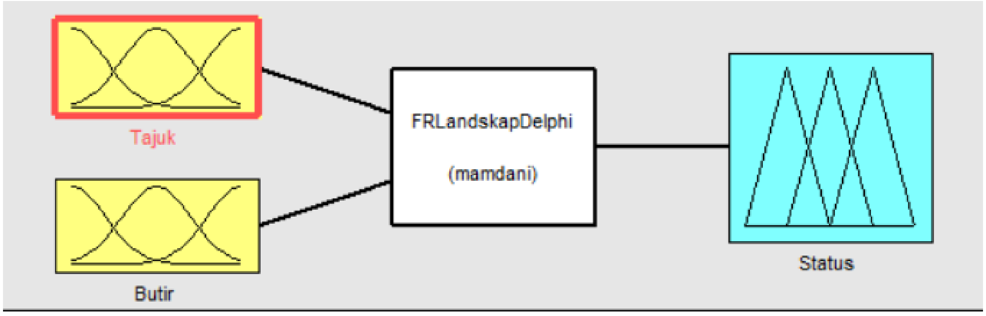

Figure 3.7: FIS for FT1 Real Number

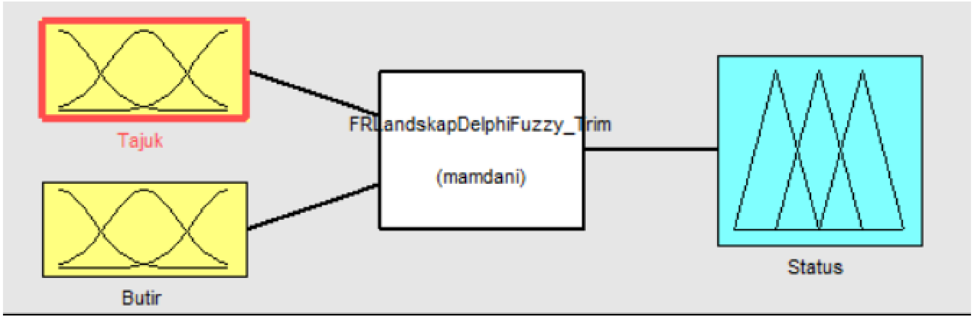

Figure 3.8: FIS for FT1 Fuzzy Number

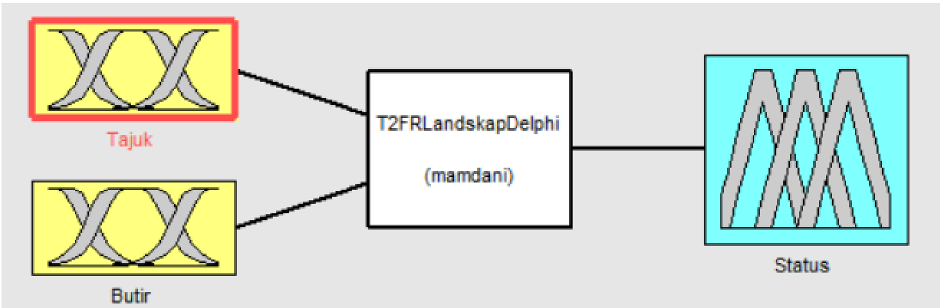

Figure 3.9: FIS for IT2 Real Number

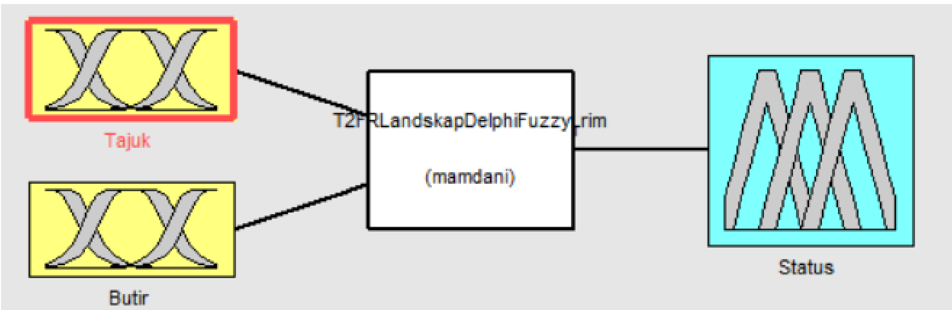

Figure 3.10: FIS for IT2 Fuzzy Number

The input MFs component of the FIS model created referring to characteristics value identified by the experts. As seen in Figure 3.7, Figure 3.8, Figure 3.9, and Figure 3.10, there is two input parameter which is *Tajuk* (principal complaint) and *Butir* (complaint details). These input linguistic parameters are defined respectively as:

Tajuk (principal complaint) = {Low, Moderate, High}

Butir (complaint details) = { Low, Moderate, High }

The output linguistic parameter is the status final value of the complaint, and this is represented by the term sets as:

Status = {Very Low, Low, Moderate Low, Moderate, Moderate High, High, Very High}

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:

$$FR = V_1L_1 \ x \ V_2L_2 \tag{15}$$

Where *FR* = Number of fuzzy rules, *VnLn* = Number of variable linguistics terms. Based on formula (15) there are nine fuzzy rules as shown in Table 3.5. These rules will be used to determine the final value of the complaints.

The final component is to automate the process based on the previous explanation on IT2FM by writing a program using Matlab programming language. The processes involved in the programming are loading the data, extracting the complaint characteristics, assigning a value for each matching complaint characteristics, aggregating the complaint characteristics value, evaluating the aggregating value using FIS and ranking the complaint. Figure 3.11 shows the complaint ranking program pseudo code for the program known as Complaint Ranking Program.

Table 3.5: 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

```
1 Start
2 Read complaint data
3 While complaint data != end data
     4 Search_complaint_characteristic()
     5 Extract characteristic aggregated value for
       Principal and Details complaint into fuzzy
       rules
     6 Calculate_final_score()
     7 Rank_the_complaint()
9 End While
10 End
     4 Search complaint characteristic()
          Compare word in the complaint with
          complaint specification reference
          If match == "Yes"
               value == matching_value
          aggregated_value = aggregated_value + value
     6 Calculate_final_score()
          Extract aggregated_value for Principal and
          Details complaint
          Map with fuzzy MF and fuzzy rules
          Produce final_score
     7 Rank_the_complaint()
          Extract final_score
          Map final_score with complaint
          classification mapping scheme
```

Figure 3.11: Complaint Ranking Program Pseudo Code

The process for this experiment is start with reading complaint data based on provided loading data based on three domains as mentioned earlier. The loading is starting with domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The second main process is to search matching complaint characteristic and produce the complaint aggregated value. Next, the third main process is to extract the complaint aggregated value for both Principal and Details complaint for the fuzzy processing. Later, the final score from the fuzzy processing will be mapped with complaint classification mapping scheme to get the complaint classification.

The details process for search complaint characteristic process involves the comparison of each word in the complaint with the complaint specification reference to identify the matching complaint characteristic. Once the matching characteristic is found, the matching characteristics will be assigned with a weighted value. Next process, if several matching characteristic is founded the matching value will be calculated to produce the complaint aggregated value. This process is continue until the end of the complaint data.

Next, the calculate final score process will extract the complaint aggregated value for both Principal and Details complaint into the fuzzy engine. Those values will be processed based on MF, established fuzzy rules and mapping (FIS evaluation) to produce the final score. Lastly, the final score will be mapped with the complaint classification mapping scheme to identify the classification of the complaint.

3.6 Evaluation Method

The verification of the proposed model will involve the evaluation of the accuracy, reliability, and validity. In this study, the verification process involved two types of verification; (i) Comparison of Proposed Model and Conventional Model (ii) Comparison of Proposed Model and Human Experts Benchmark. The reliability will verify the consistency of IT2FM. The first verification, the proposed model will be evaluated with the conventional model to compare the accuracy results for complaint handling process. This evaluation will conclude either the proposed model can improve the existing conventional model by producing better accuracy on the complaint ranking results. Furthermore, the evaluation for this study need to use descriptive measures like the mean square error that quantifies the error rate in the proposed approach. Thus, for performance comparison of the proposed model this study calculates the Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE) and the values are compared with the results of the previous method. The MSE and MAPE are given by equation (16) and equation (17) where, O_i denotes the optimized value and A_i denotes the actual value of data (Gupta et al., 2018).

$$MSE = \frac{\sum_{i=1}^{n}(O_i - A_i)^2}{n}$$

(16)

$$MAPE = \frac{I}{N}\sum \|(O_i - A_i)/\|A_i * 100\%$$

(17)

On the other hand, for the second verification, Ambati and Chen (2015) suggested a comparison of the system produced results against the gold standard annotated data (human-generated benchmark). If the resource is large enough like English, it is easier to have freely available gold standard data. However, for less-resourced languages, human-annotated data is vital to measure the accuracy. For example, Hwa et al. (2005) and Yarowsky et al., (2001) compared the precision and recall over human-annotated data. Human benchmarking is "an evaluation procedure by which a system's performance is judged based on a sample of people's performance on tasks with psychological fidelity" (O'Neil et al., 2013).

Seven experts have been selected to involve in the process of developing IT2FM. Specific tasks for those experts are establishing complaint specification reference and to prepare human experts generated benchmark complaint result. In the evaluation, IT2FM results are compared to these set of humans' generated results.

The human experts' benchmark results generated by the experts based on the characteristics value that identified for the complaint specification references. These results manually generated by the experts and compared with the extracted customer complaint information. Once the accuracy of the results is satisfied the experts, the generated results for all three domains used as the human experts benchmark results for the evaluation task.

Hence, in this research, the comparison process involves two types of fuzzy approach; (i) FT1 and (ii) IT2, two types of complaint specification reference value; (i) real number and (ii) fuzzy number and three of complaint domains; (i) domain landscape and recreation (ii) domain enforcement and (iii) domain mechanical and electrical engineering. The two types of fuzzy approach have been selected to identify which approach produce more accurate results for complaint handling process. The two types value also have been used to know which value can generate more accurate results when processing the complaints. Then, the three domains have been used to recognize the consistency of IT2FM. The results of these evaluations are discussed in Chapter 4.

3.7 Summary

At present, most of the complaints handling process focus on English. Research on fuzzy approach for wording is also concentrating more on the English word. This is the reason that categorized English as one of the rich-resourced languages. Most of complaint handling process and fuzzy approach based on English findings and tools are publicly available for academic and research use. On the other hand, a different scenario can be seen in Malay computational linguistic research. Malay has limited development of standardized language assessment tools that can be applied in Malay linguistic research. Hence, complaint handling process involving Malay needs proper categorized Malay linguistics reference to apply with new improvements and innovative model that using Fuzzy approach.

In this chapter, a new improves and innovative method referred IT2FM based on fuzzy approach is created. IT2FM is introduced to perform complaint handling process which involved real customer complaint based on services provided by local government in Kuala Lumpur. Currently, the customer complaint manually identified by the experts to categorize the status of the complaint before the proper solution is suggested to solve the complaint. The proposed model will allow and simplifies the categorizing process automatically based on complaint domains.

CHAPTER 4

RESULTS AND DISCUSSION

This chapter provides the findings on IT2FM and consists of six sections. Section 4.1 presented the fundamental references used for IT2FM. This section consists of fundamental reference for domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The computational result and the analysis for IT2FM are presented based on two experiments using fuzzy type-1 (FT1) technique and interval type-2 fuzzy (IT2) technique. Section 4.2 presented results based on FT1 while Section 4.3 presented results based on IT2. Both sections provide the findings for three domains that use for these experiments. Section 4.4 focuses on verification of reliability and validity for IT2FM while section 4.5 provides discussion on final findings for IT2FM based on presented results. Section 4.7 is a summary of all the findings in this chapter.

4.1 Complaint Specification Reference for IT2FM

There are two experiments to proof the concept of complaint handling and ranking process using fuzzy logic as proposed in this thesis. The first experiment is using FT1 approach while the second experiment is using IT2 approach. These experiments involve three domains which are domain landscape and recreation (LR), domain enforcement (E) and lastly domain mechanical and electrical engineering (ME). As explained in Chapter 3, three complaint specification references created for each domain. The complaint specification reference is the second objective of the thesis which also known as fundamental complaint reference. There are two level fundamental references for each domain which are *Tajuk* (principal complaint) and *Butir* (complaint details). These fundamental references identified by the experts and used to handle complaint data for classification and ranking process.

Since to date, no similar work has found on Malay word for complaint domain. Therefore, the benchmarks of the system generated results are using the human expert’s benchmark decision. A small set of human benchmark consist of complaint data was extracted for this purpose involves 406 data from domain landscape and recreation, 487 data from domain enforcement and 557 data from domain mechanical and electrical engineering.

4.1.1 Fundamental References for Domain Landscape and Recreation

Table 4.1 shows *Tajuk* (principal complaint) characteristics identified by experts for domain landscape and recreation. There are five characteristics identified by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values based on real number format. This *Tajuk* (principal complaint) has one primary characteristic based on highest weighted value with 8.46 for characteristic *pokok* (tree). The lowest weighted value is characteristic *rumput* (grass) with a value of 1.54.

Table 4.2 shows *Tajuk* (principal complaint) characteristics identified by experts for domain landscape and recreation. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. The most important characteristic remain for *pokok* (tree) with a value of 0.967, and the lowest weighted value is 0.110 for characteristic *rumput* (grass).

Table 4.3 shows *Butir* (complaint details) characteristics identified by experts for domain landscape and recreation. There are 17 characteristics identified by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values based on real number format. This *Butir* (complaint details) has one primary characteristic based on highest weighted value with 8.73 for characteristic *pokok* (tree). The lowest weighted value is characteristic *berfungsi* (function) with a value of 1.50.

Table 4.1: *Tajuk* (principal complaint) weightage (Landscape & Recreation: 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

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,

W_i – Weighted Average

Table 4.2: *Tajuk* (principal complaint) weightage (Landscape & Recreation: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
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

W_i – Weighted Average

Table 4.3: *Butir* (complaint details) weightage (Landscape & Recreation: 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

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,

W_i – Weighted Average

Table 4.4 shows *Butir* (complaint details) characteristics identified by experts for domain landscape and recreation. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. The most important characteristic remain for *pokok* (tree) with a value of 0.967, and the lowest weighted value is 0.110 for characteristic *berfungsi* (function).

4.1.2 Fundamental References for Domain Enforcement

Table 4.5 shows *Tajuk* (principal complaint) characteristics identified by experts for domain enforcement. There are 22 characteristics identified by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values based on real number format. These weighted values based on real number format. This *Tajuk* (principal complaint) has one primary characteristic based on highest weighted value with 7.95 for characteristic *lalulintas* (traffic). The lowest weighted value is characteristic *barang* (goods) with a value of 1.62.

Table 4.6 shows *Tajuk* (principal complaint) characteristics identified by experts for domain enforcement. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. The most important characteristic remain for *lalulintas* (traffic) with a value of 0.967, and the lowest weighted value is 0.114 for characteristic *barang* (goods).

Table 4.7 shows *Butir* (complaint details) characteristics identified by experts for domain enforcement. There are 26 characteristics identified by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values based on real number format. This *Butir* (complaint details) has one primary characteristic based on highest weighted value with 9.00 for characteristic *lalulintas* (traffic). The lowest weighted value is characteristic *biar* (let) with a value of 1.48.

Table 4.4: *Butir* (complaint details) weightage (Landscape & Recreation: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
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

W_i – Weighted Average

Table 4.5: *Tajuk* (principal complaint) weightage (Enforcement: 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	
Halang (to block)		7		4.20			4	3.60		9		5.40		7		4.20		8		4.80		7		4.20			6	5.40	4.50
Kereta (car)	8			2.40	6			1.80	8			2.40	7			2.10	9			2.70	8			2.40	7			2.10	2.25
Kenderaan (transport)	8			2.40	6			1.80	8			2.40	8			2.40	9			2.70	8			2.40	8			2.40	2.34
Parking	7			2.10	6			1.80	5			1.50	6			1.80	8			2.40	8			2.40	7			2.10	1.99
Haram (illegal)			8	7.20			9	8.10			7	6.30		9		5.40			8	7.20			9	8.10			8	7.20	7.01
Penjaja (hawker)	6			1.80	7			2.10	6			1.80	8			2.40	7			2.10	6			1.80	6			1.80	1.96
Binaan (construction)	7			2.10	8			2.40	8			2.40	7			2.10	6			1.80	7			2.10	8			2.40	2.18
Peniaga (business)	6			1.80	6			1.80	7			2.10	7			2.10	5			1.50	6			1.80	7			2.10	1.87
Gerai	6			1.80	7			2.10	7			2.10	6			1.80	8			2.40	7			2.10	8			2.40	2.09
Illegal		9		5.40		10		6.00			4	3.60			3	2.70		9		5.40		8		4.80		10		6.00	4.68
Lori (lorry)	5			1.50	7			2.10	8			2.40	7			2.10	6			1.80	6			1.80	7			2.10	1.95
Struktur (structure)		7		4.20		8		4.80		7		4.20		6		3.60		7		4.20		8		4.80		7		4.20	4.27
Lesen (license)		8		4.80		9		5.40		6		3.60		7		4.20		8		4.80		8		4.80		8		4.80	4.60
Lalulintas (traffic)			9	8.10			10	9.00			9	8.10			8	7.20			9	8.10			8	7.20			9	8.10	7.95
Sesak (congested)	5			1.50	6			1.80	5			1.50	7			2.10	8			2.40	7			2.10	8			2.40	1.94
Ganggu (disturbance)	7			2.10	8			2.40	7			2.10	6			1.80	6			1.80	7			2.10	8			2.40	2.09

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	
Parkir (parking)		9		5.40		8		4.80		8		4.80		9		5.40		8		4.80		7		4.20		7		4.20	4.78
Sisa (leftovers)		8		4.80		8		4.80		8		4.80		7		4.20		7		4.20		7		4.20		8		4.80	4.53
Sampah (trash)		7		4.20		6		3.60		6		3.60		7		4.20		8		4.80		7		4.20		7		4.20	4.10
Barang (goods)	5			1.50	5			1.50	6			1.80	6			1.80	5			1.50	6			1.80	5			1.50	1.62
Saman (summons)		7		4.20		8		4.80		8		4.80		6		3.60		7		4.20		8		4.80		7		4.20	4.35
Bahu (sidewalk)		7		4.20		7		4.20		7		4.20		7		4.20		7		4.20		8		4.80		8		4.80	4.36

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,

W_i – Weighted Average

Table 4.6: *Tajuk* (principal complaint) weightage (Enforcement: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Halang (to block)	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.7	0.9	1	0.300	0.586	1.000	0.629
Kereta (car)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Kenderaan (transport)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Parking	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Haram (illegal)	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
Penjaja (hawker)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Binaan (construction)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Peniaga (business)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0.000	0.086	0.300	0.129
Gerai	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Illegal	0.3	0.5	0.7	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.300	0.557	0.900	0.586
Lori (lorry)	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.086	0.300	0.129
Struktur (structure)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Lesen (license)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Lalulintas (traffic)	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
Sesak (congested)	0	0	0.1	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.071	0.300	0.124

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Ganggu (disturbance)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Parkir (parking)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Sisa (leftovers)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Sampah (trash)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Barang (goods)	0	0	0.1	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0	0.1	0.000	0.043	0.300	0.114
Saman (summons)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Bahu (sidewalk)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500

W_i – Weighted Average

Table 4.7: *Butir* (complaint details) weightage (Enforcement: 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	
Letak (put)	6			1.80	5			1.50	5			1.50	6			1.80	6			1.80	7			2.10	6			1.80	1.75
Kereta (car)	6			1.80	7			2.10	7			2.10	5			1.50	7			2.10	5			1.50	5			1.50	1.78
Kenderaan (transport)	9			2.70		3		1.80	10			3.00		4		2.40		2		1.20		3		1.80	9			2.70	2.14
Halang (to block)			9	8.10			9	8.10			8	7.20			10	9.00			9	8.10			10	9.00			8	7.20	8.07
Parking		8		4.80		9		5.40		8		4.80		8		4.80		9		5.40		7		4.20		7		4.20	4.78
Ganggu (disturbance)		9		5.40		10		6.00		9		5.40		8		4.80		8		4.80		8		4.80		9		5.40	5.21
Laluan (passage)	7			2.10	7			2.10	6			1.80	7			2.10	6			1.80	6			1.80	7			2.10	1.97
Sesak (congested)	5			1.50	7			2.10	6			1.80	6			1.80	5			1.50	5			1.50	7			2.10	1.74
Haram (illegal)			8	7.20			9	8.10			7	6.30			7	6.30			7	6.30			7	6.30			8	7.20	6.78
Gerai (stall)		9		5.40		9		5.40		8		4.80		8		4.80		9		5.40		9		5.40		7		4.20	5.04
Lori (lorry)	7			2.10	7			2.10	6			1.80	7			2.10	7			2.10	8			2.40	8			2.40	2.13
Biar (let)	5			1.50	4			1.20	5			1.50	5			1.50	6			1.80	6			1.80	4			1.20	1.48
Meja (table)	7			2.10	7			2.10	7			2.10	6			1.80	7			2.10	7			2.10	6			1.80	2.01
Bahaya (dangerous)		5		3.00		6		3.60		6		3.60		5		3.00		6		3.60		6		3.60		5		3.00	3.33
Kerusi (chair)	7			2.10	7			2.10	8			2.40	6			1.80	6			1.80	7			2.10	6			1.80	2.00
Lalulintas (traffic)			10	9.00			9	8.10			10	9.00			8	7.20			10	9.00			10	9.00			10	9.00	8.59
Bahu		9		5.40		10		6.00		9		5.40		8		4.80		9		5.40		9		5.40		9		5.40	5.39

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	
(sidewalk)																													
Tinggal (stay)	6			1.80	5			1.50	6			1.80	5			1.50	6			1.80	6			1.80	6			1.80	1.71
Lalu lintas (traffic)			10	9.00			10	9.00			10	9.00			10	9.00			10	9.00			10	9.00			10	9.00	9.00
Saman (summons)		8		4.80		7		4.20		8		4.80		7		4.20		7		4.20		8		4.80		7		4.20	4.45
Kotor (dirty)		7		4.20		6		3.60		7		4.20		7		4.20		6		3.60		6		3.60		8		4.80	4.01
Sisa (leftovers)		6		3.60		5		3.00		6		3.60		7		4.20		6		3.60		7		4.20		7		4.20	3.75
Tersadai (stranded)			8	7.20			7	6.30		9		5.40		8		4.80			7	6.30			8	7.20			6	5.40	6.02
Buang (throw away)		9		5.40		9		5.40		9		5.40		7		4.20		7		4.20		8		4.80		9		5.40	4.94
Mengotor (make dirty)		7		4.20		6		3.60		7		4.20		6		3.60		6		3.60		7		4.20		6		3.60	3.85
Minyak (oil)		7		4.20		7		4.20		8		4.80		7		4.20		7		4.20		6		3.60		8		4.80	4.27

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,
W_i – Weighted Average

Table 4.8 shows *Butir* (complaint details) characteristics identified by experts for domain enforcement. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. There are three characteristics with the highest value of 0.967. Those characteristics are *halang* (to block), *lalulintas* (traffic) and *lalu lintas* (traffic). The lowest weighted value is 0.110 for characteristic *biar* (let).

4.1.3 Fundamental References for Domain Mechanical and Electrical Engineering

Table 4.9 shows *Tajuk* (principal complaint) characteristics identified by experts in domain mechanical and electrical engineering. There are two characteristics determined by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values based on real number format. The highest weighted value is 8.35 for characteristic *lampu* (light).

Table 4.10 shows *Tajuk* (principal complaint) characteristics identified by experts in domain mechanical and electrical engineering. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. The highest characteristic is *lampu* (light) with a weighted value of 0.967.

Table 4.8: *Butir* (complaint details) weightage (Enforcement: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Letak (put)	0	0.1	0.3	0	0	0.1	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.071	0.300	0.124
Kereta (car)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0	0.1	0	0	0.1	0.000	0.057	0.300	0.119
Kenderaan (transport)	0	0.1	0.3	0.1	0.3	0.5	0	0.1	0.3	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5	0	0.1	0.3	0.000	0.214	0.500	0.238
Halang (to block)	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
Parking	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Ganggu (disturbance)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Laluan (passage)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Sesak (congested)	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0	0.1	0	0.1	0.3	0.000	0.057	0.300	0.119
Haram (illegal)	0.9	1	1	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	0.700	0.943	1.000	0.881
Gerai (stall)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Lori (lorry)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Biar (let)	0	0	0.1	0	0	0.1	0	0	0.1	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0.000	0.029	0.300	0.110
Meja (table)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Bahaya (dangerous)	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.100	0.414	0.700	0.405
Kerusi (chair)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Lalulintas (traffic)	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
Bahu (sidewalk)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Tinggal (stay)	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.071	0.300	0.124

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Lalu lintas (traffic)	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
Saman (summons)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Kotor (dirty)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Sisa (leftovers)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Tersadai (stranded)	0.9	1	1	0.7	0.9	1	0.3	0.5	0.7	0.3	0.5	0.7	0.7	0.9	1	0.9	1	1	0.7	0.9	1	0.300	0.814	1.000	0.705
Buang (throw away)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Mengotor (make dirty)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Minyak (oil)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500

W_i – Weighted Average

Table 4.9: *Tajuk* (principal complaint) weightage (Mechanical and Electrical Engineering: 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	
Lampu (light)			9	8.10			10	9.00			9	8.10			9	8.10			9	8.10			9	8.10			10	9.00	8.35
Light		8		4.80		7		4.20		8		4.80		8		4.80		9		5.40		8		4.80		8		4.80	4.79

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,

W_i – Weighted Average

Table 4.10: *Tajuk* (principal complaint) weightage (Mechanical and Electrical Engineering: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Lampu (light)	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
Light	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500

W_i – Weighted Average

Table 4.11 shows *Butir* (complaint details) characteristics identified by experts in domain mechanical and electrical engineering. There are 22 characteristics identified by the experts, and each of the characteristics has the weighted value based on equation (1) and equation (2) explained in Chapter 3. These weighted values are based on real number format. This *Butir* (complaint details) has two primary characteristic based on highest weighted value with 8.73 for characteristic *rosak* (broken) and *tidak berfungsi* (not functioning). The lowest weighted values are characteristics *siang* (daytime) and *langgar* (hit) with a value of 1.87.

Table 4.12 shows *Butir* (complaint details) characteristics identified by experts in domain mechanical and electrical engineering. The characteristics weighted values for this reference is using fuzzy number format and based on equation (3) and equation (4) as mentioned in Chapter 3. There are four characteristics with the highest value of 0.967. Those characteristics are *lokasi* (location), *tidak menyala* (no light), *rosak* (broken) and *tidak berfungsi* (not functioning). The lowest weighted value is 0.129 for characteristic tutup (close), siang (daytime) and *langgar* (hit).

4.2 Experiment I: Classification and Ranking using Fuzzy Type-1

The first experiment is to prove the concept of complaint handling and ranking process using FT1 approach. The main objective of this experiment is to identify the consistency of the proposed method result with the expert's human benchmark result. The experiment involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The analysis for this experiment consists of three categories. First, the accuracy compares 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. As mentioned earlier this experiment divided into two types of characteristics value; (i) real number and (ii) fuzzy number. This experiment used five membership function and ten combinations membership function. The main purpose is to identify the best membership function in producing the best result for all analysis categories.

Table 4.11: *Butir* (complaint details) weightage (Mechanical and Electrical Engineering: 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	
Lokasi (location)			10	9.00			9	8.10			9	8.10			8	7.20			8	7.20			8	7.20			8	7.20	7.69
Tidak menyala (no light)			9	8.10			9	8.10			10	9.00			9	8.10			9	8.10			10	9.00			10	9.00	8.47
Rosak (broken)			10	9.00			10	9.00			10	9.00			9	8.10			10	9.00			9	8.10			10	9.00	8.73
Gelap (dark)		9		5.40		8		4.80		8		4.80		10		6.00		9		5.40		9		5.40		8		4.80	5.21
Tidak berfungsi (not functioning)			10	9.00			10	9.00			10	9.00			9	8.10			10	9.00			9	8.10			10	9.00	8.73
Bahaya (dangerous)		8		4.80		9		5.40		10		6.00		9		5.40			8	7.20			7	6.30			7	6.30	5.87
Tidak bernyala (no light)		9		5.40			6	5.40		8		4.80		9		5.40		8		4.80		9		5.40		9		5.40	5.22
Tiada (not any)	7			2.10	7			2.10	8			2.40	6			1.80	6			1.80	6			1.80	7			2.10	2.00
Tutup (close)	6			1.80	8			2.40	7			2.10	8			2.40	5			1.50	6			1.80	6			1.80	1.95
Siang (daytime)	7			2.10	6			1.80	7			2.10	7			2.10	5			1.50	6			1.80	6			1.80	1.87
Padam (go out)		8		4.80		7		4.20		8		4.80		7		4.20		7		4.20		7		4.20		8		4.80	4.45
24 jam (24 hours)		8		4.80		8		4.80		8		4.80		6		3.60		6		3.60		6		3.60		6		3.60	4.07
Awal (early)	7			2.10	7			2.10	7			2.10	6			1.80	7			2.10	7			2.10	6			1.80	2.01
Tumbang (fall)		7		4.20		6		3.60		8		4.80		8		4.80		7		4.20		8		4.80		7		4.20	4.35
Timing		8		4.80		7		4.20		8		4.80		7		4.20		6		3.60		7		4.20		7		4.20	4.27
Wayar (wire)		9		5.40		9		5.40		8		4.80		8		4.80		7		4.20		8		4.80		8		4.80	4.87
Langgar (hit)	6			1.80	7			2.10	5			1.50	6			1.80	7			2.10	6			1.80	7			2.10	1.87

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	
Hilang (dissapear)	7			2.10	7			2.10	6			1.80	7			2.10	7			2.10	6			1.80	7			2.10	2.01
Timming		8		4.80		7		4.20		8		4.80		8		4.80		7		4.20		8		4.80		8		4.80	4.62
Bakar (burn)	6			1.80	7			2.10	7			2.10	7			2.10	6			1.80	6			1.80	6			1.80	1.92
Lewat (late)		7		4.20		6		3.60		7		4.20		7		4.20		7		4.20		7		4.20		7		4.20	4.11
Tak berfungsi (not working)		8		4.80		6		3.60		6		3.60		7		4.20		8		4.80		8		4.80		8		4.80	4.34

N – Normal, I – Important, VI – Very Important, W – Characteristic Weight,

W_i – Weighted Average

Table 4.12: *Butir* (complaint details) weightage (Mechanical and Electrical Engineering: fuzzy number)

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Lokasi (location)	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
Tidak menyala (no light)	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
Rosak (broken)	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
Gelap (dark)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Tidak berfungsi (not functioning)	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)	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.9	1	1	0.7	0.9	1	0.7	0.9	1	0.300	0.686	1.000	0.662
Tidak bernyala (no light)	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	0.3	0.5	0.7	0.3	0.5	0.7	0.300	0.557	1.000	0.619
Tiada (not any)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Tutup (close)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0.000	0.086	0.300	0.129
Siang (daytime)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0.000	0.086	0.300	0.129
Padam (go out)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
24 jam (24 hours)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Awal (early)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Tumbang (fall)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Timing	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Wayar (wire)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Langgar (hit)	0	0.1	0.3	0	0.1	0.3	0	0	0.1	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.086	0.300	0.129

Characteristics	Exp1			Exp2			Exp3			Exp4			Exp5			Exp6			Exp7			Final			W_i
Hilang (dissapear)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Timming	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Bakar (burn)	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0.000	0.100	0.300	0.133
Lewat (late)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500
Tak berfungsi (not working)	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	0.3	0.5	0.7	0.300	0.500	0.700	0.500

W_i – Weighted Average

4.2.1 Experimental Setup

The experiment is using two types of characteristics value which are a real number and fuzzy number based on the fundamental reference identified by the experts as mentioned previously. This experiment involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The data provided for each domain is 406 numbers of data for domain landscape and recreation, 487 numbers of data for domain enforcement and 557 numbers of data for domain mechanical and electrical engineering. Chapter 3 explained the flow of a process for this experiment which involves six main steps. In 4.1 explained the result of step 1 until step 3 which is a fundamental reference for each domain. The fundamental reference is essential and the key to extracting specific characteristics in the complaint data for the analysis. Next paragraph explained the details process flow involves the remaining steps of Chapter 3.

The design of FIS depended on the type of membership function that used to produce the final score. For this experiment Mamdani FIS with five single membership functions and ten combination membership functions used to generate final score. 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) GaussianCurve-Trapezoidal-Triangular (GTTrim) (ii) GaussianCurve -Triangular-Trapezoidal (GTTrap) (iii) Triangular-GaussianCurve-Trapezoidal (TGTrap) (iv) Trapezoidal-GaussianCurve-Triangular (TGTrim) (v) Trapezoidal-Triangular-GaussianCurve (TrapTG) (vi) Triangular-Trapezoidal-GaussianCurve (TrimTG) (vii) Gaussian2Curve-Triangular-Trapezoidal (G2TTrap) (viii) GeneralBell-Triangular-Trapezoidal (BTTrap) (ix) GaussianCurve-GaussianCurve-Triangular (GGTrim) and (x) GaussianCurve-GaussianCurve-Trapezoidal (GGTrap). The purpose of applying these membership functions is to compare final score results that produced by each of membership function. Then, the results will identify which membership functions produced the most accurate results. The design of FIS involves two input variables and one output variables. The input variables are *Tajuk* (principal complaint) and *Butir* (complaint details) while the output variable is *Status* (final score). Both input variables have a range of value which identified through characteristic value aggregation process. The aggregation process identified minimum and the maximum value of the characteristic value and applied to a range of value for input variables.

The last process is to rank the complaint data based on a final score which identified either the complaint is in category normal, serious or critical. The whole process is handling by the individual program for different membership function in both characteristics value type which is a real number and fuzzy number. Overall, there are 30 individual programs to handle each membership function for characteristic value using the real number and another 30 individual programs to handle each membership function for characteristic value using the fuzzy number for domain landscape and recreation.

The same process used for another two domains which are domain enforcement for 487 numbers of data and domain mechanical and electrical engineering 557 numbers of data. The experiment for these two domains continues performing using two types of characteristic value which are a real number and fuzzy number. The difference for this experiment, the process used only the best five membership function identified from the previous experiment. Thus, ten FIS design for each membership function and ten programs to experiment with each remaining domains.

As mentioned in chapter 3, human experts' benchmark on the complaint handling process used to evaluate the accuracy and consistency of IT2FM. The experts processed the complaint data for the three domains and used the established fundamental reference as a reference for related complaint characteristic in each domain. The experts have to manually perform the complaint handling process to establish the benchmark information for the experiment comparison.

4.2.2 Results

The results for this experiment are presented separately based on complaint domain. The discussion will start with domain landscape and recreation, domain enforcement and domain mechanical and electrical engineering respectively. The highlighted results are focused on the accuracy of the proposed model compare to the human experts' benchmark results.

4.2.2.1 Domain Landscape and Recreation

Figure 4.1 shows the accuracy using real numbers for five FT1 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%, followed 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.

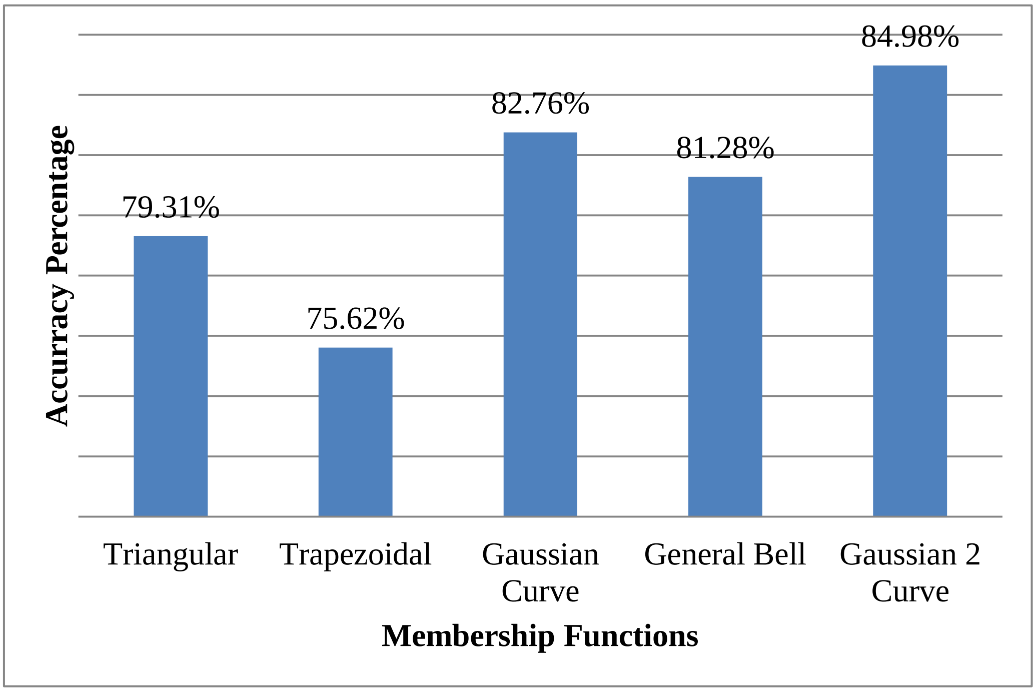

Figure 4.1: Accuracy Percentage Comparison between FIS Membership Functions (LR: FT1 Real Numbers)

Next, Figure 4.2 shows the accuracy using real numbers for ten combination FT1 membership functions. The results indicate 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.

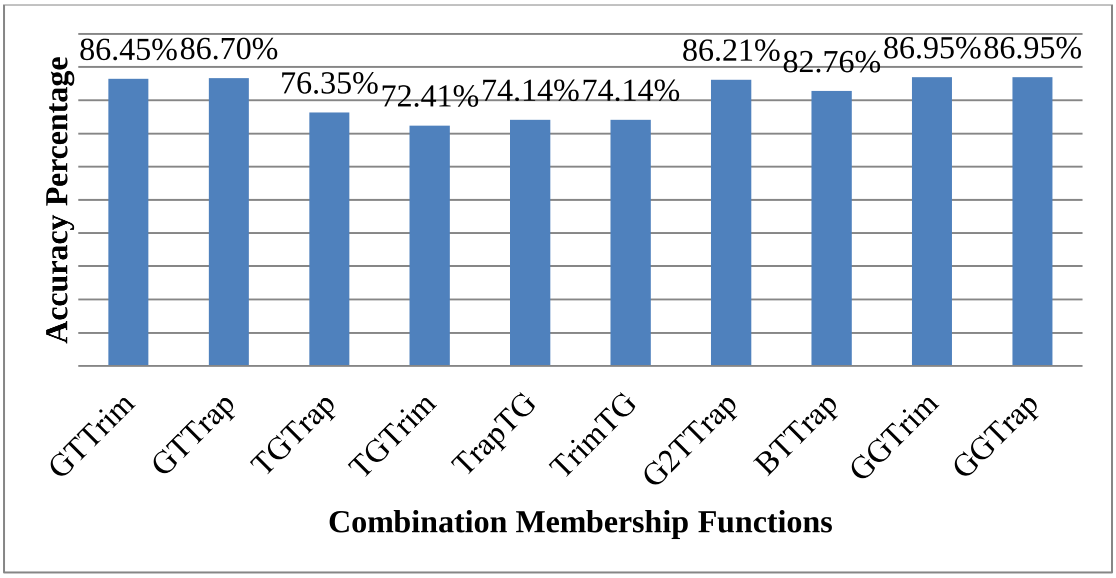

Figure 4.2: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: FT1 Real Numbers)

Meanwhile, Figure 4.3 shows the accuracy using fuzzy numbers for five FT1 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.

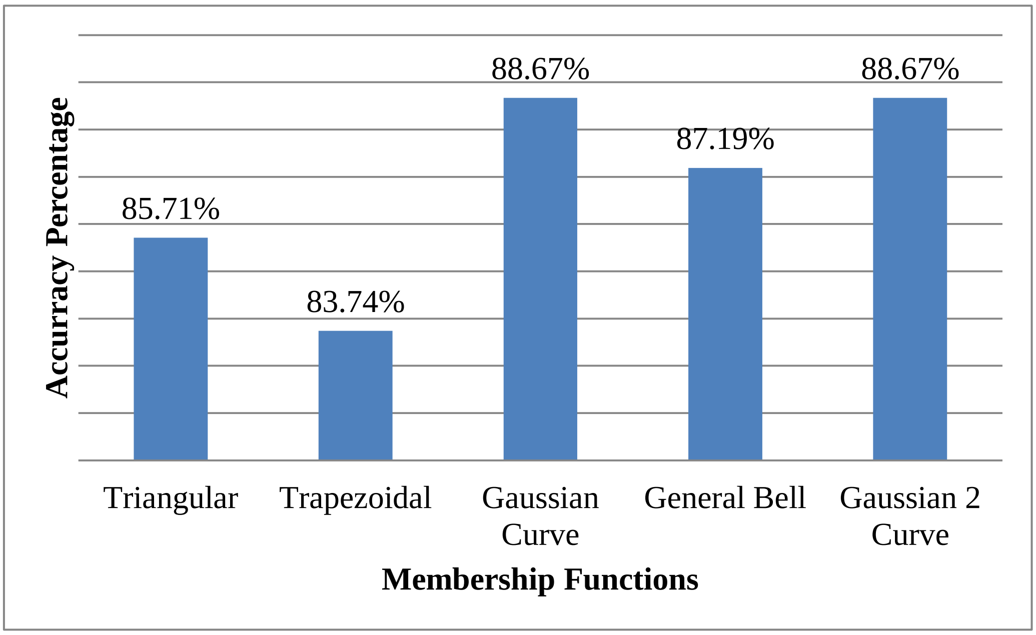

Figure 4.3: Accuracy Percentage Comparison between FIS Membership Functions (LR: FT1 Fuzzy Numbers)

Then, Figure 4.4 shows the accuracy using fuzzy numbers for ten combination FT1 membership functions. The results indicate that GGTrim and GGTrap have the highest accuracy with 93.35% compare to others.

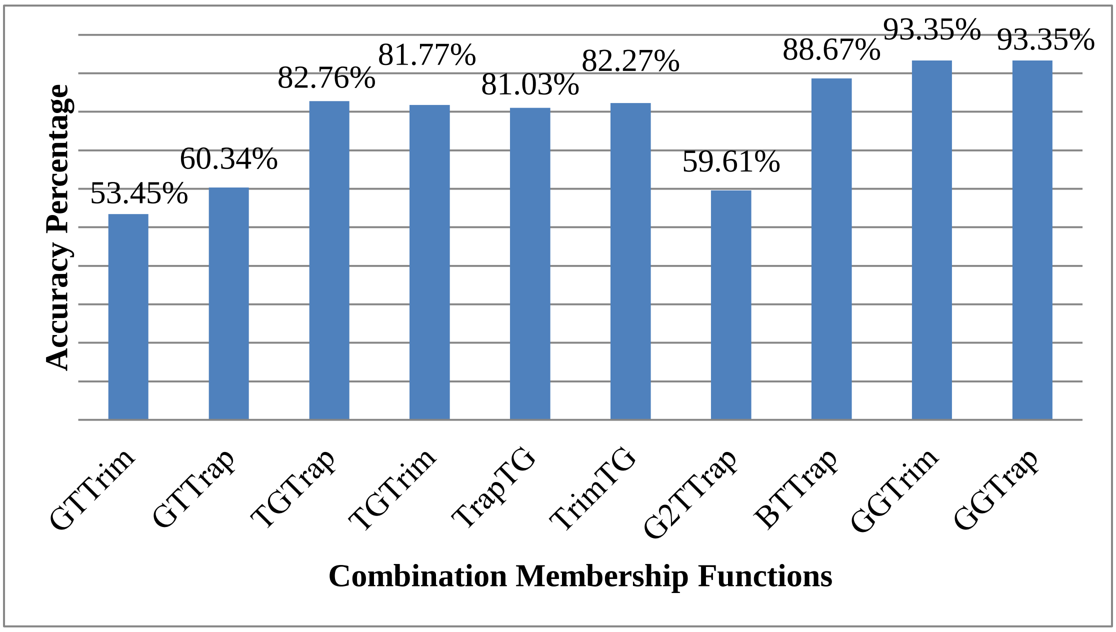

Figure 4.4: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: FT1 Fuzzy Numbers)

As conclusion, from these four results, as shown in Figure 4.1, Figure 4.2, Figure 4.3 and Figure 4.4, GGTRim and GGTrap membership functions using fuzzy numbers have the highest accuracy for FT1 membership functions. Additionally, classification category trend for real numbers has serious category while for fuzzy numbers has critical category shows the MFs degree value is optimal compared to others category.

4.2.2.2 Domain Enforcement

Figure 4.5 shows the accuracy using real numbers for five FT1 membership functions; (i) Triangular (ii) Gaussian Curve (iii) Gaussian 2 Curve (iv) GGTrim and (v) GGTrap have implemented. It can see that Gaussian Curve has the highest accuracy of 81.52%, followed by GGTrim and GGTrap with 81.31% accuracy. The fourth one is Gaussian 2 Curve with 80.90% accuracy and last, follow by Triangular with 57.08% accuracy.

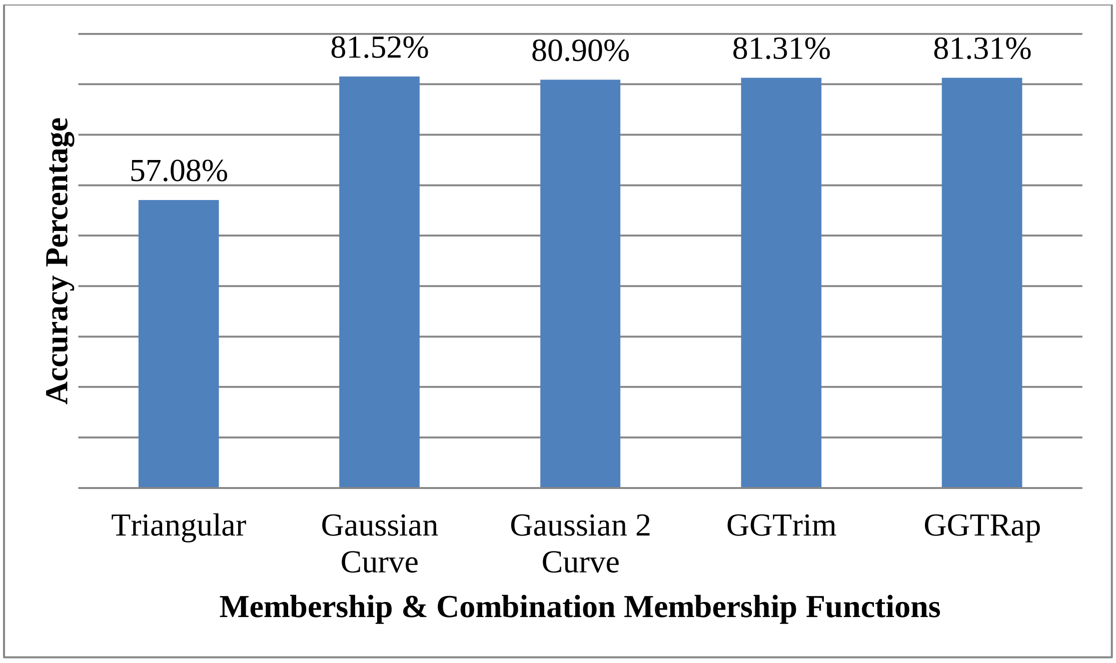

Figure 4.5: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: FT1 Real Numbers)

Next, Figure 4.6 shows the accuracy using fuzzy numbers for five FT1 membership functions. The results indicate in sequence starting from highest accuracy are; (i) GGTRim and GGTrap with 83.78% accuracy (ii) Gaussian Curve and Gaussian 2 Curve with 83.57% accuracy and (iii) Triangular with 56.67% accuracy.

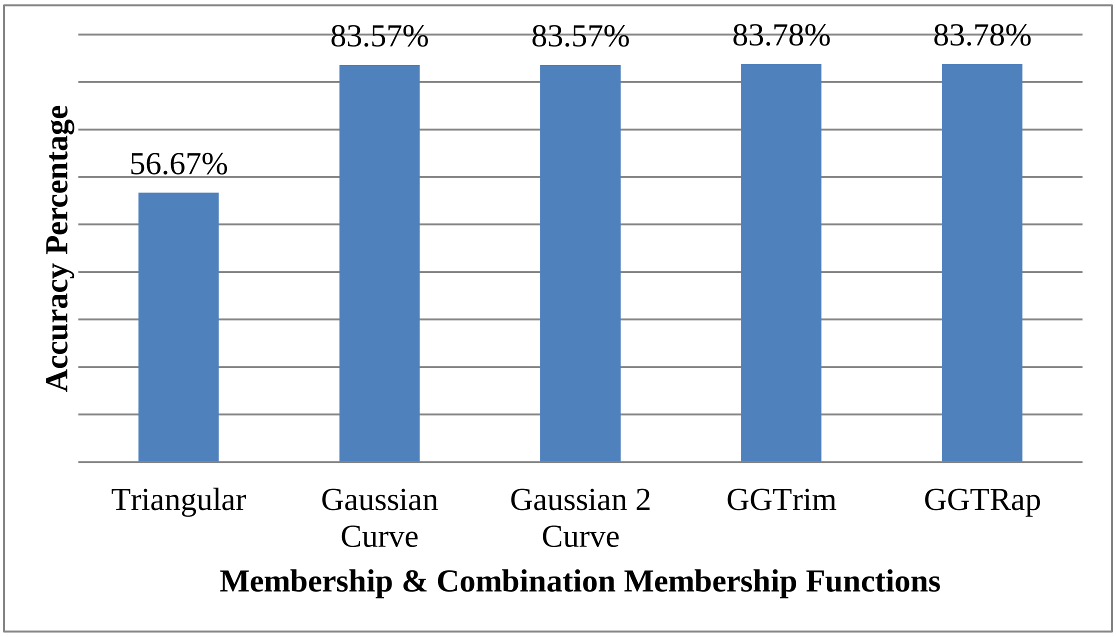

Figure 4.6: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: FT1 Fuzzy Numbers)

As conclusion, from the results, as shown in Figure 4.5 and Figure 4.6, GGTRim and GGTrap membership functions using fuzzy numbers have the highest accuracy for FT1 membership functions. Additionally, classification category trend for both real numbers and fuzzy numbers has critical category shows the MFs degree value is optimal compared to others category.

4.2.2.3 Domain Mechanical and Electrical Engineering

Figure 4.7 shows the accuracy using real numbers for five FT1 membership functions; (i) Triangular (ii) Gaussian Curve (iii) Gaussian 2 Curve (iv) GGTrim and (v) GGTrap have implemented. It can see that Gaussian 2 Curve, GGTrim, and GGTrap have the highest accuracy of 79.89%, followed by Gaussian Curve with 78.99% accuracy. The last is Triangular with 77.20% accuracy.

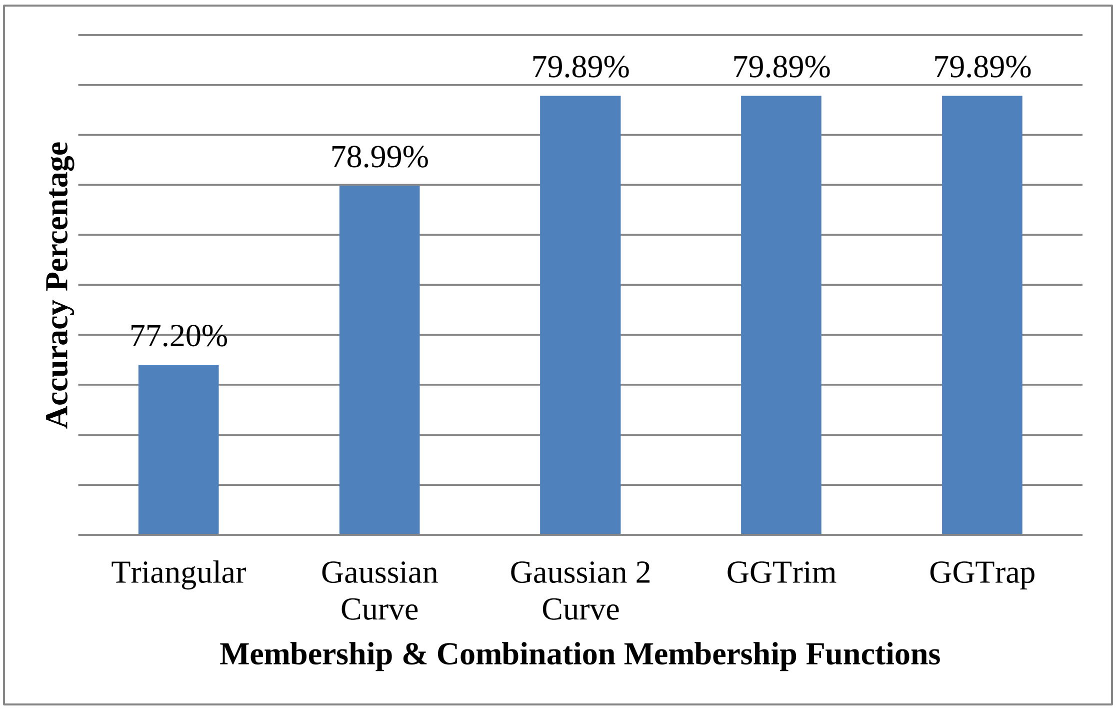

Figure 4.7: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: FT1 Real Numbers)

Next, Figure 4.8 shows the accuracy using fuzzy numbers for five FT1 membership functions. The results indicate in sequence starting from highest accuracy are; (i) Gaussian 2 Curve, GGTRim and GGTrap with 90.31% accuracy (ii) Triangular with 87.79% accuracy and (iii) Gaussian Curve with 87.25% accuracy.

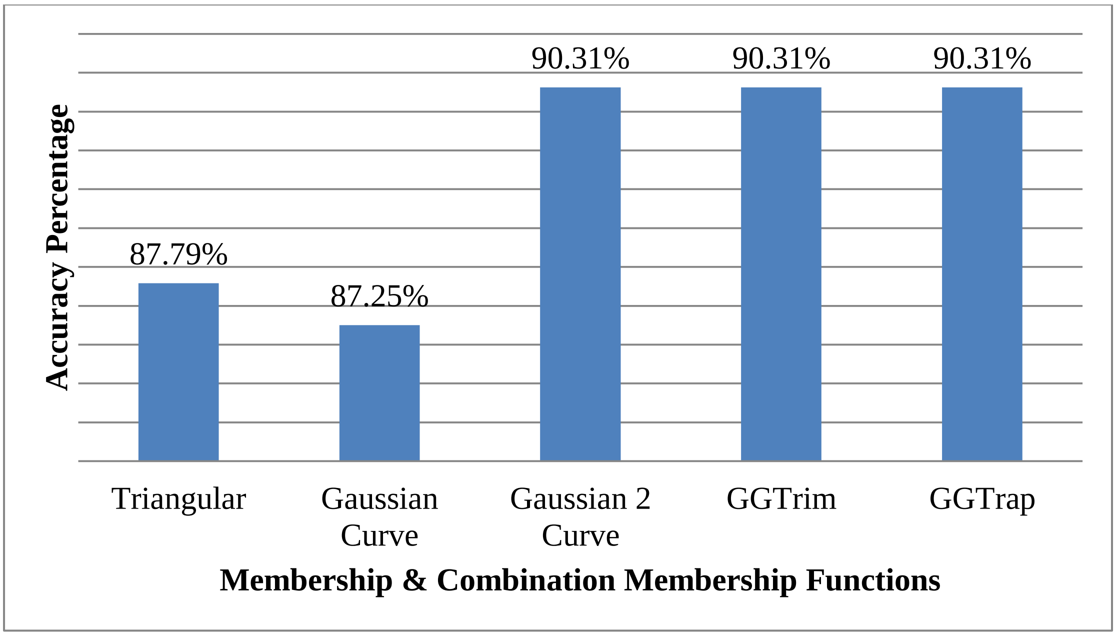

Figure 4.8: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: FT1 Fuzzy Numbers)

As the conclusion, from results, as shown in Figure 4.7 and Figure 4.8, GGTRim and GGTrap membership functions using fuzzy numbers have the highest accuracy for FT1 membership functions. Additionally, classification category trend for both real numbers and fuzzy numbers has normal category shows the MFs degree value is optimal compared to others category.

4.2.3 Discussion

This experiment involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The data provided for each domain is 406 numbers of data for domain landscape and recreation, 487 numbers of data for domain enforcement and 557 numbers of data for domain mechanical and electrical engineering. The experiment using FT1 fuzzy approach and two types of complaint specification reference value; (i) real number and (ii) fuzzy number for comparison to identify which one can produce better accuracy and consistent against human experts' benchmark. The results of the experiment, as presented in section 4.2.2 are further analyzed in this section.

Table 4.13 shows the accuracy comparison results of the membership function for domain landscape and recreation. The results show on the table is arrange from the three highest of accuracy for single membership function and the five highest of accuracy for combination membership function for both real number and fuzzy number. From the results identified that GGTrim and GGTrap have the highest accuracy for both using the real number and fuzzy number with an accuracy of 86.95% and 93.35% respectively. As conclusion, this study discovered that GGTrap membership function using fuzzy number is the most appropriate membership function for customer handling process using FT1 approach for domain landscape and recreation.

The results of this experiment show FT1 approach for customer handling process give high accuracy results with the human experts' benchmark. This result proved that FT1 approach manages to solve vagueness issue in the complaint to classify real complaint and successfully used for complaint handling process in the Malay language. Hence, conclude that FT1 approach efficiently integrated into IT2FM and produced accurate results. Furthermore, the results show that combination Gaussian Curve with Trapezoidal and Gaussian Curve with Triangular produced better results compared to others MFs. This finding is consistent with the previous research that identified three commonly preferred MFs including Gaussian, trapezoidal and triangular (Kayacan et al., 2018; Li et al., 2018).

Table 4.13: Membership Function Result Comparison for Domain Landscape and Recreation (FT1)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
GGTrap	86.95	GGTrap	93.35
GGTrim	86.95	GGTrim	93.35
GTTrap	86.70	BTTrap	88.67
GTTrim	86.45	Gaussian Curve	88.67
G2Trap	86.21	Gaussian 2 Curve	88.67
Gaussian 2 Curve	84.98	General Bell	87.19
Gaussian Curve	82.76	TGTrap	82.76
General Bell	81.28	TrimTG	82.27

Next, Table 4.14 shows the accuracy comparison results of the membership function for domain enforcement. The results indicate that Gaussian Curve has the highest accuracy of 81.52% using real number. In another hand, the results for fuzzy number identified that GGTrim and GGTrap have the highest accuracy of 83.78%. As conclusion, based on the consistency of the result and the highest accuracy discovered that GGTrap membership function using fuzzy number is the most appropriate membership function for customer handling process using FT1 approach for domain enforcement.

The results of this experiment show FT1 approach for customer handling process consistently give high accuracy results with the human experts' benchmark in different domain and amount of data. This result proved that FT1 approach is reliable to solve vagueness issue in the complaint to classify real complaint. Also, this experiment shows FT1 approach successfully used for complaint handling process in the Malay language. Hence, conclude that FT1 approach efficiently integrated into IT2FM and consistently produce accurate results.

Table 4.14: Membership Function Result Comparison for Domain Enforcement (FT1)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
Gaussian Curve	81.52	GGTrim	83.78
GGTrim	81.31	GGTrap	83.78
GTTrap	81.31	Gaussian Curve	83.57
Gaussian 2 Curve	80.90	Gaussian 2 Curve	83.57
Triangular	57.08	Triangular	56.67

Similarly, Table 4.15 shows the accuracy comparison results of the membership function for domain mechanical and electrical engineering. The results indicate that GGTrap has the highest accuracy of 79.89%. Again, GGTrap has the highest accuracy of 90.31% using the fuzzy number. As conclusion, from these results identified that GGTrap membership function using fuzzy number is the most appropriate membership function for customer handling process using FT1 approach for domain mechanical and electrical engineering.

The results of this experiment also show an FT1 approach to customer handling process consistently give high accuracy results with the human experts' benchmark in different domain and amount of data. This result proved that FT1 approach is reliable to solve vagueness issue in the complaint to classify real complaint. This experiment also shows FT1 approach successfully used for complaint handling process in the Malay language. Hence, conclude that FT1 approach efficiently integrated into IT2FM and consistently produce accurate results. Furthermore, the results show in all three domains can conclude the experiment using FT1 approach for IT2FM discovered that GGTrap combination membership function using fuzzy number is the most appropriate membership function for customer handling process.

Table 4.15: Membership Function Result Comparison for Domain Mechanical & Electrical Engineering (FT1)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
GGTrap	79.89	GGTrap	90.31
GGTrim	79.89	GGTrim	90.31
Gaussian Curve	79.89	Gaussian 2 Curve	90.31
Gaussian 2 Curve	78.99	Triangular	87.79
Triangular	77.20	Gaussian Curve	87.25

4.3 Experiment II: Classification and Ranking using Interval Type-2 Fuzzy

The second experiment is to prove the concept of complaint handling and ranking process using IT2 approach. The main objective of this experiment is to identify the consistency of the proposed method result with the expert's human benchmark result. The experiment involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The analysis for this experiment consists of three categories. First, the accuracy compares 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. As mentioned earlier this experiment divided into two types of characteristics value; (i) real number and (ii) fuzzy number. This experiment used five membership function and ten combinations membership function. The main purpose is to identify the best membership function in producing the best result for all analysis categories.

4.3.1 Experimental Setup

The whole process explained in 4.2.1 for Experiment I is replicate for Experiment II using IT2 approach. The different is on the FIS design which based on IT2 approach. The range of value for the input variables is using real number and fuzzy number format.

4.3.2 Results

The results for this experiment are presented separately based on complaint domain. The discussion will start with domain landscape and recreation, domain enforcement and domain mechanical and electrical engineering respectively. The highlighted results are focused on the accuracy of the proposed model compare to the human experts' benchmark results.

4.3.2.1 Domain Landscape and Recreation

Figure 4.9 shows the accuracy using real numbers for five IT2 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%, followed 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.

Next, Figure 4.10 shows the accuracy using real numbers for ten combination IT2 membership functions. The results show that GTTrap has the highest accuracy of 92.86% compare to others.

As the conclusion, from results, as shown in Figure 4.9 and Figure 4.10, Trapezoidal membership functions have the highest accuracy using real numbers.

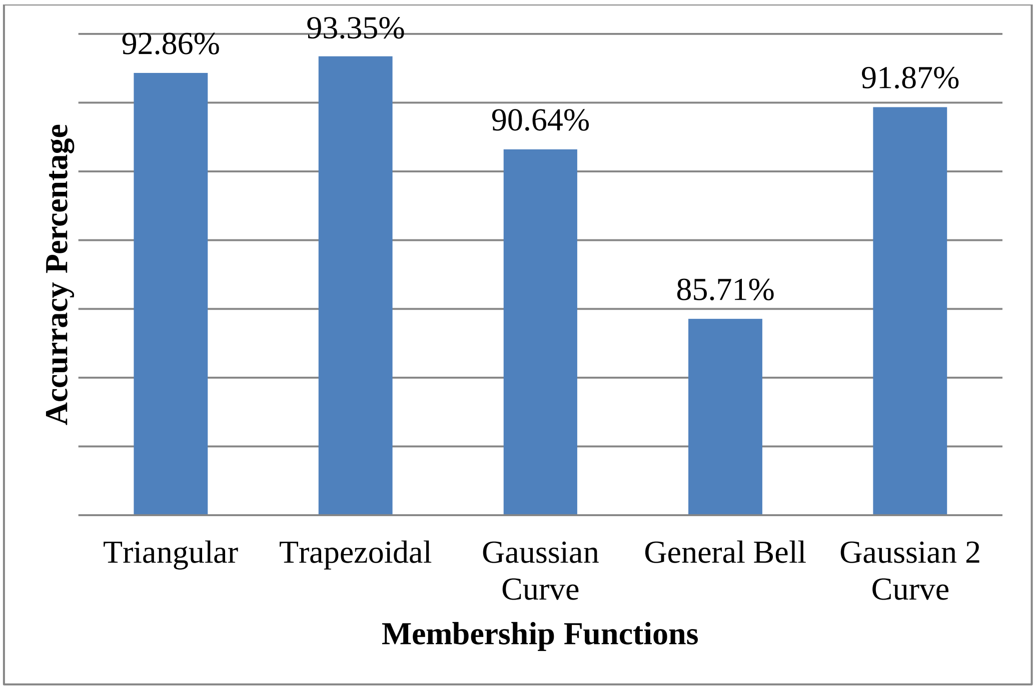

Figure 4.9: Accuracy Percentage Comparison between FIS Membership Functions (LR: IT2 Real Numbers)

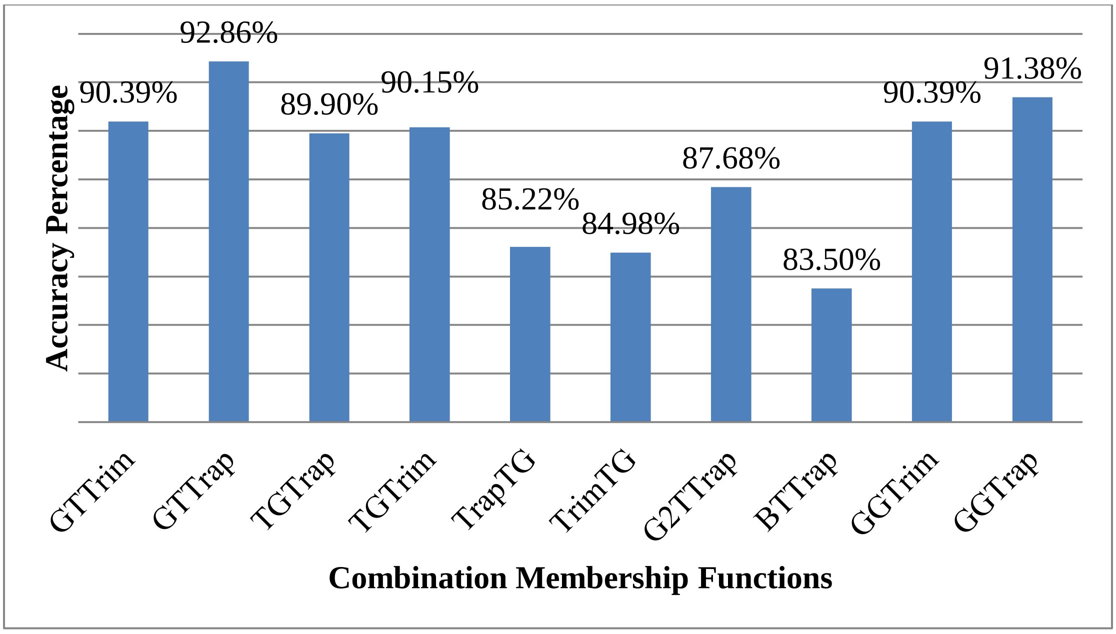

Figure 4.10: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: IT2 Real Numbers)

Next, Figure 4.11 shows the accuracy using fuzzy numbers for five IT2 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%, followed by Trapezoidal with 91.38% accuracy, the third followed by Gaussian 2 Curve with 91.13% accuracy, the fourth followed by Gaussian Curve with 88.92% accuracy and last is General Bell with 86.45% accuracy.

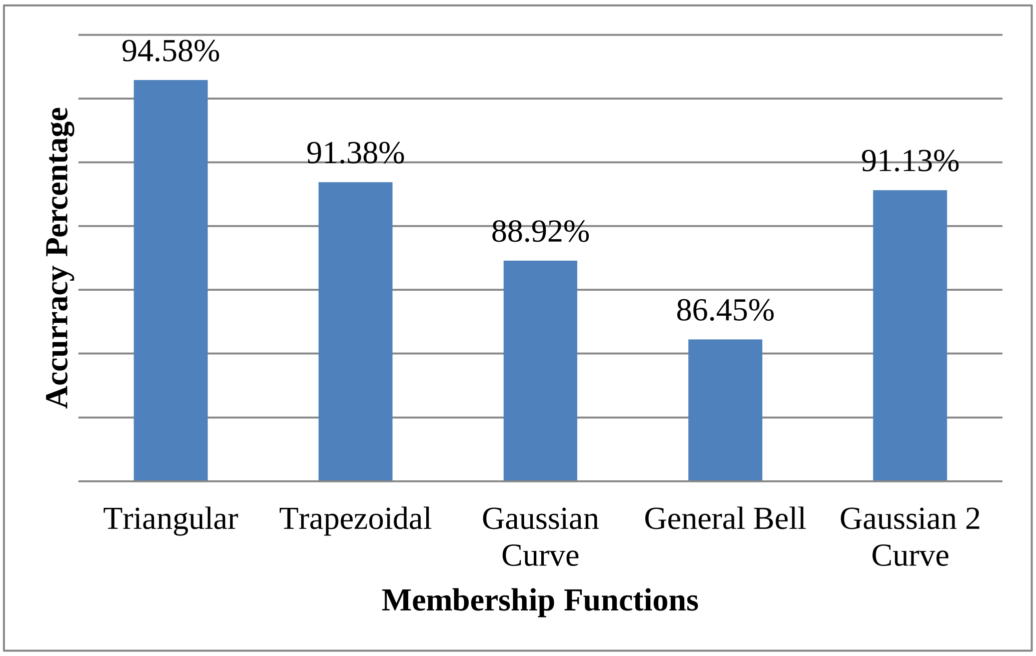

Figure 4.11: Accuracy Percentage Comparison between FIS Membership Functions (LR: IT2 Fuzzy Numbers)

Next, Figure 4.12 shows the accuracy using fuzzy numbers for ten combination IT2 membership functions. The results indicate that GTTrap, GGTrim, and GGTrap have the highest accuracy with 91.13% compare to others.

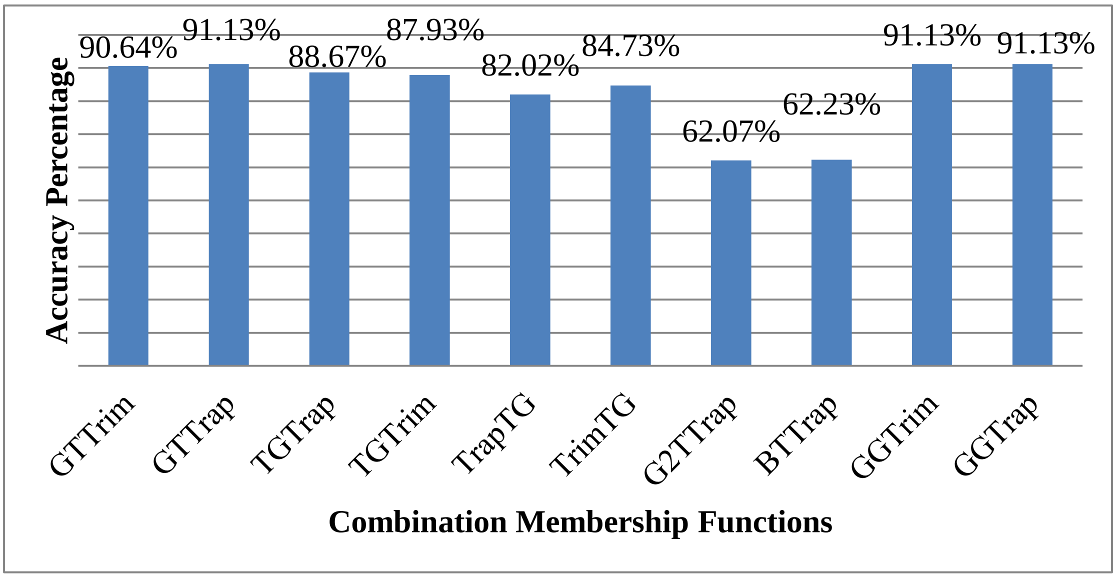

Figure 4.12: Accuracy Percentage Comparison between Combination FIS Membership Functions (LR: IT2 Fuzzy Numbers)

As the conclusion, from these four results, as shown in Figure 4.9, Figure 4.10, Figure 4.11 and Figure 4.12, Triangular membership functions using fuzzy numbers have the highest accuracy for IT2 membership functions. Additionally, classification category trend for both real numbers and fuzzy numbers has critical category shows the MF degree value is optimal compared to others category.

4.3.2.2 Domain Enforcement

Figure 4.13 shows the accuracy using real numbers for five IT2 membership functions; (i) Triangular (ii) Trapezoidal (iii) GTTrap (iv) GGTrim and (v) GGTrap have implemented. It can see that Triangular has the highest accuracy of 82.14%, followed by GGTrim with 81.72% accuracy. The third one is Trapezoidal, GTTrap, and GGTrap with 81.52% accuracy.

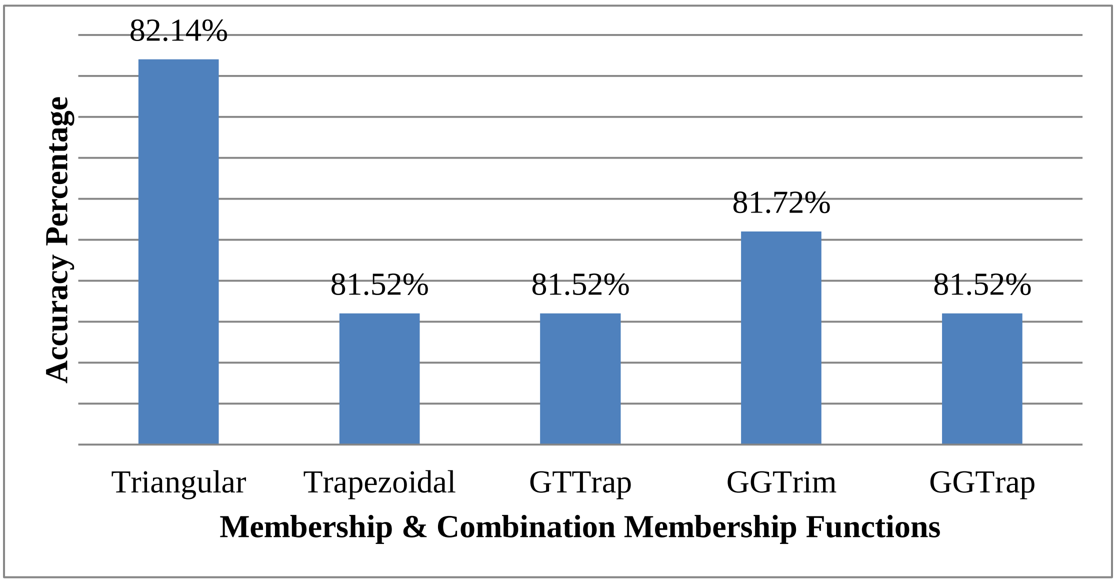

Figure 4.13: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: IT2 Real Numbers)

Next, Figure 4.14 shows the accuracy using fuzzy numbers for five IT2 membership functions. The results indicate in sequence starting from highest accuracy are; (i) GGTRim and GGTrap with 83.78% accuracy (ii) Trapezoidal with 82.34% accuracy (iii) Triangular with 81.93% accuracy and (iv) GTTrap with 80.29% accuracy.

As the conclusion, from results, as shown in Figure 4.13 and Figure 4.14, GGTRim and GGTrap membership functions using fuzzy numbers have the highest accuracy for IT2 membership functions. Additionally, classification category trend for both real numbers and fuzzy numbers has critical category shows the MF degree value is optimal compared to others category.

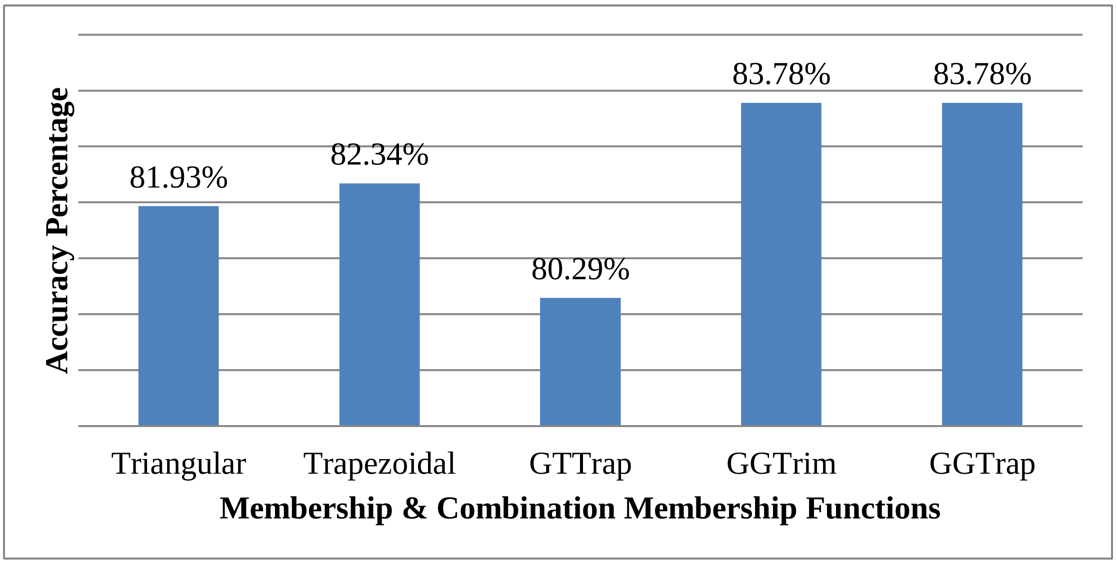

Figure 4.14: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (E: IT2 Fuzzy Numbers)

4.3.2.3 Domain Mechanical and Electrical Engineering

Figure 4.15 shows the accuracy using real numbers for five IT2 membership functions; (i) Triangular (ii) Trapezoidal (iii) GTTrap (iv) GGTrim and (v) GGTrap have implemented. It can see that Triangular, Trapezoidal GGTrim, and GGTrap have the highest accuracy of 79.89%, followed by GTTrap with 77.74% accuracy.

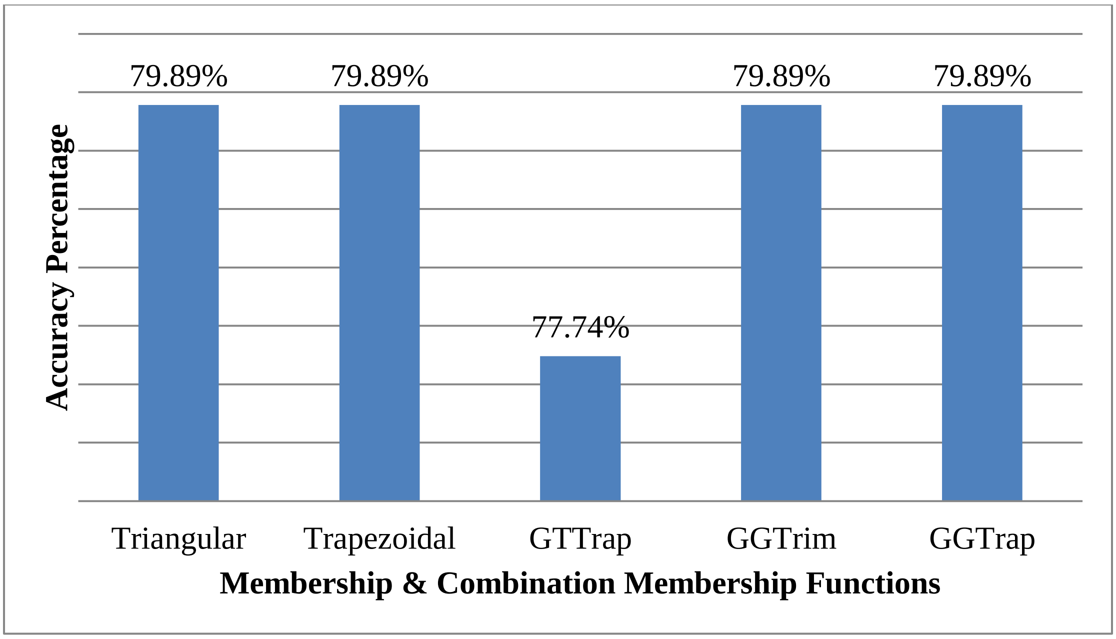

Figure 4.15: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: IT2 Real Numbers)

Next, Figure 4.16 shows the accuracy using fuzzy numbers for five IT2 membership functions. The results indicate in sequence starting from highest accuracy are; (i) Triangular and Trapezoidal with 90.48% accuracy (ii) GGTrim and GGTrap with 90.31% accuracy and (iii) GTTrap with 88.15% accuracy.

As the conclusion, from results, as shown in Figure 4.15 and Figure 4.16, Triangular and Trapezoidal membership functions using fuzzy numbers have the highest accuracy for IT2 membership functions. Additionally, classification category trend for both real numbers and fuzzy numbers has normal category shows the MF degree value is optimal compared to others category.

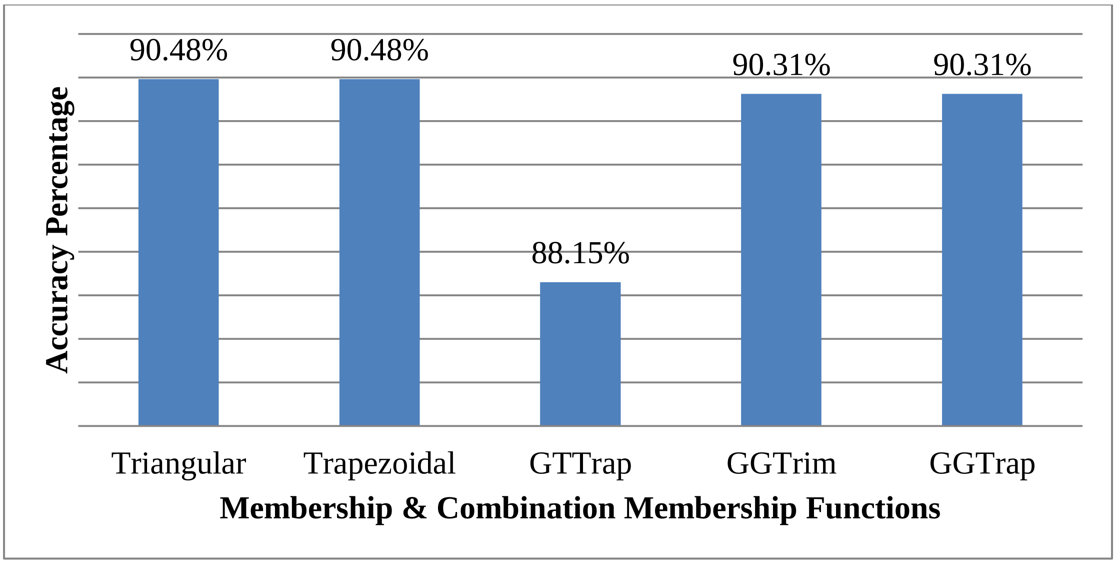

Figure 4.16: Accuracy Percentage Comparison between Single & Combination FIS Membership Functions (ME: IT2 Fuzzy Numbers)

4.3.3 Discussion

This experiment involves three domains which are domain landscape and recreation, domain enforcement and lastly domain mechanical and electrical engineering. The data provided for each domain is 406 numbers of data for domain landscape and recreation, 487 numbers of data for domain enforcement and 557 numbers of data for domain mechanical and electrical engineering. The experiment using IT2 fuzzy approach and two types of complaint specification reference value; (i) real number and (ii) fuzzy number for comparison to identify which one can produce better accuracy and consistent against human experts' benchmark. The results of the experiment, as presented in section 4.3.2 are further analyzed in this section.

Table 4.16 shows the accuracy comparison results of the membership function for domain landscape and recreation. The results shows that Trapezoidal has the highest accuracy with 93.35% using the real number and Triangular using fuzzy number is the highest accuracy with 94.58%. As conclusion, this experiment discovered that Triangular membership function using fuzzy number is the most appropriate membership function for customer handling process using IT2 approach for domain landscape and recreation.

The results of this experiment show IT2 approach for customer handling process give high accuracy results with the human experts' benchmark. This result proved that IT2 approach manages to solve vagueness issue in the complaint to classify real complaint and successfully can be used to process complaint in the Malay language. Hence, conclude that IT2 approach efficiently integrated into IT2FM and produced accurate results. Furthermore, the results also show that combination Gaussian Curve with Trapezoidal and Gaussian Curve with Triangular give more accurate results compared to others MFs. This finding consistent with previous research that identified three commonly preferred MFs including Gaussian, trapezoidal and triangular (Sahin & Yip, 2017; Tan et al., 2017).

Table 4.16: Membership Function Result Comparison for Domain Landscape and Recreation (IT2)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
Trapezoidal	93.35	Triangular	94.58
Triangular	92.86	Trapezoidal	91.38
GTTrap	92.86	Gaussian 2 Curve	91.13
Gaussian 2 Curve	91.87	GGTrim	91.13
GGTrap	91.38	GTTrap	91.13
GGTrim	90.39	GGTrap	91.13
GTTrim	90.39	GTTrim	90.64
TGTrim	90.15	TGTrim	87.93

Next, The results of this experiment show IT2 approach for customer handling process consistently give high accuracy results with the human experts' benchmark in different domain and amount of data. This result proved that IT2 approach is reliable to solve vagueness issue in the complaint to classify real complaint. This experiment also shows IT2 approach successfully used for handling complaint process in the Malay language. Hence, conclude that IT2 approach efficiently integrated into IT2FM and consistently produce accurate results.

Table 4.17 shows the accuracy comparison results of the membership function for domain enforcement. The results indicate that Triangular has the highest accuracy of 82.14% using a real number. For the fuzzy number, GGTrim has the highest accuracy of 83.78%. As conclusion, this experiment discovered that GGTrim membership function using fuzzy number is the most appropriate membership function for customer handling process using IT2 approach for domain enforcement.

The results of this experiment show IT2 approach for customer handling process consistently give high accuracy results with the human experts' benchmark in different domain and amount of data. This result proved that IT2 approach is reliable to solve vagueness issue in the complaint to classify real complaint. This experiment also shows IT2 approach successfully used for handling complaint process in the Malay language. Hence, conclude that IT2 approach efficiently integrated into IT2FM and consistently produce accurate results.

Table 4.17: Membership Function Result Comparison for Domain Enforcement (IT2)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
Triangular	82.14	GGTrim	83.78
GGTrim	81.72	GGTrap	83.78
GGTrap	81.52	Trapezoidal	82.34
GTTrap	81.52	Triangular	81.93
Trapezoidal	81.52	GTTrap	80.29

Similarly, Table 4.18 shows the comparison results of the membership function for domain mechanical and electrical engineering. The results indicate that GGTrim, GGTrap, Triangular, and Trapezoidal have the highest accuracy of 79.89% for real number. However, for the fuzzy number, Triangular and Trapezoidal have the highest accuracy of 90.48%. As conclusion, this experiment discovered that Triangular membership function using fuzzy number is the most appropriate membership function for customer handling process using IT2 approach for domain mechanical and electrical engineering.

Table 4.18: Membership Function Result Comparison for Domain Mechanical & Electrical Engineering (IT2)

MFs (Real Number)	Accuracy (%)	MFs (Fuzzy Number)	Accuracy (%)
GGTrim	79.89	Triangular	90.48
GGTrap	79.89	Trapezoidal	90.48
Triangular	79.89	GGTrap	90.31
Trapezoidal	79.89	GGTrim	90.31
GTTrap	77.74	GTTrap	88.15

The results of this experiment also show an IT2 approach to customer handling process consistently give high accuracy results with the human experts' benchmark in different domain and amount of data. This result proved that IT2 approach is reliable to solve vagueness issue in the complaint to classify real complaint. This experiment also shows IT2 approach successfully used for complaint handling process in the Malay language. Hence, conclude that IT2 approach efficiently integrated into IT2FM and consistently produce accurate results. Furthermore, the results show in all three domains can conclude the experiment using IT2 approach for IT2FM discovered that Triangular membership function using fuzzy number is the most appropriate membership function for customer handling process.

4.4 Verification of IT2FM

The verification of model evaluated the reliability and validity of IT2FM. The reliability will verify the consistency of IT2FM. The validity of IT2FM is verified by comparing its performance against conventional complaint handling model and the human experts' benchmark.

4.4.1 IT2FM and Conventional Fuzzy

Figure 4.17 shows the accuracy results between IT2FM and conventional fuzzy method using FT1 approach for best five MFs results as discussed in 4.2.2.1. The results identified that IT2FM outperformed the conventional fuzzy method. The difference between IT2FM and conventional fuzzy method in using real number format is 16% to 36% based on types of MF.

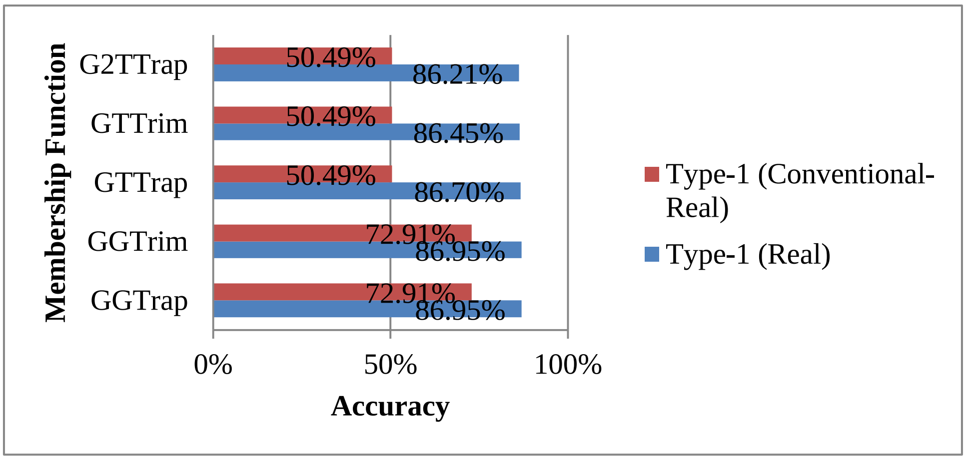

Figure 4.17: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using FT1 Approach (Real Number)

Furthermore, Table 4.19 shows that IT2FM has the smaller Mean Square Error and the smaller Mean Absolute Percentage Error as compared to conventional fuzzy method using real number for all MFs. Thus, IT2FM gets higher accuracy results for complaint handling process than the conventional fuzzy method.

Table 4.19: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using FT1 Approach (Real Number)

	Type-1 (Real)	Type-1 (Conventional Real)	Type-1 (Real)	Type-1 (Conventional Real)
Membership Function	MSE	MSE	MAPE	MAPE
GGTrap	0.1305	0.2709	7.7176	14.4089
GGTrim	0.1305	0.2709	7.7176	14.4089
GTTrap	0.1330	0.4951	8.9491	21.4696
GTTrim	0.1355	0.4951	9.1133	21.4696
G2TTrap	0.1379	0.4951	9.1954	21.4696

Meanwhile, Figure 4.18 also shows the accuracy results between IT2FM and conventional fuzzy method using FT1 approach for best five MFs results. Again, the results discovered that IT2FM outperformed the conventional fuzzy method. The difference between IT2FM and conventional fuzzy method in using fuzzy number format is 20% to 42%. Hence, both results suggested that IT2FM has better accuracy to handle complaint handling process compare to a conventional fuzzy method for the FT1 approach.

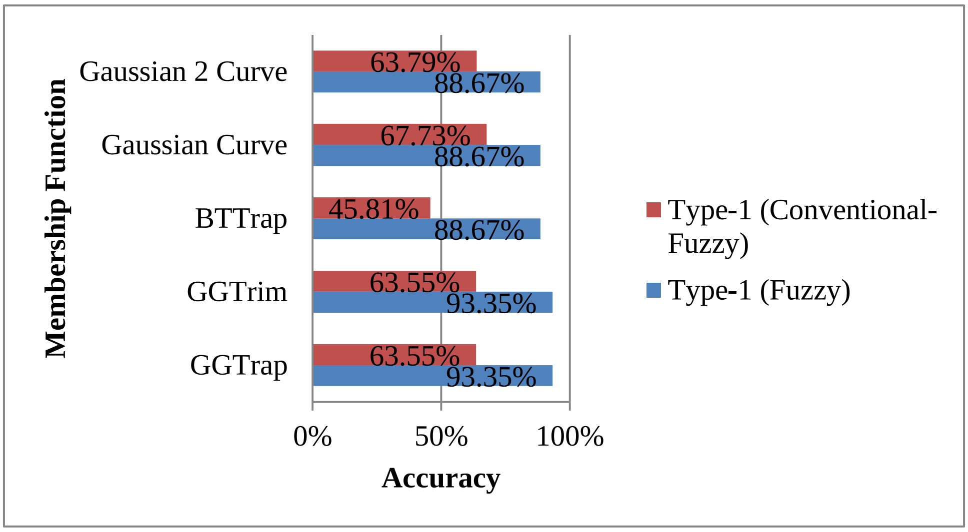

Figure 4.18: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using FT1 Approach (Fuzzy Number)

Besides, those results is supported by the smaller the smaller Mean Square Error and the smaller Mean Absolute Percentage Error as compared to conventional fuzzy method using fuzzy number for all MFs as shown in Table 4.20. For that reason identified that IT2FM has better accuracy results for complaint handling process than the conventional fuzzy method.

Table 4.20: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using FT1 Approach (Fuzzy Number)

	Type-1 (Fuzzy)	Type-1 (Conventional Fuzzy)	Type-1 (Fuzzy)	Type-1 (Conventional Fuzzy)
Membership Function	MSE	MSE	MAPE	MAPE
GGTrap	0.0665	0.3645	3.0788	18.2266
GGTrim	0.0665	0.3645	3.0788	18.2266
BTTrap	0.1133	0.5419	7.3892	23.4401
Gaussian Curve	0.1133	0.3227	7.7586	16.1330
Gaussian 2 Curve	0.1133	0.3621	7.6355	18.1034

Next, Figure 4.19 shows the accuracy results between IT2FM and conventional fuzzy method using IT2 approach for best five MFs results as discussed in 4.3.2.1. The results identified that IT2FM outperformed the conventional fuzzy method. The difference between IT2FM and conventional fuzzy method in using real number format is 14% to 17% based on types of MF.

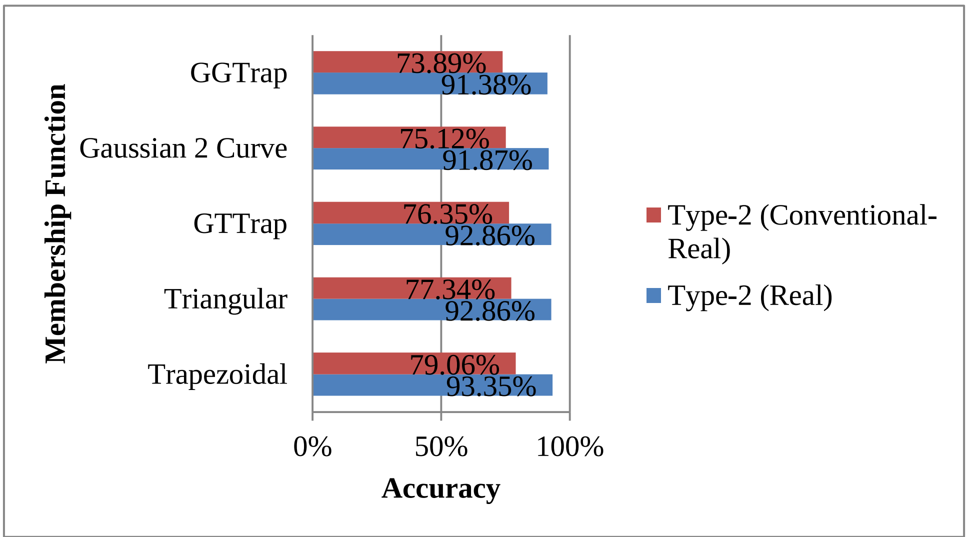

Figure 4.19: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using IT2 Approach (Real Number)

Again, Table 4.21 shows that IT2FM has the smaller Mean Square Error and the smaller Mean Absolute Percentage Error as compared to conventional fuzzy method using real number for all MFs. Thus, IT2FM produced higher accuracy results for complaint handling process than the conventional fuzzy method.

Table 4.21: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using IT2 Approach (Real Number)

	Type-2 (Real)	Type-2 (Conventional Real)	Type-2 (Real)	Type-2 (Conventional Real)
Membership Function	MSE	MSE	MAPE	MAPE
Trapezoidal	0.0739	0.6576	4.9672	25.0821
Triangular	0.0788	0.6626	5.1724	25.2874
GTTrap	0.0714	0.6552	5.0082	25.1232
Gaussian 2 Curve	0.0813	0.6650	5.1724	25.2874
GGTrap	0.0862	0.6650	5.3366	25.2463

Meanwhile, Figure 4.20 also shows the accuracy results between IT2FM and conventional fuzzy method using IT2 approach for best five membership results. Again, the results discovered that IT2FM outperformed the conventional fuzzy method. The difference between IT2FM and conventional fuzzy method in using fuzzy number format is 14% to 17%. Hence, both results suggested that IT2FM has better accuracy to handle complaint handling process compare to a conventional fuzzy method for the IT2 approach.

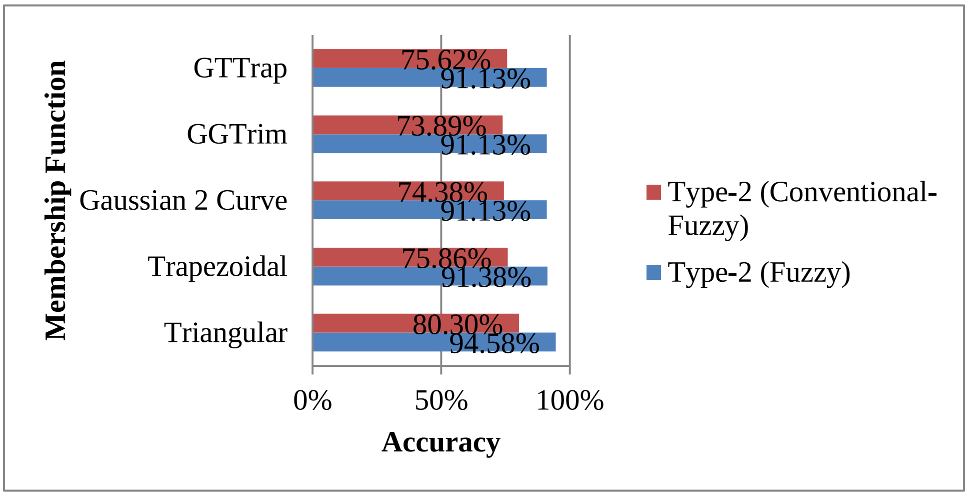

Figure 4.20: Accuracy Percentage between IT2FM and Conventional Fuzzy Method Using IT2 Approach (Fuzzy Number)

Likewise, those results is supported by the smaller the smaller Mean Square Error and the smaller Mean Absolute Percentage Error as compared to conventional fuzzy method using fuzzy number for all MFs as shown in Table 4.22. For that reason identified that IT2FM has better accuracy results for complaint handling process than the conventional fuzzy method.

As a conclusion, all the results supported to suggest IT2FM produced better accuracy in processing customer complaint for both FT1 and IT2 approach. Furthermore, the findings also supported that FT1 and IT2 approach efficiently integrated into IT2FM and produced accurate results. Hence, this conclude that new characteristics value generated for complaint specification reference using FDM, successfully produced better accuracy than conventional fuzzy model in complaint handling process. The implementation of FDM is managed to solve the uncertainties issues between the experts for generating final characteristics value in the complaint specification reference. As well, the development of fuzzy rules specifically focus on the value used for the MFs which applied from the complaint specification reference successfully producing higher accuracy results for complaint handling process. Therefore, all objectives for this study are being fulfilled successfully.

Table 4.22: Mean Square Errors and Mean Absolute Percentage Error Comparison for IT2FM and Conventional Fuzzy Method Using IT2 Approach (Fuzzy Number)

	Type-2 (Fuzzy)	Type-2 (Conventional Fuzzy)	Type-2 (Fuzzy)	Type-2 (Conventional Fuzzy)
Membership Function	MSE	MSE	MAPE	MAPE
Triangular	0.0542	1.0296	4.1461	91.1330
Trapezoidal	0.0862	1.0296	7.3481	91.1330
Gaussian 2 Curve	0.0887	0.9631	5.2956	88.9163
GGTrim	0.0887	0.9483	0.0961	88.4236
GTTrap	0.0887	1.0025	5.2956	90.3941

4.4.2 IT2FM and Human Experts' Benchmark

Table 4.23 shows the accuracy percentage for the best-selected membership function across three domains using FT1 approach for both real and fuzzy number. The accuracy percentage arranged from the highest to the lowest. First observation identified that fuzzy number produced higher accuracy compared to a real number. These results are consistent for all three domains for the majority of the membership functions. Second observation discovered that GGTrap has the highest accuracy in four experiments out of six. This result shows GGTrap performed consistent results in producing highest accuracy and reliable to handle complaint process. On the other hand, for the last observation from all six experiments on FT1 two out of six the accuracy exceeds 90% accuracy and both produced by GGTrap membership function.

Table 4.23: Accuracy Percentage between Domains Using FT1 Approach

Domain Landscape & Recreation		Domain Enforcement		Domain Mechanical & Electrical Engineering	
Membership Function	Accuracy (%)	Membership Function	Accuracy (%)	Membership Function	Accuracy (%)
Real Number		Real Number		Real Number	
GGTrap	86.95	Gaussian Curve	81.52	GGTrap	79.89
GGTrim	86.95	GGTrim	81.31	GGTrim	79.89
GTTrap	86.7	GGTrap	81.31	Gaussian 2 Curve	79.89
GTTrim	86.45	Gaussian 2 Curve	80.9	Gaussian Curve	78.99
G2TTrap	86.21	Triangular	57.08	Triangular	77.2
Fuzzy Number		Fuzzy Number		Fuzzy Number	
GGTrap	93.35	GGTrim	83.78	GGTrap	90.31
GGTrim	93.35	GGTrap	83.78	GGTrim	90.31
BTTrap	88.67	Gaussian Curve	83.57	Gaussian 2 Curve	90.31
Gaussian Curve	88.67	Gaussian 2 Curve	83.57	Triangular	87.79
Gaussian 2 Curve	88.67	Triangular	56.67	Gaussian Curve	87.25

Table 4.24 shows the accuracy percentage for the best-selected membership function across three domains using IT2 approach for both real and fuzzy number. The accuracy percentage arranged from the highest to the lowest. First observation identified that fuzzy number produced higher accuracy compared to a real number. These results are consistent for all three domains for the majority of the membership functions. Second observation discovered that Triangular has the highest accuracy in

three experiments out of six. This result shows Triangular performed consistent results in producing highest accuracy and reliable to handle complaint process. On the other hand, for the last observation from all six experiments on IT2 three out of six the accuracy exceeds 90% accuracy and all those three produced by a Triangular membership function.

Table 4.24: Accuracy Percentage between Domains Using IT2 Approach

Domain Landscape & Recreation		Domain Enforcement		Domain Mechanical & Electrical Engineering	
Membership Function	Accuracy (%)	Membership Function	Accuracy (%)	Membership Function	Accuracy (%)
Real Number		Real Number		Real Number	
Trapezoidal	93.35	Triangular	82.14	GGTrap	79.89
Triangular	92.86	GGTrim	81.72	GGTrim	79.89
GTTrap	92.86	GGTrap	81.52	Triangular	79.89
Gaussian 2 Curve	91.87	GTTrap	81.52	Trapezoidal	79.89
GGTrap	91.38	Trapezoidal	81.52	GTTrap	77.74
Fuzzy Number		Fuzzy Number		Fuzzy Number	
Triangular	94.58	GGTrap	83.78	Triangular	90.48
Trapezoidal	91.38	GGTrim	83.78	Trapezoidal	90.48
Gaussian 2 Curve	91.13	Trapezoidal	82.34	GGTrap	90.31
GGTrim	91.13	Triangular	81.93	GGTrim	90.31
GTTrap	91.13	GTTrap	80.29	GTTrap	88.15

Overall, the results of this experiment showed the proposed model using FT1 and IT2 approach produced high accuracy and relatively highly consistent with the human experts. The evident show in Table 4.23 and Table 4.24 suggest that fuzzy number has higher accuracy compared to a real number for both using FT1 and IT2 approach. Generally, proposed model based on FT1 approach using GGTrap membership function produce the highest accuracy while Triangular membership function produces the highest accuracy for the IT2 approach. The results of the experiment also suggest that IT2 approach consistently produce higher accuracy compared to the FT1 approach in all three complaint domains which lead by a Triangular membership function. These results supported findings in the previous research, which claimed Triangular MFs used extensively due to its simple formulas and computational efficiency (Ali et al., 2015; Bobyr et al., 2017; Carvalho & Costa, 2017; Gul et al., 2018; Mohanty & Shankar, 2017). Therefore, it can conclude IT2 approach has better accuracy than FT1 approach for proposed model implementation.

4.5 Discussion

This chapter mainly focuses on four major things related to this study which answering majority of the research questions mentioned in chapter 1. First, IT2FM was successfully designed and found suitable to implement for complaint handling process. Although two experiments are using two approaches, both approaches for proposed model in this study has shown its accuracy, consistency and provide an efficient solution for the complaint handling process. Secondly, fundamental reference was successfully developed and reliable to provide a solution for the complaint handling process. Thirdly, both IT2FM and fundamental reference has important implications for complaint handling process in producing highly consistent results with the human experts. The fourth, even using the Malay language the result from the experiments successfully shows a good result which proves the fuzzy approaches can use in the Malay language with the proper model design.

As conclusion, both approaches FT1 and IT2 produce highly consistent results with the human experts. There are three best membership functions in each FT1 and IT2 approach with good results in each of categories. Overall, from the good results identified that complaint handling process could use both approaches. Specifically, membership function Triangular using the fuzzy number for the IT2 approach is the best membership function for complaint handling process. The results also show for FT1 approach discovered that combination MFs are suitable to handle complaint process. From this three combination MFs identified that GGTrap applying fuzzy number is the best MF for complaint handling process. The difference between FT1 and IT2 approach specific on MF Triangular and combination MFs GGTrap only 1.23%. Therefore, shows that IT2 is the better approach for complaint handling process. Furthermore, this experiment successfully proves the proposed model improve complaint handling process efficiency and less time consuming and fulfill all the objectives of this study.

4.6 Summary

In summary, the IT2FM using FT1 and IT2 approaches have been successfully implemented for complaint handling process. The fundamental reference tables successfully created by the experts and prove important in producing an accurate result to identify real complaint and non-real complaint besides to evaluate the priority of the complaint. Five single membership functions and ten combination membership functions used for both approaches to produce the complaint handling results.

Three different sets of data have been used for the experiment and analysis. The data provided for each set is 406 numbers of data for domain landscape and recreation, 487 numbers of data for domain enforcement and 557 numbers of data for domain mechanical and electrical engineering. The data have been used to identify the accuracy, consistency and successfully of the proposed model.

The intelligent technique developed in this study has displayed the accuracy and consistency of the results. The fuzzy method successfully identifies the real complaint and rank the complaint based on produces value. These significant values later can use to set priority which complaint needs to focus the most. This technique overcomes the uncertainty of complaint handling process which involved various types of input. The technique also overcomes the uncertainty that exists between experts in producing characteristics value in each domain. Overall, the proposed model is successful in producing highly consistent results with the human experts. The results also show that IT2 is the most suitable approaches to implement for complaint handling process.

CHAPTER 5

CONCLUSION

This thesis is about designing a complaint handling model to automate the process of customer complaint with immediate, reliable and good response. The model presented in this thesis, which is referred as Interval Type-2 Fuzzy Model (IT2FM), allows the service provider to process the vague customer complaint using fuzzy linguistic values. This permits them to identify real complaint and non-real complaint, besides ranking the complaint based on priority automatically without having to go through the complaint one by one.

This thesis is also about implementing the model, IT2FM, using fuzzy type-1 (FT1) and interval fuzzy type-2 (IT2) method. This allows IT2FM to manage and minimize the effects of uncertainties, namely accuracy, and precision that exist in complaint management environment. The uncertainties are the results of the dynamic and ever-changing nature of complaint management environment.

5.1 Summary of the Thesis

To conclude, all the objectives of this research have successfully been achieved. The first objective, which is to derive fundamental reference by creating complaint specification references in the Malay language. This fundamental reference is achieved with the involvement of seven experts. The activities begin with selecting specific characteristics from each three complaint domains and assign a significance value based on predefined scale. Then, the different value for each characteristic from all experts is solved by using Fuzzy Delphi to produce final characteristic weighted value.

The second objective is to establish an approach for constructing FT1 and IT2 MFs and rules based on real complaint data, has been achieved by introducing a complete approach that comprises a sequence of five activities. The approach begins with extracting three different domains of complaint data and selecting seven experts that aim to create complaint fundamental reference for all three used data domains. In this research, specific characteristics are used to carry out part of the complaint handling process. Then, the experts selecting specific characteristics and assign a significance value based on specific complaint domain. Next, the different value for each characteristic from all experts is solved by using Fuzzy Delphi to produce final characteristic weighted value. Then, in this third activities, fuzzy rules is created consists of FIS, five single membership functions, and ten combination membership functions. The FIS rules are generated by referring to the techniques used in the previous research. Later, complaint characteristics are extracted from complaint data and produced aggregated value. Lastly, the complaint aggregated value is processed using fuzzy rules that established to produce the final score.

The third objective is to design FIS models based on the mathematical models described in the previous paragraph. There FIS models are both for FT1 and IT2. These FIS models implementation using combination membership function for the input and output process. The different implementation shows the process of handling the linguistics value is more efficient and produces better results.

The fourth objective is to experiment and evaluate the performance of the proposed models against the human-generated benchmark using a different set of real complaint data. IT2FM is focused on designing and developing a model that can evaluate complaint data and identify either the complaint is a real complaint or non-real complaint. Subsequently, the process to categorize the priority of the complaint can be done and easier for the service provider to take proper action to entertain the complaint. The experiment is done using three sets of different domains complaint data and produces good results and efficient performance.

Overall, one of the outcomes of this research is a complete approach for constructing FT1 and IT2 MFs and rules from real complaint data, where a new combination membership function method has been proposed. The other outcomes of this research are the new fuzzy type-1 (FT1) and interval type-2 fuzzy (IT2) based mathematical model to classify and rank the complaint. Next, the last outcome of this research is the fundamental reference by creating complaint specification references in the Malay language based on complaint domains. The conducted experiment has validated that the constructed mathematical models are correct regarding producing highly consistent results with the human experts. Furthermore, the conducted experiments have also found that proposed approach using IT2 has been able to outperform FT1 regarding accuracy and consistency under the condition of uncertainties. This research has successfully answered the six questions, namely "How can fuzzy approach handle the vagueness in complaint handling process to classify real complaint?"; "How could fuzzy approach in other languages with different structures be leveraged into the Malay language?"; "How can fuzzy approach be effectively imposed in the development of the proposed complaint handling model?"; "Can those existing fuzzy methods handle the uncertainties issues between experts to develop fundamental reference based on the Malay language?"; "How reliable the fundamental reference in the complaint handling process to produce highly consistent results with the human experts?" and "How the proposed complaint is handling model can produced highly consistent results with the human experts?"

5.2 Research Contributions

The overall contributions of this research are summarized below:

1. This research introduces an approach for constructing FT1 and IT2 MFs and rules from real complaint data. This approach includes the introduction of the development of combination FT1 and IT2 MFs from existing MFs method. Other than this new method, the approach is also unique in a way that it comprises complete step-by-step activities/methods that are needed to construct FT1 and IT2 MFs from complaint data. Existing works mainly describe each or some of the methods without formalizing all of them as a complete approach.

2. This research introduces a new model for complaint handling process using fuzzy method for both FT1 and IT2. The model has been developed in two forms, namely mathematical model and FIS model. The formulated mathematical model is translated into programming algorithm, which means that it can be implemented in other programming languages than that of the language used in this research, i.e., Matlab. Moreover, both of the mathematical and FIS models are constructed based on the actual complaint data. Hence they can carry out similar activities on complaint handling process in different domains under complaint data environment.

3. This research introduces a complaint specification reference which established from experts' input. The process is using FDM to solve uncertainties issues that exist based on inputs from a group of experts. The MF value identified in the FIS model extract from the complaint specification value.

4. This research puts forward complaint handling process based on linguistic values-based categorize. The main problem with complaint handling process is that difficult in evaluating the validity of the complaints due to immeasurable quantity of complaints and the existence of uncertainties in the complaints itself. Failure of the classifying process to identify complaints and non-complaints will impact on the solving part. Hence, through linguistic values-based categorize, the service provider immediate recognize the priority of the complaints and allow them to proceed with proper action on solving the complaints. For example, the priority of the complaint can identify as: *Critical*, *Serious* or *Normal*.

5. Another contribution gained from the proposed linguistic values-based categorize is its ability to adapt to uncertainties. Customer complaints contain uncertainties that resulted from dynamic and unpredictable behaviors from complainants. Subjective perception of complainants towards services also cause the uncertainties. Different complainants may perceive complaints differently upon the same service. By the same token, the same complainants may perceive a service differently at the different time. Previous method and approach do not have tolerance towards these uncertainties and hence could not effectively handle the vagueness in the complaints. This eventually affects the accuracy and precision of classifying the complaints.

6. This research suggests a more accurate way of classifying the complaints. Customer complaints environment is dynamic; hence, it contains high degrees of uncertainty. Theoretically, and based on previous works, existing complaint handling method and approach cannot minimize the accuracy effect of uncertainty due to its nature of hard computation. About that, this research has shown that the proposed IT2FM that using IT2 approach has better ability than FT1 approach at handling and minimizing this accuracy effect.

7. This research shows a more optimized way of classifying complaints. Uncertainties affect both efficient and consistent. In this research, the experiments have shown that the proposed IT2FM using IT2 approach outperforms FT1 approach regarding efficiency and consistency.

8. This research has filled the knowledge gap on handling vagueness and uncertainties in the field of complaint handling process. It is believed that there has been a significant need for researching vagueness and uncertain information in complaint management environments; hence the outcomes of this research have contributed to the body of knowledge.

As conclusion, this research contributes four novelties. Firstly is the consideration of two combinations of parameters that are principal and details characteristics to determine real complaint. Secondly is the deriving of fundamental reference by creating complaint specification references based on the Malay language to classify real complaint automatically. Thirdly is the design and development of IT2FM to improve the classification and ranking model in the complaint handling process. Lastly, an application in Matlab is developed to demonstrate the research ideas. This application serves as the initial module to complement the complaint handling research.

5.3 Future Work

The proposed future works are to investigate the performance of IT2FM that is constructed using different types of implementation, specifically on the choices of FIS and MFs. The other choices of MFs may include sigmoid MFs. The motivation for such work would be to find the IT2 implementation that produces the most accurate and precise monitoring results. Also, researcher can further study to extend IT2FM's features to self-learning on new complaint case in the specific domain by identifying significant characteristics to improve the fundamental reference.

REFERENCES

Abaei, G., Selamat, A., & Dallal, J. Al. (2018). A Fuzzy Logic Expert System to Predict Module Fault Proneness using Unlabeled Data. *Journal of King Saud University - Computer and Information Sciences*. http://doi.org/https://doi.org/10.1016/j.jksuci.2018.08.003

Aguwa, C., Monplaisir, L., & Olya, M. H. (2017). Modeling of Fuzzy-based Voice of Customer for Business Decision Analytics. *Knowledge-Based Systems*, *125*, 136–145. http://doi.org/10.1016/j.knosys.2017.03.019

Aguwa, C., Olya, M. H., & Monplaisir, L. (2017). Modeling of fuzzy-based voice of customer for business decision analytics. *Knowledge-Based Systems*, *125*, 136–145. http://doi.org/https://doi.org/10.1016/j.knosys.2017.03.019

Alavi, N. (2013). Quality determination of Mozafati dates using Mamdani fuzzy inference system. *Journal of the Saudi Society of Agricultural Sciences*, *12*(2), 137–142. http://doi.org/https://doi.org/10.1016/j.jssas.2012.10.001

Ali, O. A. M., Ali, A. Y., & Sumait, B. S. (2015). Comparison between the Effects of Different Types of Membership Functions on Fuzzy Logic Controller Performance. *International Journal of Emerging Engineering Research and Technology*, *3*(3), 76–83. Retrieved from https://pdfs.semanticscholar.org/ba50/d3d49ed072528c449b14527825abaa5ea2ac.pdf

Alias, M. A., Hashim, S. Z. M., & Samsudin, S. (2009). Using fuzzy analytic hierarchy process for Southern Johor River ranking. *International Journal of Advances in Soft Computing and Its Applications*, *1*, 63–77.

Almaraashi, M., John, R., Hopgood, A., & Ahmadi, S. (2016). Learning of interval and general type-2 fuzzy logic systems using simulated annealing: Theory and practice. *Information Sciences*, *360*, 21–42. http://doi.org/https://doi.org/10.1016/j.ins.2016.03.047

Ambati, V., & Chen, W. (2015). Cross Lingual Syntax Projection for Resource- Poor Languages Cross Lingual Syntax Projection for. *Associations for Computational Linguistics*, (August).

Anders, G. (2009). Customer satisfaction with service recovery. *Journal of Business Research*, *62*(11), 1220–1222. http://doi.org/10.1016/j.jbusres.2008.11.001

Arnold, T. J., Fang, E. (Er), & Palmatier, R. W. (2011). The effects of customer acquisition and retention orientations on a firm's radical and incremental innovation performance. *Journal of the Academy of Marketing Science*, *39*(2), 234–251. http://doi.org/10.1007/s11747-010-0203-8

Au, N., Buhalis, D., & Law, R. (2009). Complaints on the Online Environment — The Case of Hong Kong Hotels. In W. Höpken, U. Gretzel, & R. Law (Eds.), *Information and Communication Technologies in Tourism 2009* (pp. 73–85). Springer Vienna. http://doi.org/10.1007/978-3-211-93971-0_7

Back, T., Hammel, U., & Schwefel, H.-P. (1997). Evolutionary computation: Comments on the history and current state. *IEEE Transactions on Evolutionary Computation*, *1*(1), 3–17.

Bailey, D., Goonetilleke, A., & Campbell, D. A. (2003). Information analysis and dissemination for site selection decisions using a fuzzy algorithm in GIS. (W. Chu, Ed.)*Information and Knowledge Sharing*. ACTA Press. Retrieved from http://eprints.qut.edu.au/4321/

Baykasoğlu, A., & Gölcük, İ. (2017). Development of an interval type-2 fuzzy sets based hierarchical MADM model by combining DEMATEL and TOPSIS. *Expert Systems with Applications*, *70*, 37–51. http://doi.org/https://doi.org/10.1016/j.eswa.2016.11.001

Bobillo, F., & Straccia, U. (2017). Generalizing type-2 fuzzy ontologies and type-2 fuzzy description logics. *International Journal of Approximate Reasoning*, *87*, 40–66. http://doi.org/https://doi.org/10.1016/j.ijar.2017.04.012

Bobyr, M. V, Milostnaya, N. A., & Kulabuhov, S. A. (2017). A method of defuzzification based on the approach of areas' ratio. *Applied Soft Computing*, *59*, 19–32. http://doi.org/https://doi.org/10.1016/j.asoc.2017.05.040

Boumella, N., & Djouani, K. (2010). A type-2 fuzzy logic decision system for call admission control in next generation mobile networks. In *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE* (pp. 1–6). IEEE.

Bouzon, M., Govindan, K., Rodriguez, C. M. T., & Campos, L. M. S. (2016). Identification and analysis of reverse logistics barriers using fuzzy Delphi method and AHP. *Resources, Conservation and Recycling*, *108*, 182–197. http://doi.org/https://doi.org/10.1016/j.resconrec.2015.05.021

Carvalho, J. G., & Costa, C. T. (2017). Identification method for fuzzy forecasting models of time series. *Applied Soft Computing*, *50*, 166–182. http://doi.org/https://doi.org/10.1016/j.asoc.2016.11.003

Chang-Shing, L., Mei-Hui, W., & Hagras, H. (2010). A Type-2 Fuzzy Ontology and Its Application to Personal Diabetic-Diet Recommendation. *Fuzzy Systems, IEEE Transactions On*, *18*(2), 374–395.

Chao, C.-C., Lirn, T.-C., & Lin, H.-C. (2017). Indicators and evaluation model for analyzing environmental protection performance of airports. *Journal of Air Transport Management*, *63*, 61–70. http://doi.org/https://doi.org/10.1016/j.jairtraman.2017.05.007

Chen, Y.-C. (2002). An application of fuzzy set theory to the external performance evaluation of distribution centers in logistics. *Soft Computing*, *6*(1), 64–70. http://doi.org/10.1007/s005000100149

Chiao-Chen, C., & Yang-Chieh, C. (2011). Comparing consumer complaint responses to online and offline environment. *Internet Research*, *21*(2), 124–137. http://doi.org/10.1108/10662241111123720

Choudhary, A. (2014). A Review of Various Soft Computing Techniques in the Domain of Handwriting Recognition. *International Journal of Information & Computation Technology*, *4*(6), 601–606.

Comas, D. S., Meschino, G. J., Nowé, A., & Ballarin, V. L. (2017). Discovering knowledge from data clustering using automatically-defined interval type-2 fuzzy predicates. *Expert Systems with Applications*, *68*, 136–150. http://doi.org/https://doi.org/10.1016/j.eswa.2016.10.018

Coussement, K., & Van den Poel, D. (2008). Improving customer complaint management by automatic email classification using linguistic style features as predictors. *Decision Support Systems*, *44*(4), 870–882. http://doi.org/10.1016/j.dss.2007.10.010

Cózar, J., DelaOssa, L., & Gámez, J. A. (2018). Learning compact zero-order TSK fuzzy rule-based systems for high-dimensional problems using an Apriori + local search approach. *Information Sciences*, *433–434*, 1–16. http://doi.org/https://doi.org/10.1016/j.ins.2017.12.026

Crie, Dominique ; Ladwein, R., & Crie, D. (2002). Complaint letters and commitment theory : An empirical approach in mail-order selling. *Journal of Targeting, Measurement and Analysis for MArketing*, *11*(1), 45–55. http://doi.org/10.1057/palgrave.jt.5740066

Cui, X., Cai, S., & Qin, Y. (2017). Similarity-based approach for accurately retrieving similar cases to intelligently handle online complaints. *Kybernetes*, *46*(7), 1223–1244.

D'Urso, P. (2017). Informational Paradigm, management of uncertainty and theoretical formalisms in the clustering framework: A review. *Information Sciences*, *400–401*, 30–62. http://doi.org/https://doi.org/10.1016/j.ins.2017.03.001

Dalkey, N. C., & Rourke, D. L. (1971). Experimental Assessment of Delphi Procedures with Group Value Judgments.

Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management Science*, *9*(3), 458–467.

Dasgupta, T., Dey, L., & Verma, I. (2016). Fuzzy Multi-label Classification of Customer Complaint Logs Under Noisy Environment. In V. Flores, F. Gomide, A. Janusz, C. Meneses, D. Miao, G. Peters, … Y. Yao (Eds.), (pp. 376–385). Cham: Springer International Publishing. http://doi.org/10.1007/978-3-319-47160-0_34

Davidow, M., & Dacin, P. a. (1997). Understanding and influencing consumer complaint behavior: improving organizational complaint management. *Advances in Consumer Research*, *24*, 450–456. Retrieved from http://www.acrwebsite.org/volumes/display.asp?id=8085

Dereli, T., Baykasoglu, A., Altun, K., Durmusoglu, A., & Türksen, I. B. (2010). Industrial applications of type-2 fuzzy sets and systems: A concise review. *Computers in Industry*, *In Press*,. http://doi.org/10.1016/j.compind.2010.10.006

Dereli, T., Baykasoglu, A., Altun, K., Durmusoglu, A., & Türksen, I. B. (2011). Industrial applications of type-2 fuzzy sets and systems: A concise review. *Computers in Industry*, *62*(2), 125–137.

Dhimish, M., Holmes, V., Mehrdadi, B., & Dales, M. (2018). Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection. *Renewable Energy*, *117*, 257–274. http://doi.org/https://doi.org/10.1016/j.renene.2017.10.066

Doctor, F., Hagras, H., & Callaghan, V. (2004). A type-2 fuzzy embedded agent for ubiquitous computing environments. In *Fuzzy Systems, 2004. Proceedings. 2004 IEEE International Conference on* (Vol. 2, pp. 1105–1110). IEEE.

Doctor, F., Hagras, H., Roberts, D., & Callaghan, V. (2008). A type-2 fuzzy based system for handling the uncertainties in group decisions for ranking job applicants within Human Resources systems. In *Fuzzy Systems, 2008. FUZZ-IEEE 2008. (IEEE World Congress on Computational Intelligence). IEEE International Conference on* (pp. 481–488).

Doctor, F., Hagras, H., Roberts, D., & Callaghan, V. (2009a). A fuzzy based agent for group decision support of applicants ranking within recruitment systems. In *Intelligent Agents, 2009. IA '09. IEEE Symposium on* (pp. 8–15).

Doctor, F., Hagras, H., Roberts, D., & Callaghan, V. (2009b). A neuro-fuzzy based agent for group decision support in applicant ranking within human resources systems. In *Fuzzy Systems, 2009. FUZZ-IEEE 2009. IEEE International Conference on* (pp. 744–750).

Dongrui, W., & Mendel, J. M. (2007). Aggregation Using the Linguistic Weighted Average and Interval Type-2 Fuzzy Sets. *Fuzzy Systems, IEEE Transactions On*, *15*(6), 1145–1161.

Dubois, D., & Prade, H. (1993). Fuzzy sets and probability: misunderstandings, bridges and gaps. In *Fuzzy Systems, 1993., Second IEEE International Conference on* (pp. 1059–1068). IEEE.

Dutta, M., Bhowmik, S., & Giri, C. (2014). Fuzzy logic based implementation for forest fire detection using wireless sensor network. In *Advanced Computing, Networking and Informatics-Volume 1* (pp. 319–327). Springer.

Dymova, L., & Sevastjanov, P. (2008). Fuzzy Multiobjective Evaluation of Investments with Applications. In C. Kahraman (Ed.), *Fuzzy Engineering Economics with Applications* (Vol. 233, pp. 243–287). Springer Berlin / Heidelberg. http://doi.org/10.1007/978-3-540-70810-0_15

East, R. (2000). Complaining as planned behavior. *Psychology and Marketing*, *17*(12), 1077–1095. http://doi.org/10.1002/1520-6793(200012)17:12<1077::AID-MAR4>3.0.CO;2-W

Efendigil, T., Önüt, S., & Kahraman, C. (2009). A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comparative analysis. *Expert Systems with Applications*, *36*(3, Part 2), 6697–6707. http://doi.org/https://doi.org/10.1016/j.eswa.2008.08.058

El-Helaly, N., Ebeid, A., & El-Menbawe, A. (2015). The Role of Customer Knowledge Management Process in Service Recovery Performance: An Applied Study to the Egyptian National Railways. *International Journal of Management* *and Applied Research*, *2*(1), 1–21.

El Masri, A., Sardouk, A., Khoukhi, L., Merghem-Boulahia, L., & Gaiti, D. (2014). Multimedia support in wireless mesh networks using interval type-2 fuzzy logic system. In *New Technologies, Mobility and Security (NTMS), 2014 6th International Conference on* (pp. 1–5). IEEE.

Faed, A. (2010). Handling e-complaints in customer complaint management system using FMEA as a qualitative system. *Advanced Information Management and Service (IMS) …*, 205–209. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5713449

Faed, A., Chang, E., Saberi, M., Hussain, O. K., & Azadeh, A. (2016). Intelligent customer complaint handling utilising principal component and data envelopment analysis (PDA). *Applied Soft Computing*, *47*, 614–630. http://doi.org/10.1016/j.asoc.2015.02.018

Faed, A., Hussain, O., & Chang, E. (2014). A methodology to map customer complaints and measure customer satisfaction and loyalty. *Service Oriented Computing and Applications*, *8*(1), 33–53. http://doi.org/10.1007/s11761-013-0142-6

Feilong, L., & Mendel, J. M. (2007). An Interval Approach to Fuzzistics for Interval Type-2 Fuzzy Sets. In *Fuzzy Systems Conference, 2007. FUZZ-IEEE 2007. IEEE International* (pp. 1–6).

Figueroa, J., Posada, J., Soriano, J., Melgarejo, M., & Rojas, S. (2005). A type-2 fuzzy controller for tracking mobile objects in the context of robotic soccer games. In *Fuzzy Systems, 2005. FUZZ'05. The 14th IEEE International Conference on* (pp. 359–364). IEEE.

Filip, A. (2013). Complaint Management: A Customer Satisfaction Learning Process. *Procedia - Social and Behavioral Sciences*, *93*, 271–275. http://doi.org/10.1016/j.sbspro.2013.09.188

Fornell, C., & Wernerfelt, B. (1988). A Model for Customer Complaint Management. *Marketing Science*, *7*(3), 287–298. http://doi.org/10.1287/mksc.7.3.287

Galitsky, B. (2006). Reasoning about attitudes of complaining customers. *Knowledge-Based Systems*, *19*(7), 592–615. http://doi.org/10.1016/j.knosys.2006.03.006

Galitsky, B. A., González, M. P., & Chesñevar, C. I. (2009). A novel approach for classifying customer complaints through graphs similarities in argumentative dialogues. *Decision Support Systems*, *46*(3), 717–729.

http://doi.org/10.1016/j.dss.2008.11.015

Galitsky, B., & De La Rosa, J. L. (2011). Concept-based learning of human behavior for customer relationship management. *Information Sciences*, *181*(10), 2016–2035. http://doi.org/10.1016/j.ins.2010.08.027

Gasser, M. (2010). Expanding the Lexicon for a Resource-Poor Language Using a Morphological Analyzer and a Web Crawler. In *LREC*.

Ghalia, M. Ben, & Alouani, A. T. (1995). Artificial neural networks and fuzzy logic for system modeling and control: a comparative study. In *System Theory, 1995., Proceedings of the Twenty-Seventh Southeastern Symposium on* (pp. 258–262). IEEE.

Gronroos, C. (1988). Service Quality: The Six Criteria Of Good Perceived Service. *Review of Business*, *9*(3), 10–13. Retrieved from http://ezproxy.auckland.ac.nz/login?url=http://search.proquest.com/docview/220949893?accountid=8424

Gu, L., & Zhang, Y. (2007). Web shopping expert using new interval type-2 fuzzy reasoning. *Soft Computing - A Fusion of Foundations, Methodologies and Applications*, *11*(8), 741–751. http://doi.org/10.1007/s00500-006-0117-z

Gul, M., Celik, E., Gumus, A. T., & Guneri, A. F. (2018). A fuzzy logic based PROMETHEE method for material selection problems. *Beni-Suef University Journal of Basic and Applied Sciences*, *7*(1), 68–79. http://doi.org/https://doi.org/10.1016/j.bjbas.2017.07.002

Guo, L., Chen, F., Dai, Z., & Liu, Z. (2010). WSN cluster head selection algorithm based on neural network. In *Machine Vision and Human-Machine Interface (MVHI), 2010 International Conference on* (pp. 258–260). IEEE.

Gupta, C., Jain, A., Tayal, D. K., & Castillo, O. (2018). ClusFuDE: Forecasting low dimensional numerical data using an improved method based on automatic clustering, fuzzy relationships and differential evolution. *Engineering Applications of Artificial Intelligence*, *71*, 175–189. http://doi.org/https://doi.org/10.1016/j.engappai.2018.02.015

Gupta, M. M., & Rao, D. H. (1994). On the principles of fuzzy neural networks. *Fuzzy Sets and Systems*, *61*(1), 1–18.

Gupta, R., Sachdeva, A., & Bhardwaj, A. (2010). Selection of 3PL service provider using integrated fuzzy Delphi and fuzzy TOPSIS. In *Proceedings of the World Congress on Engineering and Computer Science* (Vol. 2, pp. 20–22).

Hagras, H. A. (2004). A hierarchical type-2 fuzzy logic control architecture for autonomous mobile robots. *IEEE Transactions on Fuzzy Systems*, *12*(4), 524–539.

Hipp, C., & Grupp, H. (2005). Innovation in the service sector: The demand for service-specific innovation measurement concepts and typologies. *Research Policy*, *34*(4), 517–535. http://doi.org/10.1016/j.respol.2005.03.002

Homburg, C., Fürst, A., & Koschate, N. (2010). On the importance of complaint handling design: a multi-level analysis of the impact in specific complaint situations. *Journal of the Academy of Marketing Science*, *38*(3), 265–287. http://doi.org/10.1007/s11747-009-0172-y

Hong, J. L. (2013). MalayWordNet — A novel lexical database for Malay language. In *2013 10th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (pp. 773–777). http://doi.org/10.1109/FSKD.2013.6816298

Hongxia, T., Jian, C., ShenSheng, Z., & Yujie, M. (2009). A fuzzy evaluation system for web services selection using extended QoS model. *Kybernetes*, *38*(3), 513–521. http://doi.org/10.1108/03684920910944236

Hsu, C.-H., Chang, A.-Y., & Luo, W. (2017). Identifying key performance factors for sustainability development of SMEs – integrating QFD and fuzzy MADM methods. *Journal of Cleaner Production*, *161*, 629–645. http://doi.org/https://doi.org/10.1016/j.jclepro.2017.05.063

Hsu, Y.-L., Lee, C.-H., & Kreng, V. B. (2010). The application of Fuzzy Delphi Method and Fuzzy AHP in lubricant regenerative technology selection. *Expert Systems with Applications*, *37*(1), 419–425. http://doi.org/http://dx.doi.org/10.1016/j.eswa.2009.05.068

Hwa, Rebecca Resnik, Philip Weinberg, Amy Cabezas, Clara Kolak, O. (2005). Bootstrapping parsers via syntactic projection across parallel texts. *Natural Language Engineering*, *11*(03), 311. http://doi.org/10.1017/S1351324905003840

Ilbahar, E., Karaşan, A., Cebi, S., & Kahraman, C. (2018). A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP & fuzzy inference system. *Safety Science*, *103*, 124–136. http://doi.org/https://doi.org/10.1016/j.ssci.2017.10.025

Ishizaka, A., & Labib, A. (2011). Review of the main developments in the analytic hierarchy process. *Expert Systems with Applications*, *38*(11), 14336–14345. http://doi.org/http://dx.doi.org/10.1016/j.eswa.2011.04.143

Ismail, Z.-A. (2017). Maintenance management system (MMS) to support facilities management at Malaysian polytechnic. *Smart and Sustainable Built Environment*, *6*(1), 19–33.

Jana, D. K., Bej, B., Wahab, M. H. A., & Mukherjee, A. (2017). Novel type-2 fuzzy logic approach for inference of corrosion failure likelihood of oil and gas pipeline industry. *Engineering Failure Analysis*, *80*, 299–311. http://doi.org/https://doi.org/10.1016/j.engfailanal.2017.06.046

Jarrar, M., Verlinden, R., & Meersman, R. (2003). *Ontology-Based Customer Complaint Management*. (R. Meersman & Z. Tari, Eds.)*On The Move to Meaningful Internet Systems 2003: OTM 2003 Workshops* (Vol. 2889). Berlin, Heidelberg: Springer Berlin Heidelberg. http://doi.org/10.1007/b94345

Jassi, N. K., & Wraich, S. S. (2014). An enhanced K-Means clustering technique with Hopfield Artificial Neural Network based on reactive clustering protocol. In *Confluence The Next Generation Information Technology Summit (Confluence), 2014 5th International Conference-* (pp. 821–825). IEEE.

Jeou-Shyan, H., Hsuan, H., Chih-Hsing, L., Lin, L., & Chang-Yen, T. (2011). Competency analysis of top managers in the Taiwanese hotel industry. *International Journal of Hospitality Management*, *30*(4), 1044–1054. http://doi.org/http://dx.doi.org/10.1016/j.ijhm.2011.03.012

John, R., & Coupland, S. (2007). Type-2 Fuzzy Logic: A Historical View. *Computational Intelligence Magazine, IEEE*, *2*(1), 57–62.

John, R., & Coupland, S. (2009). Type-2 Fuzzy Logic and the Modelling of Uncertainty in Applications. In A. Bargiela & W. Pedrycz (Eds.), *Human-Centric Information Processing Through Granular Modelling* (Vol. 182, pp. 185–201). Springer Berlin / Heidelberg. http://doi.org/10.1007/978-3-540-92916-1_8

Jonathan, M. G., & Turhan, O. (2007). Uncertain Fuzzy Reasoning: A Case Study in Modelling Expert Decision Making. *Fuzzy Systems, IEEE Transactions On*, *15*(1), 16–30.

Kannan, D. (2018). Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process. *International Journal of Production Economics*, *195*, 391–418. http://doi.org/https://doi.org/10.1016/j.ijpe.2017.02.020

Kardaras, D. K., Karakostas, B., & Mamakou, X. J. (2013). Content presentation personalisation and media adaptation in tourism web sites using Fuzzy Delphi Method and Fuzzy Cognitive Maps. *Expert Systems with Applications*, *40*(6), 2331–2342.

Kardaras, D. K., Mamakou, X. J., Karakostas, B., & Gkourakoukis, G. (2013). An approach to hotel services dynamic pricing based on the Delphi method and fuzzy cognitive maps. In *IFIP International Conference on Artificial Intelligence Applications and Innovations* (pp. 557–566). Springer.

Kartal, H., Oztekin, A., Gunasekaran, A., & Cebi, F. (2016). An integrated decision analytic framework of machine learning with multi-criteria decision making for multi-attribute inventory classification. *Computers & Industrial Engineering*, *101*(Supplement C), 599–613. http://doi.org/https://doi.org/10.1016/j.cie.2016.06.004

Kaur, J., & Rai, M. (2014). Dynamic Clustering in Wireless Sensor Network using Neural Network. *Ijaret.Org*, *5*(2), 1440–1442.

Kaur, J., & Rai, M. K. (2013). Dynamic Clustering in Wireless Sensor Network using Neural Network. *International Journal For Advance Research In Engineering And Technology*, *1*(Ii), 13–16.

Kayacan, E., Sarabakha, A., Coupland, S., John, R., & Khanesar, M. A. (2018). Type-2 fuzzy elliptic membership functions for modeling uncertainty. *Engineering Applications of Artificial Intelligence*, *70*, 170–183. http://doi.org/https://doi.org/10.1016/j.engappai.2018.02.004

Kejík, P., & Hanus, S. (2010). Comparison of fuzzy logic and genetic algorithm based admission control strategies for UMTS system. *Radioengineering*, *19*(1), 6–10.

Khanjankhani, K., Rafiei, S., Ezzatabadi, M. R., Askari, R., Abooee, F., & Shafii, M. (2016). Evaluation and Prioritization of Service Quality Dimensions Using Dematel and Topsis (A Case Study in Iran). *BALI Medical Journal*, *5*(2).

Khashei, M., Reza Hejazi, S., & Bijari, M. (2008). A new hybrid artificial neural networks and fuzzy regression model for time series forecasting. *Fuzzy Sets and Systems*, *159*(7), 769–786. http://doi.org/https://doi.org/10.1016/j.fss.2007.10.011

Kim, E., Tang, L. (Rebecca), & Bosselman, R. (2018). Measuring customer perceptions of restaurant innovativeness: Developing and validating a scale. *International Journal of Hospitality Management*, *74*, 85–98. http://doi.org/https://doi.org/10.1016/j.ijhm.2018.02.018

Kisi, O. (2013). Applicability of Mamdani and Sugeno fuzzy genetic approaches for modeling reference evapotranspiration. *Journal of Hydrology*, *504*, 160–170. http://doi.org/https://doi.org/10.1016/j.jhydrol.2013.09.043

Ko, M., Tiwari, A., & Mehnen, J. (2010). A review of soft computing applications in supply chain management. *Applied Soft Computing*, *10*(3), 661–674.

Latifah, A. L., Ramli, B., & Fard, P. Y. (2010). Improving accessibility and responsiveness in a complaints management system. *E-Leader Singapore*.

Lee, C.-H., Wang, Y.-H., & Trappey, A. J. C. (2015). Ontology-based reasoning for the intelligent handling of customer complaints. *Computers & Industrial Engineering*, *84*, 144–155. http://doi.org/10.1016/j.cie.2014.11.019

Li, D.-C., Lin, W.-K., Chen, C.-C., Chen, H.-Y., & Lin, L.-S. (2018). Rebuilding sample distributions for small dataset learning. *Decision Support Systems*, *105*, 66–76. http://doi.org/https://doi.org/10.1016/j.dss.2017.10.013

Li, W., Yu, S., Pei, H., Zhao, C., & Tian, B. (2017). A hybrid approach based on fuzzy AHP and 2-tuple fuzzy linguistic method for evaluation in-flight service quality. *Journal of Air Transport Management*, *60*, 49–64. http://doi.org/10.1016/j.jairtraman.2017.01.006

Lin, C. (2013). Application of fuzzy Delphi method (FDM) and fuzzy analytic hierarchy process (FAHP) to criteria weights for fashion design scheme evaluation. *International Journal of Clothing Science and Technology*, *25*(3), 171–183. http://doi.org/10.1108/09556221311300192

Lin, Q.-L., Liu, L., Liu, H.-C., & Wang, D.-J. (2013). Integrating hierarchical balanced scorecard with fuzzy linguistic for evaluating operating room performance in hospitals. *Expert Systems with Applications*, *40*(6), 1917–1924. http://doi.org/http://dx.doi.org/10.1016/j.eswa.2012.10.007

Linder, A., & Schmitt, R. (2015). Data-oriented Technical Complaint Management for Sustainable Problem Solution. *Procedia CIRP*, *29*, 591–596. http://doi.org/10.1016/j.procir.2015.02.008

Lupo, T. (2013). Handling stakeholder uncertain judgments in strategic transport service analyses. *Transport Policy*, *29*(0), 54–63. http://doi.org/http://dx.doi.org/10.1016/j.tranpol.2013.04.002

Lynch, C., Hagras, H., & Callaghan, V. (2005). Embedded type-2 FLC for real-time speed control of marine and traction diesel engines. In *Fuzzy Systems, 2005. FUZZ'05. The 14th IEEE International Conference on* (pp. 347–352). IEEE.

Mahjouri, M., Ishak, M. B., Torabian, A., Manaf, L. A., & Halimoon, N. (2017). The application of a hybrid model for identifying and ranking indicators for assessing the sustainability of wastewater treatment systems. *Sustainable Production and Consumption*, *10*, 21–37. http://doi.org/https://doi.org/10.1016/j.spc.2016.09.006

Majeed, S., Gupta, A., Raj, D., & Rhee, F. C.-H. (2018). Uncertain fuzzy self-organization based clustering: interval type-2 fuzzy approach to adaptive resonance theory. *Information Sciences*, *424*, 69–90. http://doi.org/https://doi.org/10.1016/j.ins.2017.09.062

Makropoulos, C. K., Butler, D., & Maksimovic, C. (2003). Fuzzy Logic Spatial Decision Support System for Urban Water Management. *Journal of Water Resources Planning and Management*, *129*(1), 69–77. Retrieved from http://link.aip.org/link/?QWR/129/69/1

Martin, A., Lakshmi, T. M., & Venkatesan, V. P. (2014). An information delivery model for banking business. *International Journal of Information Management*, *34*(2), 139–150.

McCulloch, W., & Pitts, W. (1990). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biology*, *52*(1–2), 99–115. http://doi.org/10.1007/BF02459570

Melgarejo, M. A., Garcia, R. A., & Peña-Reyes, C. A. (2004). Pro-two: A hardware based platform for real time type-2 fuzzy inference. In *Fuzzy Systems, 2004. Proceedings. 2004 IEEE International Conference on* (Vol. 2, pp. 977–982). IEEE.

Melin, P., & Castillo, O. (2002). Intelligent control of non-linear dynamic plants using type-2 fuzzy logic and neural networks. In *Fuzzy Information Processing Society, 2002. Proceedings. NAFIPS. 2002 Annual Meeting of the North American* (pp. 22–27). IEEE.

Mendel, J. (2013). Interval Type-2 Fuzzy Logic Systems and Perceptual Computers: Their Similarities and Differences. In A. Sadeghian, J. M. Mendel, & H. Tahayori (Eds.), *Advances in Type-2 Fuzzy Sets and Systems SE - 1* (Vol. 301, pp. 3–17). Springer New York. http://doi.org/10.1007/978-1-4614-6666-6_1

Mendel, J. M. (2001). *Uncertain Rule-Based Fuzzy Logic Systems: Introduction and New Directions*. Prentice-Hall, Upper Saddle River, NJ.

Mendel, J. M. (2003). Fuzzy sets for words: a new beginning. In *Fuzzy Systems, 2003. FUZZ'03. The 12th IEEE International Conference on* (Vol. 1, pp. 37–42).

IEEE.

Mendel, J. M. (2007). Computing with words: Zadeh, turing, popper and occam. *IEEE Computational Intelligence Magazine*, *2*(4), 10–17.

Mendel, J. M. (2009). On answering the question “Where do I start in order to solve a new problem involving interval type-2 fuzzy sets?” *Information Sciences*, *179*(19), 3418–3431. http://doi.org/10.1016/j.ins.2009.05.008

Mendel, J. M., & John, R. I. B. (2002). Type-2 fuzzy sets made simple. *Fuzzy Systems, IEEE Transactions On*, *10*(2), 117–127.

Min Gyung, K., Chenya, W., & Anna, S. M. (2010). The relationship between consumer complaining behavior and service recovery: An integrative review. *International Journal of Contemporary Hospitality Management*, *22*(7), 975–991. http://doi.org/10.1108/09596111011066635

Minaei-Bidgoli, B., & Akhondzadeh, E. (2010). A New Approach of Using Association Rule Mining in Customer Complaint Management. *International Journal of Computer Science Issues(IJCSI)*, *7*(5).

Mohanty, M., & Shankar, R. (2017). Modelling uncertainty in sustainable integrated logistics using Fuzzy-TISM. *Transportation Research Part D: Transport and Environment*, *53*, 471–491. http://doi.org/https://doi.org/10.1016/j.trd.2017.04.034

Moharrer, M., Tahayori, H., Livi, L., Sadeghian, A., & Rizzi, A. (2015). Interval type-2 fuzzy sets to model linguistic label perception in online services satisfaction. *Soft Computing*, *19*(1), 237–250.

Muduli, L., Jana, P. K., & Mishra, D. P. (2018). Wireless sensor network based fire monitoring in underground coal mines: A fuzzy logic approach. *Process Safety and Environmental Protection*, *113*, 435–447. http://doi.org/https://doi.org/10.1016/j.psep.2017.11.003

Murray, T. J., Pipino, L. L., & van Gigch, J. P. (1985). A pilot study of fuzzy set modification of Delphi. *Human Systems Management*, *5*(1), 76–80.

Najar, A. S., Al-Sukhni, H. A., & Aghakhani, N. (2010). The Application of Service-Oriented Architecture in E-complaint System. In *Communication Software and Networks, 2010. ICCSN ’10. Second International Conference on* (pp. 280–283).

Najjar, M. S., Smith, A. K., & Kettinger, W. J. (2010). ‘Stuff’Happens: A Theoretical Framework for Internal IS Service Recovery. In *AMCIS 2010 Proceedings* (pp. 1–8). Lima, Peru. Retrieved from http://aisel.aisnet.org/amcis2010/505

Nimbalkar, J. K. (2012). Use of neural network in wsns: A survey. *International Journal of Advancement in Electronics and Computer Engineering (IJAECE)*, *1*(3), 93–98.

O'Neil Jr, H. F., Ni, Y., Jacoby, A., & Swigger, K. M. (2013). *Human benchmarking for the evaluation of expert systems*. *Echnology Assessment in Software Applications*. Routledge.

Ouyang, X., & Guo, F. (2017). Intuitionistic fuzzy analytical hierarchical processes for selecting the paradigms of mangroves in municipal wastewater treatment. *Chemosphere*. http://doi.org/https://doi.org/10.1016/j.chemosphere.2017.12.102

Ozen, T., Garibaldi, J. M., & Musikasuwan, S. (2004). Modelling the variation in human decision making. In *Fuzzy Information, 2004. Processing NAFIPS '04. IEEE Annual Meeting of the* (Vol. 2, pp. 617–622).

Panagiotis, V. P., & Ioannis, G. (2009). A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank. *Career Development International*, *14*(4), 372–387. http://doi.org/10.1108/13620430910979853

Pangsub, P., & Lekcharoen, S. (2010). An adaptive type-2 fuzzy for control policing mechanism over high speed networks. In *Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON), 2010 International Conference on* (pp. 914–918). IEEE.

Park, Y., & Lee, S. (2011). How to design and utilize online customer center to support new product concept generation. *Expert Systems with Applications*, *38*(8), 10638–10647. http://doi.org/10.1016/j.eswa.2011.02.125

Phatak, S. A., & Nisar, A. (2017). Design and Implementation of an Intra Public Sector Collaboration Framework using Technology. *INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND NETWORK SECURITY*, *17*(5), 101–114.

Phoemphon, S., So-In, C., & Niyato, D. (Tao). (2018). A hybrid model using fuzzy logic and an extreme learning machine with vector particle swarm optimization for wireless sensor network localization. *Applied Soft Computing*, *65*, 101–120. http://doi.org/https://doi.org/10.1016/j.asoc.2018.01.004

Potey, M., & Sinha, P. K. (2015). Review and analysis of machine learning and soft computing approaches for user modeling. *International Journal of Web & Semantic Technology*, *6*(1), 39.

Prenesti, E., & Gosmaro, F. (2015). Trueness, precision and accuracy: a critical overview of the concepts as well as proposals for revision. *Accreditation and Quality Assurance*, *20*(1), 33–40.

Pyon, C. U., Woo, J. Y., & Park, S. C. (2011). Service improvement by business process management using customer complaints in financial service industry. *Expert Systems with Applications*, *38*(4), 3267–3279. http://doi.org/10.1016/j.eswa.2010.08.112

Qian, Y. (2006). An application based on K-means algorithm for clustering companies listed. In *Service Operations and Logistics, and Informatics, 2006. SOLI'06. IEEE International Conference on* (pp. 723–727). IEEE.

Quek, C., Pasquier, M., & Lim, B. (2009). A novel self-organizing fuzzy rule-based system for modelling traffic flow behaviour. *Expert Systems with Applications*, *36*(10), 12167–12178. http://doi.org/10.1016/j.eswa.2009.03.048

Raina, R., & Thomas, M. (2012). Fuzzy vs. probabilistic techniques to address uncertainty for radial distribution load flow simulation. *Energy and Power Engineering*, *4*(02), 99.

Rampersad, H. (2001). 75 painful questions about your customer satisfaction. *The TQM Magazine*, *13*(5), 341–347. http://doi.org/10.1108/09544780110401907

Razali, R., Halim, K. N. A., & Jusoff, K. (2011). Quality Improvement of Services in Universiti Teknologi Mara Pahang from a Management Perspective. *Management Science and Engineering*, *5*(1), 71–80.

Rodzman, S. B. bin, Ismail, N. K., Rahman, N. A., & Nor, Z. M. (2017). The implementation of fuzzy logic controller for defining the ranking function on malay text corpus. In *2017 IEEE Conference on Big Data and Analytics (ICBDA)* (pp. 93–98). http://doi.org/10.1109/ICBDAA.2017.8284113

Rosario, S., Benveniste, A., Haar, S., & Jard, C. (2008). Probabilistic qos and soft contracts for transaction-based web services orchestrations. *IEEE Transactions on Services Computing*, *1*(4), 187–200.

Sa'ad, H. H. Y., Isa, N. A. M., Ahmed, M. M., & Sa'd, A. H. Y. (2018). A robust structure identification method for evolving fuzzy system. *Expert Systems with Applications*, *93*, 267–282. http://doi.org/https://doi.org/10.1016/j.eswa.2017.10.011

Sahin, B., & Yip, T. L. (2017). Shipping technology selection for dynamic capability based on improved Gaussian fuzzy AHP model. *Ocean Engineering*, *136*, 233–

242. http://doi.org/https://doi.org/10.1016/j.oceaneng.2017.03.032

Salaken, S. M., Khosravi, A., Nguyen, T., & Nahavandi, S. (2017). Output uncertainty score for decision making processes using interval type-2 fuzzy systems. *Engineering Applications of Artificial Intelligence*, *65*, 159–167. http://doi.org/https://doi.org/10.1016/j.engappai.2017.07.019

Sander, S., Göran, S., Terje, S., & Bo, E. (2010). A DIP-construct of perceived justice in negative service encounters and complaint handling in the Norwegian tourism industry. *Managing Service Quality*, *20*(1), 26–45. http://doi.org/10.1108/09604521011011612

Saridakis, K. M., & Dentsoras, A. J. (2008). Soft computing in engineering design–A review. *Advanced Engineering Informatics*, *22*(2), 202–221.

Saxena, A., & Saxena, A. (2013). Review of soft computing techniques used in robotics application. *International Journal of Information and Computation Technology*, *3*(3), 101–106.

Sepúlveda, R., Castillo, O., Melin, P., Rodríguez-Díaz, A., & Montiel, O. (2007). Experimental study of intelligent controllers under uncertainty using type-1 and type-2 fuzzy logic. *Information Sciences*, *177*(10), 2023–2048.

Shahin, A. (1997). Customer complaints management and empowerment. In *4th International Management Conference, Germany*.

Shahin, A., Khodadady, Z., & Shirouyehzad, H. (2015). Ranking electronic customer complaints by FMEA and TOPSIS with a case study in Isfahan Province Gas Company. *International Journal of Process Management and Benchmarking*, *5*(1), 19. http://doi.org/10.1504/IJPMB.2015.066027

Shahraki, A. R., & Paghaleh, M. J. (2011). Ranking the voice of customer with fuzzy DEMATEL and fuzzy AHP. *Indian Journal of Science and Technology*, *4*(12).

Shao, X. (2011). Based on Two Swarm Optimized Algorithm of Neural Network to Prediction the Switch's Traffic of Coal. In *Computer Science and Society (ISCCS), 2011 International Symposium on* (pp. 299–302). IEEE.

Sharifian, A., Ghadi, M. J., Ghavidel, S., Li, L., & Zhang, J. (2018). A new method based on Type-2 fuzzy neural network for accurate wind power forecasting under uncertain data. *Renewable Energy*, *120*, 220–230. http://doi.org/https://doi.org/10.1016/j.renene.2017.12.023

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of Marketing*

Research, *36*(3), 356–372.

Soh, S. (2010). A decision model for evaluating third-party logistics providers using fuzzy analytic hierarchy process. *African Journal of Business Management*, *4*, 339–349. Retrieved from http://academicjournals.org/AJBM/PDF/pdf2010/Mar/Soh.pdf

Stauss, B., & Schoeler, A. (2004). Complaint management profitability: what do complaint managers know? *Managing Service Quality: An International Journal*, *14*(2/3), 147–156. http://doi.org/10.1108/09604520410528572

Stephens, N., & Gwinner, K. (1998). Why don't some people complain? A cognitive-emotive process model of consumer complaint behavior. *Journal of the Academy of Marketing Science*, *26*(3), 172–189. http://doi.org/10.1177/0092070398263001

Stevens, J. L., Spaid, B. I., Breazeale, M., & Esmark-Jones, C. L. (2018). Timeliness, transparency, and trust: A framework for managing online customer complaints. *Business Horizons*. http://doi.org/https://doi.org/10.1016/j.bushor.2018.01.007

Sultan, A. B. M., Abidin, K. Z., & Abdullah, M. T. (2008). The Implementation of Agent-based Complaint Management System. *IJCSNS*, *8*(5), 205–207.

Sun, D., & Liao, Q. (2018). Type-2 Fuzzy logic based time-delayed shared control in online-switching tele-operated and autonomous systems. *Robotics and Autonomous Systems*. http://doi.org/https://doi.org/10.1016/j.robot.2017.12.010

Tahmasebi, P., & Hezarkhani, A. (2012). A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. *Computers & Geosciences*, *42*(Supplement C), 18–27. http://doi.org/https://doi.org/10.1016/j.cageo.2012.02.004

Tan, Y., Shuai, C., Jiao, L., & Shen, L. (2017). An adaptive neuro-fuzzy inference system (ANFIS) approach for measuring country sustainability performance. *Environmental Impact Assessment Review*, *65*, 29–40. http://doi.org/https://doi.org/10.1016/j.eiar.2017.04.004

Tarasyev, A. A., Agarkov, G. A., Acosta, C. A. O., & Koksharov, V. A. (2018). Fuzzy Logic and Optimization of Educational Paths. *IFAC-PapersOnLine*, *51*(2), 511–516. http://doi.org/https://doi.org/10.1016/j.ifacol.2018.03.086

Tavana, M., Fallahpour, A., Di Caprio, D., & Santos-Arteaga, F. J. (2016). A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection. *Expert Systems with Applications*, *61*(Supplement C), 129–144.

http://doi.org/https://doi.org/10.1016/j.eswa.2016.05.027

Tax, S. S., Brown, S. W., & Chandrashekaran, M. (1998). Customer evaluations of service complaint experiences: implications for relationship marketing. *The Journal of Marketing*, *62*(2), 60–76.

Tomar, A. S., Singh, M., Sharma, G., & Arya, K. V. (2018). Traffic Management using Logistic Regression with Fuzzy Logic. *Procedia Computer Science*, *132*, 451–460. http://doi.org/https://doi.org/10.1016/j.procs.2018.05.159

Trappey, A. J. C., Ching-Hung, L., Wen-Pin, C., & Trappey, C. V. (2010). A framework of customer complaint handling system. In *Service Systems and Service Management (ICSSSM), 2010 7th International Conference on* (pp. 1–6).

Trappey, C., Hsin-Ying, W., & Kuan-Liang, L. (2012). Knowledge discovery of customer satisfaction and dissatisfaction using ontology-based text analysis of critical incident dialogues. In *Computer Supported Cooperative Work in Design (CSCWD), 2012 IEEE 16th International Conference on* (pp. 470–475). http://doi.org/10.1109/cscwd.2012.6221860

Tseng, M.-L. (2017). Using social media and qualitative and quantitative information scales to benchmark corporate sustainability. *Journal of Cleaner Production*, *142*, 727–738. http://doi.org/https://doi.org/10.1016/j.jclepro.2016.05.062

Tseng, M.-L., & Bui, T.-D. (2017). Identifying eco-innovation in industrial symbiosis under linguistic preferences: A novel hierarchical approach. *Journal of Cleaner Production*, *140*, 1376–1389. http://doi.org/https://doi.org/10.1016/j.jclepro.2016.10.014

Tseng, M.-L., Lim, M. K., Wong, W.-P., Chen, Y.-C., & Zhan, Y. (2018). A framework for evaluating the performance of sustainable service supply chain management under uncertainty. *International Journal of Production Economics*, *195*, 359–372. http://doi.org/https://doi.org/10.1016/j.ijpe.2016.09.002

Tseng, M.-L., Lim, M., Wu, K.-J., Zhou, L., & Bui, D. T. D. (2018). A novel approach for enhancing green supply chain management using converged interval-valued triangular fuzzy numbers-grey relation analysis. *Resources, Conservation and Recycling*, *128*, 122–133. http://doi.org/https://doi.org/10.1016/j.resconrec.2017.01.007

Veronica Gonzalez, B., & Francisco Tamayo, E. (2005). TQM and QFD: exploiting a customer complaint management system. *International Journal of Quality & Reliability Management*, *22*(1), 30–37.

http://doi.org/10.1108/02656710510572977

Vieira, J., Dias, F. M., & Mota, A. (2004). Neuro-fuzzy systems: a survey. In *5th WSEAS NNA International Conference on Neural Networks and Applications, Udine, Italia*.

Vos, J. F. J., Huitema, G. B., & Lange-Ros, E. de. (2008). How organisations can learn from complaints. *The TQM Journal*, *20*(1), 8–17. http://doi.org/10.1108/09544780810842866

Wang, D., Zeng, X.-J., & Keane, J. A. (2013). A simplified structure evolving method for Mamdani fuzzy system identification and its application to high-dimensional problems. *Information Sciences*, *220*, 110–123. http://doi.org/https://doi.org/10.1016/j.ins.2011.12.033

Wang, Y.-S., Wu, S.-C., Lin, H.-H., & Wang, Y.-Y. (2011). The relationship of service failure severity, service recovery justice and perceived switching costs with customer loyalty in the context of e-tailing. *International Journal of Information Management*, *31*(4), 350–359. http://doi.org/10.1016/j.ijinfomgt.2010.09.001

Wang, Y. (2016). Type-2 fuzzy event parallel computing system: Overcoming computer int index limitation in big data. *Applied Soft Computing*, *38*, 1076–1087. http://doi.org/https://doi.org/10.1016/j.asoc.2015.06.050

Wang, Y., & Yeo, G.-T. (2016). A Study on International Multimodal Transport Networks from Korea to Central Asia: Focus on Secondhand Vehicles. *The Asian Journal of Shipping and Logistics*, *32*(1), 41–47. http://doi.org/https://doi.org/10.1016/j.ajsl.2016.03.005

Waqas, M., Ali, H., & Khan, M. A. (2014). An investigation of effects of justice recovery dimensions on students' satisfaction with service recovery in higher education environment. *International Review on Public and Nonprofit Marketing*, *11*(3), 263–284.

Wilrich, P.-T. (2007). Robust estimates of the theoretical standard deviation to be used in interlaboratory precision experiments. *Accreditation and Quality Assurance*, *12*(5), 231–240.

Wu, D., & Mendel, J. M. (2009). A comparative study of ranking methods, similarity measures and uncertainty measures for interval type-2 fuzzy sets. *Information Sciences*, *179*(8), 1169–1192. http://doi.org/10.1016/j.ins.2008.12.010

Wu, D., & Tan, W. W. (2004). A type-2 fuzzy logic controller for the liquid-level process. In *Fuzzy Systems, 2004. Proceedings. 2004 IEEE International Conference on* (Vol. 2, pp. 953–958). IEEE.

Wu, T., Liu, X., & Qin, J. (2018). A linguistic solution for double large-scale group decision-making in E-commerce. *Computers & Industrial Engineering*, *116*, 97–112. http://doi.org/https://doi.org/10.1016/j.cie.2017.11.032

Yang, X., Yan, L., & Zeng, L. (2013). How to handle uncertainties in AHP: The Cloud Delphi hierarchical analysis. *Information Sciences*, *222*(0), 384–404. http://doi.org/http://dx.doi.org/10.1016/j.ins.2012.08.019

Yarowsky, D., Ngai, G., & Wicentowski, R. (2001). Inducing multilingual text analysis tools via robust projection across aligned corpora. In *HLT '01: Proceedings of the first international conference on Human language technology research* (pp. 1–8). http://doi.org/10.3115/1072133.1072187

Yazgan, H. R., Boran, S., & Goztepe, K. (2009). An ERP software selection process with using artificial neural network based on analytic network process approach. *Expert Systems with Applications*, *36*(5), 9214–9222. http://doi.org/https://doi.org/10.1016/j.eswa.2008.12.022

Yilmaz, C., Varnali, K., & Kasnakoglu, B. T. (2016). How do firms benefit from customer complaints? *Journal of Business Research*, *69*(2), 944–955.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning--I. *Information Sciences*, *8*(3), 199–249. http://doi.org/10.1016/0020-0255(75)90036-5

Zadeh, L. A. (1994). Fuzzy Logic, Neural Networks, and Soft Computing. *Commun. ACM*, *37*(3), 77–84. http://doi.org/10.1145/175247.175255

Zhang, J. (2017). Evaluating regional low-carbon tourism strategies using the fuzzy Delphi- analytic network process approach. *Journal of Cleaner Production*, *141*, 409–419. http://doi.org/https://doi.org/10.1016/j.jclepro.2016.09.122

APPENDICES

APPENDIX A (APPROVAL APPLICATION LETTER FOR DATA EXTRACTION ON E-ADUAN (ISPAAA) FROM DBKL)

UNIVERSITI
TEKNOLOGI
PETRONAS

Tarikh: 21 Februari 2013

Dr. Ismail Stapa
Pengarah Jabatan Perancangan Korporat
Tingkat 5 Menara DBKL 2
Jalan Raja Laut
50350 Kuala Lumpur

U.P: Puan Nor Nazariah Binti Kamardin
Unit Aduan Awam & Khidmat Pelanggan

Assalamualaikum Warahmatullahi Wabarakatuh dan Salam Sejahtera

Tuan,

MEMOHON KEBENARAN BAGI MENDAPATKAN DATA E-ADUAN (ISPAAA) BAGI TUJUAN PENYELIDIKAN Ph.D.

Dengan segala hormatnya perkara di atas adalah dirujuk.

Untuk makluman pihak tuan pelajar di bawah seliaan saya yang bernama **Razulaimi Bin Razali,** No Pelajar: **G01393** sedang membuat penyelidikan Ph.D. di Universiti Teknologi Petronas yang bertajuk **'A Type-2 Fuzzy Based Ranking Algorithm for Complaint Management.'** Berikutan dengan itu, penyelidikan tersebut memerlukan data bagi melaksanakan ujikaji yang berkaitan. Sehubungan dengan itu pihak kami memohon kerjasama dan kebenaran dari pihak tuan bagi menggunakan data E-Aduan (ISPAAA) bagi tujuan tersebut. Pelajar saya akan berhubung dengan pihak tuan bagi memberikan maklumat terperinci spesifikasi data yang diperlukan.

Saya berharap permohonan ini akan mendapat pertimbangan dan kelulusan dari pihak tuan. Kerjasama dari pihak tuan mengenai perkara ini amat saya hargai.

Sekian, terima kasih.

Wassalam.

Yang benar,

DR. JAFREEZAL BIN JAAFAR
Ketua Jabatan Komputer dan Sains Maklumat
Universiti Teknologi Petronas
Tel: 05-3687400/7402 Fax: 05-3656188
Email: jafree@petronas.com.my

s.k: Tuan Haji Jaafar Bin Haji Abd. Rahman
Pengarah Jabatan Pengurusan Maklumat

UNIVERSITI TEKNOLOGI PETRONAS
INSTITUTE OF TECHNOLOGY PETRONAS SDN. BHD.
(Company No: [illegible]) Wholly-owned subsidiary of PETRONAS
Bandar Seri Iskandar, 31750 Tronoh, Perak Darul Ridzuan, Malaysia

Tel. General Line : 605-3688000 D. Line No : HRMA 605-3688285 Finance 605-3688283 IRC 605-3688455
Corporate Services 605-3688237 Student Support Services 605-368 8410 Registry 605-3688345 Security 605-3688315
Fax : HRMA 605-3654075 Finance 605-3654087 IRC 605-3657672 Student Support Services 605-3667746 Registry 605-3654082 Website http://www.utp.edu.my

APPENDIX B (APPROVAL LETTER FOR DATA EXTRACTION ON E-ADUAN (ISPAAA) FROM DBKL)

DEWAN BANDARAYA KUALA LUMPUR

JABATAN PERANCANGAN KORPORAT
TINGKAT 5
MENARA DBKL 1
JALAN RAJA LAUT
50350 KUALA LUMPUR

Bil.(99)dlm.DBKL/JP/05/2010/8002-01

11 Mac 2013
28 Rabiulakhir 1434H

Tuan Dr. Jafreezal bin Jaafar
Universiti Teknologi Petronas
Bandar Seri Iskandar,
31750 Tronoh, Perak

SURAT INI TELAH DIHANTAR MELALUI FAKSIMILI PADA : 11/3/2013

Tuan,

MEMOHON KEBENARAN BAGI MENDAPATKAN DATA E-ADUAN (ISPAAA) BAGI TUJUAN PENYELIDIKAN

Dengan segala hormatnya saya merujuk kepada perkara tersebut diatas.

2. Untuk makluman tuan, Pihak DBKL dengan sukacita menerima permohonan tuan untuk mendapatkan data E-Aduan (ISPAAA) bagi tujuan penyelidikan. Oleh itu, untuk mendapatkan maklumbalas selanjutnya tuan bolehlah menghubungi **Puan Nor Nazariah binti Kamardian** di talian **03-20282877**.

3. Kerjasama dan perhatian tuan dalam perkara ini amatlah dihargai.

Sekian, terima kasih.

"BERKHIDMAT UNTUK NEGARA"
"BERSEDIA MENYUMBANG BANDARAYA CEMERLANG"

Saya yang menurut perintah,

(NOR NAZARIAH BINTI KAMARDIN)
Dewan Bandaraya Kuala Lumpur
b.p. Datuk Bandar Kuala Lumpur

Telefon : 03-2617 9000
Talian Bebas Tol : 1-800-88-3255
Laman Web : http://www.dbkl.gov.my
Faks : 03-2698 0460/03-2694 1373
Faks : 03-2697 0084 (*Call Centre*)
E-mel : jprk@dbkl.gov.my

APPENDIX C (DATA EXTRACTION DETAILS REQUIREMENT ON E-ADUAN (ISPAAA) FROM DBKL)

PERINCIAN DATA E-ADUAN (ISPAAA) YANG DIPERLUKAN BAGI TUJUAN PENYELIDIKAN Ph.D.

Tarikh data: 01/12/2012 – 28/02/2013

Jabatan:

1) Pembangunan Sosio Ekonomi
    a. Jabatan Kesihatan dan Alam Sekitar
    b. Jabatan Pemudahcara Perniagaan dan Pengurusan Penjaja
    c. Jabatan Penguatkuasaan
    d. Jabatan Pengurusan Perumahan dan Pembangunan Komuniti

2) Perlaksanaan Projek dan Penyelenggaraan
    a. Jabatan Kejuruteraan Awam dan Saliran
    b. Jabatan Kejuruteraan Mekanikal dan Elektrikal
    c. Jabatan Landskap dan Rekreasi
    d. Jabatan Pengangkutan Bandar

Maklumat yang diperlukan adalah seperti berikut:

a. Jenis
b. Tajuk
c. Butiran
d. Hasil yang dikehendaki
e. Kem / Agensi
f. Status Kes
g. Nota Penyelesaian
h. Tarikh Ditugas
i. Tarikh Terima Aduan
j. Tarikh Selesai

Format yang diperlukan bagi penyediaan maklumat ini adalah dalam format csv (comma separate value) atau sekurang-kurangnya dalam format excel.

Contoh:

Jenis	Tajuk	Butiran	Hasil yg dikehendaki	Kem / Agensi	Status Kes	Nota Penyelesaian	Tarikh Ditugas	Tarikh Terima Aduan	Tarikh Selesai

APPENDIX D (MEMO LETTER FOR DISCUSSION ON E-ADUAN (ISPAAA) WITH THE EXPERTS FROM DBKL)

JABATAN PERANCANGAN KORPORAT
UNIT PANGGILAN SETEMPAT DBKL
Tingkat 1, Menara DBKL 2,
Jalan Raja Laut,
50350 Kuala Lumpur.
Talian Am: 03-2028 2873/4 Faksimili : 03-2697 0084

MEMO

4 Disember 2013
6 Safar 1435H

Ejen Jabatan
Jabatan Kejuruteraan Awam dan Saliran
Jabatan Kesihatan dan Alam Sekitar
Jabatan Kejuruteraan Mekanikal dan Elektrikal
Jabatan Penguatkuasaan
Jabatan Landskap dan Rekreasi.

PERBINCANGAN BERSAMA MEGENAI SISTEM I-SPAAA DENGAN PIHAK UNIVERSITI TEKNOLOGI PETRONAS(UTP)

Dengan segala hormatnya saya merujuk kepada perkara tersebut di atas.

2. Untuk makluman, pihak Universiti Teknologi Petronas (UTP) ingin mengadakan perbincangan bersama mengenai proses aduan yang boleh ditambahbaik dalam sistem i-SPAAA. Tujuan perbincangan ini adalah untuk:

i) Menemubual proses ISPAAA bagi Jabatan yang dikendalikan oleh pegawai.

ii) Mengenalpasti dan memberi nilai katakunci yang telah dikenalpasti dari data yg diperolehi.

3. Sehubungan itu, pihak tuan/ puan dimohon memberi kerjasama hadir dalam perbincangan tersebut agar pihak UTP boleh menemubual dengan Ejen jabatan yang terlibat. Perbincangan akan diadakan pada:-

Tarikh: 9 Disember 2013(Isnin)
Masa: 9.30 pagi
Tempat: Tingkat 1, Pusat Panggilan Setempat
Menara DBKL 2

Sekian, terima kasih.

(NITTI SHAHERA BT ZAINUDDIN)
Penolong Pegawai Tadbir
Pusat Panggilan Setempat

APPENDIX E (SAMPLE DATA FOR DOMAIN LANDSCAPE AND RECREATION)

Ranting-ranting kayu jatuh	Pada 29 Januari 2013 jam lebih kurang 12.30 tengahari rakan sekerja saya sedang berjalan di jalan pejalan kaki menuju ke bangunan GTower di sepanjang Jalan Tun Razak berhadapan dengan Menara Tabung Haji tiba-tiba ranting-ranting kayu yang telah reput telah jatuh dan nyaris menimpa rakan sekerja saya.
Mohon bersih sisa pokok	Aduan : Pokok dah ditebang dan nak minta bersihkan sisa pokok Lokasi : 34 Jalan Medan Imbi Off Jalan Imbi, 55100 KL :
Mohon cantas pokok	Aduan : Terdapat pokok besar di hadapan rumah, dan pengadu mohon agar pihak DBKL mencantas pokok tersebut kerana dahan terlalu panjang dan besar sehingga mengganggu wayar telefon rumah pengadu. Lokasi : No. 9 jalan Wangsa Budi 6A, Wangsa Melawati
Aduan: Pokok-pokok besar yang membahayakan orang awam	Dengan hormatnya saya merujuk kepada aduan di atas. Dimaklumkan saya telah menerima banyak aduan daripada penduduk-penduduk bahawa pokok-pokok besar di sekitar tapak bola keranjang di Jalan Selinsing 6, Taman City, 51200 Segambut adalah mengancam keselamatan orang awam oleh kerana ranting-rantingnya sungguh besar dan sering jatuh apabila hujan lebat atau angin kuat. Oleh itu, saya mohon tindakan memotong ranting-ranting pokok dapat dijalankan dengan segera. Sekian, terima kasih.
DAHAN POKOK YANG PERLU DITEBANG DENGAN SEGERA	Beberapa bulan yang lalu saya ada membuat aduan melalui website DBKL tetapi sehingga kini tiada tindakan yang diambil. Pokok besar di tepi jalan beralamat di No: 2, Jalan 9D/6 (dekat Kolej TAR), Setapak kini dahan-dahan nya melintasi atas pagar rumah saya. Dahannya amat besar dan tidak boleh ditebang dengan parang. Saya berharap pihak DBKL dapat datang ke sini dan ambil tindakan segera. Sekian terima kasih.
POKOK	LOKASI 1 : JALAN BUKIT MALURI,terdapat 2 batang pokok tua sehinnga sekarang tidak ada org datang tebang. LOKASI 2: Berhadapan dgn Sime Darby Hospital.Minta trim pokok.
Pokok Besar	Aduan mengenai terdapat pokok yang terlalu besar dan mohon di tebang. Pengadu memaklumkan bahawa pokok tersebut telah condong dan mencecah wayar elektrik dan telefon hingga mengganggu wayar tersebut. Pengadu juga memaklumkan akar dari pokok tersebut juga telah mengakibatkan simen di parking kereta menjadi pecah. Daun-daun dari pokok tersebut juga terlalu banyak hingga menyebabkan kawasan menjadi kotor. Mohon siasatan dan tindakan dapat di lakukan. Lokasi aduan : Hadapan rumah, No. 34 Jalan Bukit Setiawangsa 12, Taman Setiawangsa, 54200 Kuala Lumpur. Terima Kasih
Mohon tebang pokok	Aduan : Mohon tebang pokok mangga yang sudah tua, kerana akar pokok mangga merosakkan lantai rumah dan getah pokok merosakkan kereta Lokasi : Depan rumah no . 61 Jalan BEE ENG 2, Taman Tayton View, KL
Longgokan batu	Aduan : Ada kawasan kosong di tanam pokok, ada orang longgok batu menyebabkan nampak tidak cantik Lokasi : Hala masuk Taman Ibu kota, Jalan Pahang ke Jalan Gombak
Pokok tumbang	Pengadu memaklumkan terdapat pokok tumbang 3 batang kena tiang TNB di hadapan rumah pengadu. Lokasi aduan:No 73 Jalan Midah Besar Taman Midah Kuala Lumpur.
potong pokok	pengadu memaklumkan terdapat pokok yang perlu dipotong lokasi aduan : lorong perak hadapan pintu Menara IMC
PENYELENGGARAAN POKOK	Pengadu memaklumkan bahawa terdapat pokok pokok di sekitar kawasan kediaman pengadu yang memerlukan penyelenggaraan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Sekitar Blok A, B, C dan D, Lorong Jugra, Taman Sri Limpah, Jalan Klang Lama.
TEBANG POKOK	Pengadu memaklumkan supaya pihak DBKL dapat melakukan penebangan pokok di kawasan kediaman pengadu. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Blok 40, Flat Sri Melaka. Bahagian belakang flat.
SISA SAMPAH POKOK	Pengadu memaklumkan terdapat sisa sampah pokok di lokasi yang maklumkan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Jalan Datuk Sulaiman 3, Taman Tun Dr Ismail.
Mohon trim pokok	Aduan : Pokok besar sudah lama tidak trim, daun-daun yang gugur atas bumbung telah menyebabkan bumbung bocor dan bila hujan lebat habis basah rumah pengadu. Lokasi : No. 31 Lang Hitam 4, Kepong Baru
Dahan pokok yang reput.	Di sepanjang jalan dari kepong ke bandaraya berhampiran gerai makan di jalan jinjang utara terdapat dahan pokok yang dh mati.Mohon pihak DBKL menebang sebelum dahan pokok itu jatuh terkena pengguna jalan raya
mencantas ranting pokok	Pengadu dialamat di No.84 jalan 1/149K Bandar Seri Petaling Kuala Lumpur memaklumkan terdapat daun n ranting pokok yang merendang memasuki tingkat rumah belakang rumah beliau
MOHON TEBANG POKOK	PENGADU MEMINTA KERJASAMA PIHAK DBKL MENEBANG POKOK YANG TERDAPAT DI DALAM KAWASAN VILLA FLORA CONDOMINIUM, JALAN BURHANUDDIN HELMI, TTDI.
POKOK	ADUAN BERKAITAN PERMOHONAN POTONG POKOK YANG TERLALU TINGGI. LOKASI: LOT 467, JALAN TEMBAGA, TAMAN TIARA TITIWANGSA OFF JALAN PAHANG (DI HADAPAN RUMAH).
Permohonan Tebang Pokok	Pemilik rumah No. 75, Jalan 2/27C, Seksyen 5, Wangsa Maju, 53300 KL memohon pihak DBKL untuk menebang sebatang pokok besar di hadapan rumah kerana dikhuatiri membahayakan beliau dan keluarga. Pihak DBKL pernah datang untuk menebang pokok tersebut tetapi tidak sepenuhnya.
akar pokok	Akar pokok besar yang menjalar sehingga mengenai dinding longkang menyebabkan dinding longkang itu pecah. Lokasi : Hadapan rumah No 11, Jalan Ibu Kota 10, Taman Setapak Indah, Setapak, Kuala Lumpur.
tanaman didepan rumah	Jiran menanam pokok bunga depan rumah sempadan rumah saya dan dipagarkan. Pokok itu tinggi dan berdekatan tiang tnb , pencuri sembunyi sana.

APPENDIX F (SAMPLE DATA FOR DOMAIN ENFORCEMENT)

SAMPAH SARAP DAN PARKING KENDERAAN BERLAPIS	Sampah sarap yang tidak dibersihkan oleh kontraktor/pekerja pembersihan di Jalan Bangsar Utama 1, berhadapan Menara UOA Bangsar amat memalukan terutamanya dari pelancong dan delegasi luar negara. Kenderaan yang diletakkan secara berlapis menambahkan kesesakan lalulintas serta parking motorsikal yang terhad menyebabkan keadaan menjadi tidak teratur.
sisa binaan	Didepan Rumah No.117, Lorong 6, Kg Pandan 55100 Kuala Lumpur terdapat sisa-sisa akibat kerja pembinaan yang di biarkan hampir dua bulan di dalam taman kanak-kanak tersebut
Pengutip parking haram	Aduan : Pengadu memaklumkan bahawa terdapat pihak yang tidak bertanggungjawab mengutip duit parking dari orang awam yang parking di kawasan itu. Pengadu mendakwa, mereka juga turut membuang saman yang diletakkan pada cermin kereta oleh pihak penguatkuasa dan mengutip duit parking. Mohon siasatan oleh pihak DBKL berhubung perkara ini. Lokasi : Dekat LRT Masjid Jamek
Penjaja Haram Indonesia di Taman Tasek Dato Keramat- Ahad 2feb2013	Dalam kawasan taman.Setiap petang sabtu dan Ahad ketika ramai pengunjung ke Taman Tasek Dato Keramat ini. Maka terdapat lah 3 lokasi peniaga air, kueh dan apam balik.. Dan pengguna motorsikal pun kadang2 menggunakan trek jalan kaki dlm kawasan taman. Mereka mgkin asal dr indon sbb longat bahasa mreka. Ke mana pergi nya pemantauan?
Aduan: Taman permainan kanak-kanak menjadi tempat meletak kereta	Dengan hormatnya saya merujuk kepada aduan di atas dan dilampirkan bersama di sini adalah dua gambar yang menunjukkan taman permainan kanak-kanak di Jalan Cenderuh 7, Taman Bamboo, Jalan Ipoh, 51200 Kuala Lumpur telah menjadi tempat meletak kereta khasnya pada hari hujung minggu dan waktu malam. Oleh yang demikian, saya mohon agar aduan ini disiasat dan kawasan taman permainan kanak-kanak tersebut dapat dipagarkan untuk melarang kereta diletak di dalam kawasan padang. Maklumbalas awal sangatlah dialu-alukan dan sekian, terima kasih.
Isu saman	Pengadu memaklumkan beliau dikenakan tindakan saman tetapi lokasi tidak dimaklumkan didalam saman tertera Tindakan dipohon: Penjelasan pihak tertera mengenai masalah yang dikemukakan
2 BUAH BAS MELTAK DI ATAS BAHU JALAN	LOKASI:-JALAN 22 TAMAN DATO SENU SENTUL KUALA LUMPUR PERKARA:-PENGADU MENGADU TERDAPAT DUA BUAH BUS MELETAK DI ATAS BAHU JALAN YANG MENYEMBABKAN LONGKANG PECAH/AIR BERTAKUNG DAN PENGADU MENGELAMI KESESAKAN NAFAS DI SEBABAKAN ASAP BAS
Lori keluar masuk	Aduan : Lori keluar masuk bawa tanah mengotorkan jalan Lokasi : Jalan Sibu 1
KERETA TERBIAR	Pengadu memaklumkan bahawa terdapat sebuah kenderaan yang terbiar di hadapan kediaman pengadu. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : No. 36, Lorong Awan Kecil 2, Batu 5, Taman OUG.
HALANGAN KENDERAAN	Pengadu memaklumkan bahawa terdapat penduduk di Kondominium Green Park yang meletakkan kenderaan di laluan yang tidak dibenarkan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Bahagian luar kawasan Green Park Kondominium, Jalan Awan Kerawang, Taman Yarl.
HALANGAN	Pengadu memaklumkan terdapat orang awam yang meletakkan kenderaan di tempat letak kereta penghuni Flat Sri Melaka dan menyukarkan penghuni untuk meletakkan kenderaan mereka. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Blok 40, Flat Sri Melaka.
Aduan lori kilang menggunakan kawasan perumahan untuk laluan	Saya ingin mengadu bahawa terlalu banyak lori kilang menggunakan jalan taman iaitu jalan kawasan perumahan di Jalan 26, Taman Desa Jaya, 52100 Kepong. Hal ini membahayakan anak-anak dan penghuni di Taman Desa Jaya, Kepong dimana jalan taman itu merupakan jalan pintas bagi lori-lori kilang ini. Kawasan perumahan juga dimasuki habuk dan debu.
HALANGAN PAKING	Pengadu memaklumkan terdapat orang awam yang meletakkan kenderaan (double paking) di kawasan yang dimaklumkan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Taman SA, Bukit Bandaraya (berdekatan Bangsar Shopping Mall).

APPENDIX G (SAMPLE DATA FOR DOMAIN MECHANICAL AND ELECTRICAL ENGINEERING)

LAMPU JALAN	Lampu jalan terpasang 24 jam LOKASI: Susur Lakefield daripada laluan Sg Besi ke Kg Malaysia.
LAMPU JLN	Lampu jalan tidak menyala. LOKASI: No. 26,Changkat Semantan 2,Semantan Villa, Damansara
LAMPU JALAN TIDAK MENYALA	LOKASI: Jalan 2/17, Taman Fadason LAMPU JALAN TIDAK MENYALA
Lampu jalan tidak menyala	Aduan : Lampu jalan tidak menyala (No. DBKL 4 JVKA FP-1) Lokasi : Jalan Vivikananda, Tun Sambanthan Brickfields
Lampu jalan 24 jam menyala	Aduan : Lampu jalan 24 jam menyala. Sudah sebulan Lokasi : 1. Jalan Sultan, KL 2. Petaling Street, KL
Lampu jalan tidak menyala	Aduan : Lampu jalan tidak menyala sudah sebulan Lokasi : 322 Jalan 24/39, Taman Petaling, Kepong
Lampu jalan rosak	Aduan : Lampu jalan rosak Lokasi : Jalan Beremi, Bukit Bintang Nama : Chong No. Fon :
lampu jalan tidak menyala	Lokasi: No.1 Jalan Taman Pantai,Bukit Pantai Tiang no.1 dan no.2 tidak menyala sudah lama.Mohon tindakan.
Lampu Jalan tidak menyala	Aduan : Lampu Jalan tidak menyala LOkasi : Depan Bangunan May Flower, No. 1 jalan Metro Pudu 1
Lampu jalan rosak	Aduan mengenai terdapat 4 batang tiang lampu jalan yang tidak berfungsi. Pengadu memaklumkan pihak DBKL pernah membaiki lampu tersebut tetapi tiga jam selepas di baiki lampu tersebut rosak kembali. Pengadu juga memaklumkan terdapat banyak lampu yang rosak di lorong-lorong sekitar. Mohon siasatan dan tindakan dapat di lakukan segera kerana kawasan tersebut adalah kawasan tapak penjaja. Lokasi aduan : Tapak Penjaja Haji Taib, Lorong Haji Taib, Jalan Haji Taib, Kuala Lumpur. Terima Kasih
TIANG LAMPU ROSAK	PENGADU MEMAKLUMKAN TIANG LAMPU DI HADAPAN RUMAH DI NO.146, JALAN DATUK SULAIMAN 6, TTDI ROSAK. MOHON DIBAIKPULIH SEGERA.
Aduan Lampu Jalan Tidak Menyala	Aduan mengenai lampu jalan yang tidak menyala di Jalan Sri Rampai. Lokasi yang lebih tepat adalah di sepanjang jalan hadapan Apartmen Dahlia berdekatan Rampai Bussiness Centre. Pengadu memaklumkan masalah ini telah berlarutan selama seminggu di mana amat membahayakan kepada orang ramai.
Lampu jalan tidak menyala	Aduan : Lampu jalan tidak menyala sudah beberapa hari. Lokasi : HL 393, Jalan Air Cetek, Hot Spring, Setapak, KL
Lampu Jalan Tidak Menyala	Lokasi: Jalan Kuching ke Jalan 1/42 Aduan: Lampu jalan tidak menyala
Lampu jalan tidak tutup	Aduan : Lampu jalan tidak tutup walau hari sudah siang Lokasi : Jalan Permai 2, Highway jalan kuching
LAMPU JALAN ROSAK	Pengadu memaklumkan terdapat lampu jalan rosak di kawasan yang dimaklumkan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Jalan 2/152, Taman Perindustrian OUG, Batu 6, Jalan Puchong, KL (Tiang lampu DBKL No. 5).
LAMPU JALAN ROSAK	Pengadu memaklumkan terdapat lampu jalan rsak di lokasi yang di maklumkan. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : 145, Jalan Desa Utama,Taman Desa
LAMPU JALAN ROSAK	Pengadu memaklumkan bahawa terdapat 2 lokasi lampu jalan rosak. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Dihadapan Blok D, Unit 26G dan Blok C, 9LG, Cheras Business Centre.
LAMPU JALAN ROSAK	Pengadu memaklumkan bahawa terdapat lampu jalan rosak. Pengadu juga memaklumkan lampu tidak ditutup walaupun hari siang. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : No 10, Jalan Gallawey Off Jalan Pudu. Depan IPK. Behind Swiss Garden.
Lampu jalan tidak menyala	Aduan : Lampu jalan tidak menyala, kadang kala lampu berkelip-kelip sahaja Lokasi : Berhampiran rumah No. 1 Jalan 11/105, Taman Midah Cheras
Lampu jalan tidak menyala	Aduan : Lampu jalan tidak menyala Lokasi : No 140 Jalan Bukit Segar 3, Taman Bukit Segar, KL
Lampu Jalan Rosak	Lampu jalan di sepanjang Jalan 9, Kampung Baru Salak Selatan, Kuala Lumpur rosak selama tiga hari akibat daripada ribut petir. Kawasan di sekitarnya amat gelap pada waktu malam yang mungkin menyebabkan berlakunya kes kecurian dan kemalangan.
LAMPU JALAN	PENGADU MEMAKLUMKAN LAMPU JALAN DI SEKITAR LOKASI MENYALA PADA JAM 10 MALAM SEHINGGA PAGI. LOKASI: BUKIT MANDARINA ENKLAF 2, CHERAS
curi elektrik	lokasi: lorong t.a rahman (belakang globe store) jalan t.a rahman kl aduan:terdapat tiga penjaja mengunakan lori pic up berniaga dengan menarik elektrik dari tiang lampu milik dbkl juga dari suiz box dbkl
LAMPU JALAN	DIMAKLUMKAN LAMPU JALAN DI LOKASI TERTERA TIDAK MENYALA. LOKASI: PERSIARAN SYED PUTRA 5 (DI HUJUNG JALAN). KEMASKINI ADUAN 6/3/2013 :- Menurut pengadu masih terdapat 1 tiang lagi yang masih belum nyala.Mohon Siasat dan tindakan.
LAMPU JALAN	Pengadu memaklumkan di sepanjang jalan di kawasan kediaman pengadu, lampu jalan tidak berfungsi. Mohon pihak DBKL mengambil tindakan segera berhubung aduan ini. LOKASI ADUAN : Jalan Bukit Mandarina Damai, Taman Bukit Mandarina 2nd Encleve, Cheras.

APPENDIX H (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – FIRST EVALUATER)

Expert Validation for IT2FM
(Interval Fuzzy Type-2 Model for Customer Complaint Handling Method)

Please tick mark (√) where necessary.

I, the undersigned below:

Name	First: EMIZUL EZANI Last: ZULKIFLI *
Academic Qualifications	Diploma ☐ Bachelor ☑ Master ☐ Doctorate ☐ *
E-mail Address	emizulezani@dbkl.gov.my *
Designation	SYSTEM ANALYST *
Specialisation	MULTIMEDIA PRODUCTION *
Length of Service (years)	1-5 ☐ 6-10 ☐ 11-20 ☑ 21-30 ☐ over 30 ☐ *

Have approved to the student from Faculty of Science & Information Technology, Universiti Teknologi Petronas as listed below:

Name : Razulaimi Razali

Student No. : G01393 (Doctoral of Philosophy Information Technology)

I agreed to get participate in research validation and give permission that my validation will be recorded and the content will be used for further academic purposes. I understand that the content from this validation of this study is true for improvement studies.

Name: EMIZUL EZANI BINTI ZULKIFLI

Sign:

SECTION II – Validation of Research

Please indicate your response to the following elements by using the scale indication.

Strongly Disagree	Disagree	Moderately Agree	Agree	Strongly Agree
1	2	3	4	5

ITEMS	1	2	3	4	5	COMMENT
1. The propose model is reliable for complaint handling process.	☐	☐	☐	☑	☐	
2. The research finding is able to improve complaint handling process.	☐	☐	☐	☐	☑	
3. The research finding is able to help for getting accurate results.	☐	☐	☐	☑	☐	
4. The research finding analysis results are able to analyze the accuracy of the propose model.	☐	☐	☐	☑	☐	
5. The research finding is able to show the best approach for the propose model.	☐	☐	☑	☐	☐	
6. The research finding is able to show the important of the accuracy results in complaint handling process.	☐	☐	☑	☐	☐	
7. Suggestions for further improvements.	Improvement on the language processing, cause the identified characteristics are not enough for total complaint handling process					

**Thank you for your time and completing this validation form.*

APPENDIX I (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – SECOND EVALUATER)

Expert Validation for IT2FM
(Interval Fuzzy Type-2 Model for Customer Complaint Handling Method)

Please tick mark (√) where necessary.

I, the undersigned below:

Name	First: NOR HAZREN Last: MOHD ISA *
Academic Qualifications	Diploma ☐ Bachelor ☑ Master ☐ Doctorate ☐ *
E-mail Address	norhazren@dbkl.gov.my *
Designation	SYSTEM ANALYST *
Specialisation	INTRANET *
Length of Service (years)	1-5 ☐ 6-10 ☐ 11-20 ☑ 21-30 ☐ over 30 ☐ *

Have approved to the student from Faculty of Science & Information Technology, Universiti Teknologi Petronas as listed below:

Name : Razulaimi Razali

Student No. : G01393 (Doctoral of Philosophy Information Technology)

I agreed to get participate in research validation and give permission that my validation will be recorded and the content will be used for further academic purposes. I understand that the content from this validation of this study is true for improvement studies.

Name: NOR HAZREN BINTI MOHD ISA

Sign:

SECTION II – Validation of Research

Please indicate your response to the following elements by using the scale indication.

Strongly Disagree	Disagree	Moderately Agree	Agree	Strongly Agree
1	2	3	4	5

ITEMS	1	2	3	4	5	COMMENT
1. The propose model is reliable for complaint handling process.	☐	☐	☐	☐	✔	
2. The research finding is able to improve complaint handling process.	☐	☐	☐	✔	☐	
3. The research finding is able to help for getting accurate results.	☐	☐	☐	✔	☐	
4. The research finding analysis results are able to analyze the accuracy of the propose model.	☐	☐	☐	✔	☐	
5. The research finding is able to show the best approach for the propose model.	☐	☐	✔	☐	☐	Not really clear on how the best approach being identified
6. The research finding is able to show the important of the accuracy results in complaint handling process.	☐	☐	☐	✔	☐	
7. Suggestions for further improvements.	The proposed model is good to have capability in processing both language english and malay					

**Thank you for your time and completing this validation form.*

APPENDIX J (EVALUATION FORM FROM EXPERTS ON IT2FM DESIGN – THIRD EVALUATER)

Expert Validation for IT2FM
(Interval Fuzzy Type-2 Model for Customer Complaint Handling Method)

Please tick mark (√) where necessary.

I, the undersigned below:

Name	First: NORAZLINA Last: ROSANI *
Academic Qualifications	Diploma ☐ Bachelor ☑ Master ☐ Doctorate ☐ *
E-mail Address	norazlinarosani@dbkl.gov.my *
Designation	SYSTEM ANALYST *
Specialisation	GIS *
Length of Service (years)	1-5 ☐ 6-10 ☐ 11-20 ☑ 21-30 ☐ over 30 ☐ *

Have approved to the student from Faculty of Science & Information Technology, Universiti Teknologi Petronas as listed below:

Name : Razulaimi Razali

Student No. : G01393 (Doctoral of Philosophy Information Technology)

I agreed to get participate in research validation and give permission that my validation will be recorded and the content will be used for further academic purposes. I understand that the content from this validation of this study is true for improvement studies.

Name: NORAZLINA BINTI ROSANI

Sign:

SECTION II – Validation of Research

Please indicate your response to the following elements by using the scale indication.

Strongly Disagree	Disagree	Moderately Agree	Agree	Strongly Agree
1	2	3	4	5

ITEMS	1	2	3	4	5	COMMENT
1. The propose model is reliable for complaint handling process.	☐	☐	☐	☑	☐	
2. The research finding is able to improve complaint handling process.	☐	☐	☐	☑	☐	
3. The research finding is able to help for getting accurate results.	☐	☐	☑	☐	☐	
4. The research finding analysis results are able to analyze the accuracy of the propose model.	☐	☐	☐	☑	☐	
5. The research finding is able to show the best approach for the propose model.	☐	☐	☑	☐	☐	
6. The research finding is able to show the important of the accuracy results in complaint handling process.	☐	☐	☐	☑	☐	
7. Suggestions for further improvements.	Need further details on the language processing matter					

**Thank you for your time and completing this validation form.*