The copyright © of this thesis belongs to its rightful author and/or other copyright owner. Copies can be accessed and downloaded for non-commercial or learning purposes without any charge and permission. The thesis cannot be reproduced or quoted as a whole without the permission from its rightful owner. No alteration or changes in format is allowed without permission from its rightful owner.

WEIGHTED SUBSETHOOD AND REASONING BASED FUZZY TIME SERIES FOR MOVING HOLIDAY ELECTRICITY LOAD DEMAND FORECASTING

ROSNALINI BT MANSOR

Universiti Utara Malaysia

DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2021

Awang Had Salleh
Graduate School
of Arts And Sciences

Universiti Utara Malaysia

PERAKUAN KERJA TESIS / DISERTASI
(Certification of thesis / dissertation)

Kami, yang bertandatangan, memperakukan bahawa
(We, the undersigned, certify that)

ROSNALINI MANSOR

calon untuk Ijazah **PhD**
(candidate for the degree of)

telah mengemukakan tesis / disertasi yang bertajuk:
(has presented his/her thesis / dissertation of the following title):

"WEIGHTED SUBSETHOOD AND REASONING BASED FUZZY TIME SERIES FOR MOVING HOLIDAY ELECTRICITY LOAD DEMAND FORECASTING"

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.
(as it appears on the title page and front cover of the thesis / dissertation).

Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan, sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada : ***17 September 2020.***
That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on: ***September 17, 2020.***

Pengerusi Viva: *(Chairman for VIVA)*	**Assoc. Prof. Dr. Nor Idayu Mahat**	Tandatangan *(Signature)*
Pemeriksa Luar: *(External Examiner)*	**Prof. Dr. Mohd Lazim Abdullah**	Tandatangan *(Signature)*
Pemeriksa Luar: *(External Examiner)*	**Assoc. Prof. Dr. Nazirah Ramli**	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	**Assoc. Prof. Dr. Maznah Mat Kasim**	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	**Assoc. Prof. Dr. Mahmod Othman**	Tandatangan *(Signature)*

Tarikh:
(Date) ***September 17, 2020***

PERMISSION TO USE

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to :

Dean of Awang Had Salleh Graduate School of Arts and Sciences

UUM College of Arts and Sciences

Universiti Utara Malaysia

06010 UUM Sintok

Universiti Utara Malaysia

ABSTRAK

Perayaan bergerak ialah perayaan yang tidak tetap mengikut kalendar Gregorian. Kebanyakan kajian permintaan beban elektrik menunjukkan bahawa peristiwa ini mempengaruhi ketepatan ramalan beban elektrik. Ini disebabkan oleh data sejarah perayaan bergerak yang terhad, dan tempoh data siri masa yang lebih lama diperlukan untuk mendedahkan corak siri masa tersebut. Di samping itu, perbezaan ciri setiap perayaan bergerak dan kewujudan sebilangan besar ketidaktentuan data beban elektrik juga menyumbang kepada ketidakpastian dan ketidaktepatan ramalan. Algoritma siri masa kabur (FTS) dapat mengatasi masalah ramalan permintaan beban elektrik perayaan bergerak (MH-ELD), namun algoritma FTS kurang kebolehtafsiran model akhir, kurang menterjemah kekuatan hubungan logik kabur dan tidak menyediakan proses ramalan FTS yang lengkap. Ini akan menyebabkan kurang maklumat hubungan alami tentang bagaimana manusia membuat pertimbangan dan keputusan, dan kurang panduan untuk menjalankan proses ramalan FTS yang lengkap. Oleh itu, kajian ini mengubah suai algoritma FTS konvensional dengan memanfaatkan subset-terdekat berpemberat dalam algoritma pada segmen data siri masa permintaan beban elektrik Malaysia. Algoritma yang diubah suai, Siri Masa Kabur Disegmen Subset-terdekat Berpemberat (WeSuSFTS) terdiri daripada empat fasa utama; pra-pemprosesan data, pembangunan model, pelaksanaan model dan penilaian model. Algoritma WeSuSFTS menggunakan pengendali min-mak untuk penaakulan kabur dan peraturan nyah kabur purata yang menjadikan proses tersebut lebih ringkas. Dua jenis WeSuSFTS: Satu-faktor dan M-faktor telah dilaksanakan. Hasil kajian menunjukkan bahawa model WeSuSFTS mempunyai ketepatan yang lebih tinggi berbanding model FTS konvensional, khususnya model Satu-faktor memberikan keputusan ramalan yang cemerlang dengan peratusan ralat purata mutlak terendah. Oleh itu, model WeSuSFTS berjaya meningkatkan ketepatan ramalan MH-ELD.

Universiti Utara Malaysia

Kata kerja: Permintaan beban elektrik, Peramalan, Siri masa kabur, Perayaan bergerak, Subset-terdekat berpemberat.

ABSTRACT

A Moving holiday is a non-fixed holiday according to the Gregorian calendar. Most of the electricity load demand studies showed that this event affects the accuracy of load forecasting. It is due to a limited historical data about moving holiday, and a longer time series is acquired to reveal the pattern. Besides, different characteristics of each moving holiday and existence of a great number of irregularities in the load data also contribute to the forecasting inaccuracy and uncertainty. Fuzzy time series (FTS) algorithm is able to overcome moving holiday electricity load demand (MH-ELD) forecasting problem, but the FTS algorithm lacks final model interpretation, less interpretability of fuzzy logical relationship strength, and does not provide a complete FTS forecasting process. These will provide less information about the relationship that naturally represents how humans make judgments and decisions, and less guide to conduct complete FTS forecasting process. Therefore, this study modified the conventional FTS algorithm by applying weighted subsethood in the algorithm on segmented Malaysia electricity load demand time series data. The modified algorithm, Weighted Subsethood Segmented Fuzzy Time Series (WeSuSFTS) consists of four main phases; data pre-processing, model development, model implementation and model evaluation. The WeSuSFTS algorithm uses the min-max operator for fuzzy reasoning and average rule defuzzification which make the process simpler. Two types of WeSuSFTS: One-factor and M-factor were also executed. The results show that the WeSuSFTS models have higher accuracy compared to the conventional FTS models, particularly the One-factor model gives the most outstanding forecasting results with the smallest mean absolute percentage error. Hence, the WeSuSFTS models succeed to improve the MH-ELD forecasting accuracy.

Keywords: Electricity load demand, Forecasting, Fuzzy time series, Moving holiday, Weighted-subsethood

Universiti Utara Malaysia

ACKNOWLEDGEMENT

In the name of Allah, the Most Gracious and the Most Merciful. Alhamdulillah, all praises to Allah for His blessings and providing me with the strength to complete this thesis.

First and foremost, I would like to express my deep and sincere gratitude to my supervisors, Dr. Maznah Mat Kasim, Professor, School of Quantitative Sciences (SQS), Universiti Utara Malaysia and Dr. Mahmod Othman, Associate Professor, Faculty of Science and Information Technology, Universiti Teknologi Petronas, for their supervision and constant support. They guided and encouraged me to be professional and do the right thing even when the going gets tough. Without their persistent help, the goal of this research would not have been realized. Their dynamism, vision, sincerity and motivation have deeply inspired me. It was a great privilege and honor to work and study under their guidance. I would also like to express my gratitude to SQS management and staff who have been so helpful in supporting me to complete this thesis. The physical and technical contribution of Universiti Utara Malaysia is truly appreciated for awarding me with two Research Generation University Grants (S/O code: 13878 and 14589) to carry out this research project.

I want to thank a very special person, my husband, Bahtiar Jamili Zaini for his continued and unfailing love, support and understanding during my pursuit of Ph.D degree that made the completion of thesis possible. He is always around at difficult times where I thought it is impossible to continue; he helped me to keep things in perspective. I greatly value his contribution and deeply appreciate his belief in me. I appreciate my kids, Hafiyah, Hafizah, Hasif, Hanisah and Hanif for abiding my ignorance and the patience they showed during my thesis writing process. Words would never say how grateful I am to all of you. I consider myself the luckiest person in the world to have such a lovely and caring family standing beside me with their love and unconditional support. My heartfelt gratitude also goes to my mother, Siti Normah Sulaiman and all of my family members for their love, moral support and blessing.

Last but not least, to those who indirectly contributed to this research, your kindness means a lot to me.

Thank you very much.

Universiti Utara Malaysia

TABLE OF CONTENTS

Permission to Use i
Abstrak ii
Abstract iii
Acknowledgement iv
Table of Contents v
List of Tables ix
List of Figures xi
List of Appendices xiii
List of Abbreviations xiv

CHAPTER ONE INTRODUCTION 1
1.1 Background of the Research 1
1.1.1 Electricity Load Demand (ELD) 3
1.1.2 Moving Holiday Electricity Load Demand (MH-ELD) 6
1.1.3 Electricity Load Demand (ELD) Forecasting 8
1.1.4 Moving Holiday Electricity Load Demand (MH-ELD) Forecasting 10
1.1.5 Fuzzy Time Series (FTS) Forecasting 12
1.1.6 Segmented FTS 14
1.2 Gap in Moving Holiday Electricity Load Demand Forecasting 15
1.3 Problem Statement 17
1.4 Research Questions 22
1.5 Research Objectives 22
1.6 Significance of the Study 23
1.6.1 Application Aspect 23
1.6.2 Theoretical Aspect 23
1.7 Scope of the Study 24
1.8 Thesis Organisation 25

CHAPTER TWO LITERATURE REVIEW 27
2.1 Introduction 27
2.2 Fuzzy Time Series (FTS) 27
2.2.1 Fuzzy Time Series 28
2.2.2 Linguistic Variable 29

Universiti Utara Malaysia

2.2.3 Membership Function 30
2.2.4 Fuzzy Logical Relationship 32
2.2.5 Union and Intersection of Fuzzy Sets 33
2.2.6 Fuzzy Logical Relationship Group 33
2.2.7 Fuzzy Rules 34
2.2.8 Fuzzification 34
2.2.9 Fuzzy Subsethood Value 35
2.2.10 Weighted Fuzzy Subsethood Value 35
2.2.11 *k*-means Clustering 36
2.2.12 Defuzzzification 37
2.2.13 One-factor and M-factor FTS 41
2.2.14 First and High-Order FTS 41
2.3 Fuzzy Subsethood-based Algorithm 42
2.4 Previous Studies in Fuzzy Time Series Forecasting 49
2.5 Weighted Fuzzy Time Series Methods 57
2.6 Segmented Fuzzy Time Series 61
2.7 Time Series Forecasting Model Validation 63
2.8 The Importance of Electricity Load Demand Forecasting 65
2.9 Previous Research on MH-ELD Forecasting 67
2.10 Factors Affecting MH-ELD 74
2.11 Summary 78

CHAPTER THREE METHODOLOGY 80

3.1 Introduction 80
3.2 Overview of Enhanced Algorithms 81
3.3 Phase 1: Pre-processing Data 88
3.3.1 Step (1): Segmenting Time Series 88
3.3.2 Step (2): Combining Segmented Time Series 89
3.3.3 Step (3): Dividing the Data into Modelling and Evaluation Parts 92
3.3.4 Step (4): Identifying Independent and Dependent Variables 93
3.4 Phase 2: Model Development 100
3.4.1 Step (1): Defining Universal of Discourse, *U*, and Partitioning *U* into Several Intervals 100
3.4.2 Step (2): Defining Fuzzy Sets 104

Universiti Utara Malaysia

3.4.3 Step (3): Fuzzifying Crisp Value into Fuzzy Value 107
3.4.4 Step (4): Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG) 108
3.4.5 Step (5): Calculating Fuzzy Subsethood Value 110
3.4.6 Step (6): Calculating Weighted Fuzzy Subsethood Value 113
3.4.7 Step (7): Constructing WeSuSFTS Model 115
3.5 Phase 3: Model Implementation 118
3.5.1 Step (1): Defuzzifying Fuzzy Value into Crisp Value 119
3.5.2 Step (2): Forecasting Execution 126
3.6 Phase 4: Model Evaluation 127
3.6.1 Step (1): Defining Error Measurement 127
3.6.2 Step (2): Comparing Forecasting Error Measurement among Different Defuzzification Methods 128
3.7 Summary 129

CHAPTER FOUR RESULTS AND DISCUSSIONS 132
4.1 Introduction 132
4.2 Overview of Moving Holiday Electricity Load Demand Pattern 132
4.3 Results of Phase 1: Pre-processing data 136
4.3.1 Results of Step (1): Segmenting Time Series Data 137
4.3.2 Results of Step (2): Combining Segmented Time Series Data 138
4.3.3 Results of Step (3): Dividing the Data into Modelling and Evaluation Parts 138
4.3.4 Results of Step (4): Identifying Independent and Dependent Variables 139
4.4 Results of Phase 2: Model Development 144
4.4.1 Results of Step (1): Defining Universal of Discourse, *U*, and Partitioning *U* into Several Length Intervals Length 145
4.4.2 Results of Step (2): Defining Fuzzy Sets 149
4.4.3 Results of Step (3): Fuzzifying Crisp Values into Fuzzy Values 155
4.4.4 Results of Step (4): Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG) 157
4.4.5 Results of Step (5): Calculating Fuzzy Subsethood Values 161
4.4.6 Results of Step (6): Calculating Weighted Fuzzy Subsethood Values 165
4.4.7 Results of Step (7): Constructing WeSuSFTS Model 168

4.4.7.1 One-factor WeSuSFTS Model for Forecasting MH-ELD.....168
4.4.7.2 M-factor (M=2) WeSuSFTS Model for Forecasting MH-ELD ..171
4.5 Results of Phase 3: Model Implementation 174
4.5.1 Results of Step (1): Defuzzifying Fuzzy Value into Crisp Value.....174
4.5.1.1 One-factor WeSuSFTS Model 175
4.5.1.2 M-factor (M=2) WeSuSFTS Model 179
4.5.2 Results of Step (2): Forecasting Execution.....185
4.5.2.1 One-factor WeSuSFTS Model 185
4.5.2.2 M-factor (M=2) WeSuSFTS Model 189
4.6 Results of Phase 4: Model Evaluation 192
4.7 Summary 197
CHAPTER FIVE CONCLUSION AND RECOMMENDATIONS 202
5.1 Introduction 202
5.2 Research Contribution.....202
5.2.1 Theoretical Contribution 202
5.2.2 Practical Contribution 204
5.3 Impact of this Study 205
5.4 Future Research.....205
REFERENCES.....207

Universiti Utara Malaysia

LIST OF TABLES

Table 1.1 ELD Forecasting Horizons 3
Table 2.1 SBA Values..... 43
Table 2.2 Some Previous Studies using SBA and WSBA 46
Table 2.3 Some FTS Previous Studies..... 54
Table 2.4 Some Previous Studies on Weighted FTS 59
Table 2.5 Some Previous Research in Moving Holiday Electricity Load Forecasting..... 68
Table 2.6 Summary of Factors in Moving Holiday Electricity Load Demand Forecasting .. 76
Table 3.1 List of Variables..... 97
Table 3.2 Degree of Membership Function Value..... 108
Table 3.3 Example of FLR..... 109
Table 3.4 Example of FLRG..... 109
Table 3.5 Fuzzy Subsethood Values 110
Table 3.6 Example of Fuzzy Subsethood Values..... 113
Table 3.7 Weighted Fuzzy Subsethood Values..... 113
Table 3.8 Example of Weighted Fuzzy Subsethood Values 115
Table 4.1 Percentage Change for Combined Segment Time Series 135
Table 4.2 Moving Holiday Week Segmentation..... 137
Table 4.3 Segmented Electricity Load Demand Time Series Data..... 139
Table 4.4 Data for One-factor WeSuSFTS Modelling Part 140
Table 4.5 Example of the Coincidence Day (BH_{t+1}, AH_{t+1} and SH_{t+1}) and Holiday Type (E_{t+1}) data, and the Explanations..... 142
Table 4.6 Correlation Analysis Results between Dependent Variable C_{t+1} and Six Independent Variables 142
Table 4.7 Data for M-factor (M=2) WeSuSFTS Model 143
Table 4.8 Elbow Method Results..... 146
Table 4.9 Interval Length..... 147
Table 4.10 k-means Final Cluster Center based on Elbow Method Results 147
Table 4.11 Triangular Membership Function Parameters for C_{t+1}..... 150
Table 4.12 Triangular Membership Function Parameters for L_t..... 150
Table 4.13 Triangular Membership Function parameters for C_{t+1}..... 150
Table 4.14 Membership Function of Fuzzy Sets A_1 and A_2 152
Table 4.15 Membership Function of Fuzzy Sets B_1 and B_2 153
Table 4.16 Membership Function for of Fuzzy Sets C_1 and C_2 154
Table 4.17 Fuzzifying Result of C_{t+1} 155

Universiti Utara Malaysia

Table 4.18 Fuzzifying Result for C_t 156
Table 4.19 Fuzzifying Result for L_t 157
Table 4.20 Fuzzy Logical Relationship for One-factor WeSuSFTS 158
Table 4.21 Fuzzy Logical Relationship Group for One-factor WeSuSFTS 159
Table 4.22 Fuzzy Logical Relationship for M-factor (M=2) WeSuSFTS 159
Table 4.23 Fuzzy Logical Relationship Group for M-factor (M=2) WeSuSFTS 160
Table 4.24 Fuzzy Subsethood Value for One-factor WeSuSFTS 163
Table 4.25 Fuzzy Subsethood Value for M-factor (M=2) WeSuSFTS 164
Table 4.26 Weighted Fuzzy Subsethood Value for One-factor WeSuSFTS 165
Table 4.27 Weighted Fuzzy Subsethood Value for M-factor (M=2) WeSuSFTS 166
Table 4.28 Comparison of C_{t+1} Actual and Forecasted Values from Five Defuzzification Methods 178
Table 4.29 Comparison of C_{t+1} Actual and Forecasted Values from Four Defuzzification Methods in M-factor (M=2) WeSuSFTS 183
Table 4.30 Changes of MSE 184
Table 4.31 Comparison of Actual and Forecasted ELD Values from Five Defuzzification Methods 188
Table 4.32 Comparison of Actual and Forecasted ELD Values from Four Defuzzification Methods Based on M-factor (M=2) WeSuSFTS Model 191
Table 4.33 Absolute Percentage Error (APE) for Five Defuzzification Methods and Other Forecasting Error Measurement Results for One-factor WeSuSFTS Model 193
Table 4.34 Absolute Percentage Error (APE) and Other Forecasting Error Measurements for Four Defuzzification Methods for M-factor (M=2) WeSuSFTS 194
Table 4.35 The Actual and Forecasted ELD Values Based on Three Proposed FTS Models and Two Conventional FTS Models 195
Table 4.36 FTS Models Performance Results 197

Universiti Utara Malaysia

LIST OF FIGURES

Figure 1.1. Malaysia's power system 5
Figure 1.2. Daily ELD for the financial year 2002 based on the days and weeks from week 1 to 9 7
Figure 1.3. Daily ELD for the financial year 2002 based on the days and weeks from week 10 to 18 8
Figure 1.4. Problem statement of the research 21
Figure 2.1. Linguistic variable of Temperature 29
Figure 2.2. An example for membership function 31
Figure 2.3. General fuzzy forecasting model based on SBA 43
Figure 2.4. Partitioning data based on segmented time series 65
Figure 3.1. Comparison between Chen (1996), Cheng (2008), and WeSuSFTS algorithm .. 81
Figure 3.2. The difference in steps between One-factor and M-factor for WeSuSFTS algorithm 86
Figure 3.3. WeSuSFTS forecasting algorithm 87
Figure 3.4. Example of MH week in year 2017 89
Figure 3.5. Known segmentation break 91
Figure 3.6. Data partition 92
Figure 3.7. Illustration of prototype week 94
Figure 3.8. General graphical triangular membership function fuzzy set linguistic term A_i 105
Figure 3.9. Graphical membership function of *A* 106
Figure 3.10. Graphical membership function of *A* with values from *k*-means clustering 106
Figure 3.11. General WeSuSFTS model with an independent linguistic variable (One-factor WeSuSFTS) 116
Figure 3.12. General WeSuSFTS model for multiple independent linguistic variables (M-factor WeSuSFTS) 117
Figure 3.13. An example of the WeSuSFTS full model 118
Figure 3.14. An example of the WeSuSFTS simplified model 118
Figure 3.15. Example of R_i 123
Figure 3.16. Flowchart of WeSuSFTS algorithm for forecasting problem 131
Figure 4.1. Electricity load demand from 1/6/2017 to 25/7/2017 133
Figure 4.2. Electricity load demand from 1/1/2017 to 28/2/2017 133
Figure 4.3. Electricity load demand from 31/1/2018 to 28/2/2018 134
Figure 4.4. Percentage of change in MH series 135
Figure 4.5. General triangular membership function 149

Universiti Utara Malaysia

Figure 4.6. Triangular membership function for C_{t+1} 151
Figure 4.7. One-factor WeSuSFTS forecasting model 169
Figure 4.8. The fuzzy linguistic term weights in One-factor WeSuSFTS model 170
Figure 4.9. Simpler WeSuSFTS model..... 171
Figure 4.10. M-factor (M=2) WeSuSFTS forecasting model 172
Figure 4.11. The fuzzy linguistic term weights in M-factor (M=2) WeSuSFTS model 173
Figure 4.12. Actual and forecasted ELD percent changes values based on One-factor WeSuSFTS model..... 178
Figure 4.13. Actual and forecasted ELD percent changes values based on M-factor (M=2) WeSuSFTS model..... 183
Figure 4.14. Actual and forecasted ELD values based on One-factor WeSuSFTS model .. 187
Figure 4.15. Actual and forecasted ELD values based on M-factor (M=2) WeSuSFTS model 190
Figure 4.16. Comparison of actual and forecasted ELD values based on three proposed FTS models and two conventional FTS models 196

Universiti Utara Malaysia

LIST OF APPENDICES

Appendix A Data for Figure 4.1 221
Appendix B Data for Figure 4.2..... 222
Appendix C Data for Figure 4.3..... 223
Appendix D MH-ELD Chen and Cheng Forecasting Results 224
Appendix E List of Publications 228

Universiti Utara Malaysia

LIST OF ABBREVIATIONS

ADALINE	Adaptive Linear Element
AI	Artificial Intelligent
APE	Absolute Percentage Forecasting Error
AR	Average of Rule
ARCH	Autoregressive Conditional Heteroscedasticity
ARDL	Autoregressive Distributed Lag
ARIMA	Autoregressive Integrated Moving Average
BP	Back Propagation
BSE	Bombay Stock Exchange
CNN	Convolutional Neural Network
CNY	Chinese New Year
COG	Center of Gravity
DJIA	Dow-Jones Industrial Average
DSM	Demand Side Management
ELD	Electricity Load Demand
EMD	Empirical Mode Decomposition
FGLR	Fuzzy Logical Relationship Group
FIS	Fuzzy Inference System
FISDM	Fuzzy Improved Similar Day Method
FLR	Fuzzy Logical Relationship
FM	Fuzzy Mean
FST	Fuzzy Set Theory
FTS-CNN	Convolutional Neural Network and FTS
FTS-PSO	Fuzzy Time Series with Particle Swam Optimization
Fuzzy QSBA	Fuzzy Quantifier SBA
GRNN	Generalized Regression Neural Network
H-ELD	Holiday Electricity Load Demand
HRA	Hari Raya Aidilfitri
IPPs	Independent Power Producers
IR	Industrial Revolution
LHS	Left-Hand Side
LT-LF	Long-Term Load Forecasts
MAPE	Mean Absolute Percentage Forecasting Error
MAS-OSELM-WA	Multi-Agent System Based on Online Sequential Extreme Learning Machine Neural Network with Weighted Average
MH	Moving Holiday
MH-ELD	Moving Holiday Electricity Load Demand
MSDM	Modified Similar Day Method
MSE	Mean Squared Forecasting Error
MT-LF	Medium-Term Load Forecast
MW	MegaWatt

Universiti Utara Malaysia

NQDA	N-Th Quantile Discretisation Approach
PFS	Probabilistic Fuzzy Sets
PFTS	Picture Fuzzy Time Series
PSO	Particle Swam Optimisation
RHS	Right-Hand Side
RMSE	Root Mean Squared Forecasting Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARMAX	Seasonal Autoregressive Moving Average with The Exogeneous Variable
SAS	Statistical Analysis System
SB	Single Buyer
SBA	Subsethood-Based Algorithm
SBI	State Bank of India
SPSS	Statistical Package for The Social Sciences
SSA-LRF	Singular Spectrum Analysis and Linear Recurrent Formula
SSA-LRF-FTS	Singular Spectrum Analysis and Linear Recurrent Formula with FTS
SSE	Sum of Square Error
ST-LF	Short-Term Load Forecast
Su-value	Fuzzy Subsethood Value
SVD	Singular Value Decomposition
SVR	Support Vector Regression
SWAB	Sliding Window and Bottom-Up Segmentation Algorithm
TAIEX	Taiwan Stock Exchange Capitalization Weighted Stock Index
TAIFEX	Taiwan Future Exchange
TMF	Triangular Membership Function
TNB	Tenaga Nasional Berhad
TrFN	Trapezoidal Fuzzy Numbers
VST-LF	Very Short-Term Load Forecast
WeSuSFTS	Weighted Subsethood Segmented Fuzzy Time Series
WeSuSFTS-AR_1	WeSuSFTS with AR_1 Defuzzification Method
WeSuSFTS-AR_2	WeSuSFTS with AR_2 Defuzzification Method
WeSuSFTS-AR_3	WeSuSFTS with AR_3 Defuzzification Method
WeSuSFTS-AR_4	WeSuSFTS with AR_4 Defuzzification Method
WeSuSFTS-COG	WeSuSFTS with COG Defuzzification Method
WeSu-value	Weighted Fuzzy Subsethood Value
WSBA	Weighted Subsethood Based Algorithm

Universiti Utara Malaysia

CHAPTER ONE
INTRODUCTION

1.1 Background of the Research

As a developing country, Malaysia has various developmental strategies involving enhancement of the latest technology usage, population size, and economic growth. These strategies are geared towards increasing the national economic and financial activities, such as the rising number of housing developments, establishment of new industrial parks, and upgrading certain locations' status to "city". Altogether, these activities will indirectly affect the electricity consumption, extend beyond the current electricity domestic usage and also impact the electricity load in the vicinity of new housing areas for various reasons, such as for street lighting. Meanwhile, in the context of technology advances development, a large number of electronic devices and gadgets such as computer, laptop, smartphone, and GameBox and their usage can further contribute to such increment of electricity consumption.

Universiti Utara Malaysia

Furthermore, the rise of Industrial Revolution 4.0 (IR 4.0) has contributed to a multitude of technological advancements and developments in office- and factory-based activities. Here, many human activities have been replaced with machines, which typically require the use of electricity. Therefore, the impact of IR 4.0 is further expected to cause partial or full monitoring of an activity being taken over by the machine. Examples of such shift include the Artificial Intelligent (AI) machine, which is an AI-based expert system to replace junior lawyer and may potentially to substitute for junior medical practitioners (Haseeb, 2018).

Moreover, in the context of manufacturing industries, packaging activities previously carried out by human workers have been switched to packaging machines in order to improve the level of production. The entire education sector spanning from pre-school to higher education has also seen its environmental preparation for IR 4.0 generation to yield a significant contribution to the increase of electricity usage. Some of these innovation products generally require electricity in order to generate meaningful results, thus leading to the resulting impact of the electricity load demand (ELD) in Malaysia.

ELD forecasting horizons can be categorized into four categories: very short-term load forecast (VST-LF), short-term load forecast (ST-LF), medium-term load forecast (MT-LF), and long-term load forecasts (LT-LF) (Yahaya et al., 2019). VST-LF usually ranges from a few minutes to one day. ST-LF commonly refers to one day to a week and up to a month. VST-LF and ST-LF play an important role in the day-to-day operations of a utility such as unit commitment, economic dispatch, and load management. Meanwhile, MT-LF usually ranges from one month to one year. MT-LF is necessary in planning fuel procurement, scheduling unit maintenance, energy trading, and revenue assessment for the utilities. LT-LF is forecasting for periods of more than one year. LT-LF plays an important role in electric power system planning, tariff regulation, and energy trading. LT-LF is also used to decide on the system generation and transmission expansion plans. Table 1.1 shows the categories of ELD forecast horizons and their aims (Single Buyer Department, 2017; Yahaya et al., 2019).

Universiti Utara Malaysia

Table 1.1

ELD Forecasting Horizons

Category	Period range	Aim
VS-LF	Between a few minutes to one day.	To control and adjust demand load and price in real-time.
ST-LF	One day to a month.	To makes a real-time plan for optimal generator unit commitment and economic dispatch.
MT-LF	One month to one year.	To maintain the balance between generation and demand for a few months to one year.
LT-LF	More than one year.	To plan for the future electricity network condition.

Therefore, it can be argued that accurate forecasting of electricity load is of paramount importance in the decision-making process for economic load dispatch, power unit commitment, contingency, power system operation, scheduling, security, and so on. Additionally, different categories of forecasting horizons are used for different purposes.

Universiti Utara Malaysia

In this study, the forecast time horizon that has been chosen is the ST-LF, focusing on the next day load time. ST-LF is chosen because it serves not only for advanced forecasting value alone, but more importantly for forecasting real-time load demand. Moreover, LT-LF also needs evidence from ST-LF information for its long-term decision and planning (Single Buyer Department, 2017).

1.1.1 Electricity Load Demand (ELD)

Theoretically, ELD refers to the maximum amount of power demand registered to the electricity utility company by a customer (Tenaga Nasional Berhad, 2020b). It is the electric power generated from power plants, which is termed as “electricity energy”

once it is ready for use for electric equipment. The nature of electricity itself renders it to be unstorable in an economical way or cheaply in a large volume (Brunet, 2013; Zakaria & Shamsuddin, 2016). Since electricity cannot be stored, this calls for sufficient capacity for its generation, transmission, and distribution available to meet the highest load demand.

Therefore, a study on ELD forecasting is very important to assist utility companies in developing an efficient operation of the power system, thus ensuring a balance between electricity generation and load demand (Mandal et al., 2009; Mohammad & Kim, 2019). Figure 1.1 shows the process of power system in Malaysia. In general, it involves four divisions, namely generation, transmission, distribution, and customer divisions accordingly.

The electrical energy is initially generated in the power generation system, following which a specific amount is sent to the transmission system. Then, the electricity is sourced to the distribution system for the purpose of customer usage. However, every stage in a power system is actually a complete independent system by itself (Badar & Islam, 2011). This means that the electricity demand of transmission and distribution units may be different in different areas and regions due to the area size and consumption in the area. Therefore, the ”demand” forecast refers to demand on the generation, transmission, and distribution side. It is important to understand that effective load forecasts can help to improve and properly plan these three main divisions.

Universiti Utara Malaysia

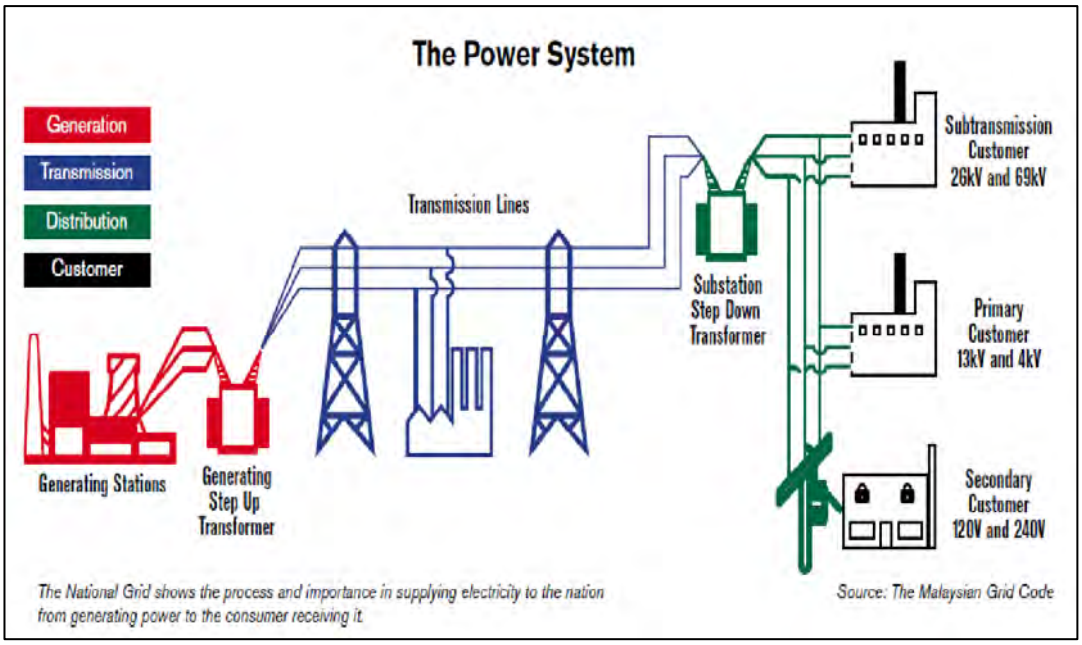


Figure 1.1. Malaysia's power system
Source: Tenaga Nasional Berhad (2007)

Moreover, ELD is sometimes referred to as the peak demand, which is the maximum amount of power electricity demand registered to the electricity utility company by a singular or a group of customers, or a system in a predetermined period of time, such as a month or a year. Its value may either be the maximum sudden load or more typically, the average load over a designated interval of time (e.g. half an hour) stated in the units of kilowatt or megawatt (Unit, 2017).

Tenaga Nasional Berhad (TNB) is the largest electricity utility company in Malaysia, whereby its core business is geared towards providing electricity to domestic businesses, homes, and industries. As the main utility company in the country, it is responsible for meeting the customers' demands of electricity usage (Tenaga Nasional Berhad, 2020a) all the time including during moving holiday seasons.

Universiti Utara Malaysia

1.1.2 Moving Holiday Electricity Load Demand (MH-ELD)

Typically, the ELD power system faces great challenges during its transmission and distribution divisions to meet the demands due to unpredictable daily and seasonal variations (Luo et al., 2014). For example, public and festive holidays may fall on different types of day, which can affect the usual variation of electricity load in a week. This is thus reflected in the manner in which the dates of major festivals celebrated in Malaysia such as Hari Raya Aidilfitri (HRA) and Chinese New Year (CNY) are based on the lunar calendar rather than Gregorian. In particular, the date for HRA celebration is chosen based on the Islamic Hijriyah calendar. Therefore, the dates of certain major holidays that do not occur on a fixed date in the Gregorian calendar will differ from year to year.

To this end, the terms "fixed" and "non-fixed" holidays originate from the Gregorian calendar's holiday category, which includes state holidays, public holidays, and festive holidays. In specific, festival holidays fall into the category of non-fixed holiday, which is otherwise known as moving holidays. The festive season can affect the normal activities of Malaysian population such as shopping behaviour, industrial production, and service activity, whereby such effect is termed as "moving holiday effect" and impacts the ELD as well. Parallel to this, a study on ELD conducted via exploratory data analysis has underlined public holidays as either fixed or moving public holidays accordingly (Ismail et al., 2016).

Some examples of load pattern changes due to holidays are as illustrated in Figures 1.2 and 1.3. Figure 1.2 reveals the usual effect of day types, namely weekends and weekdays, whereas Figure 1.3 depicts completely different patterns for the effect of moving holidays (e.g. HRA and Deepavali) and fixed holidays (e.g. Christmas, King's

birthday, and New Year) for the daily electricity load. These patterns were a reflection of the days and weeks in the financial year 2002, whereby the historical data were collected from 1st September 2001 to 31st August (Ismail et al., 2016).

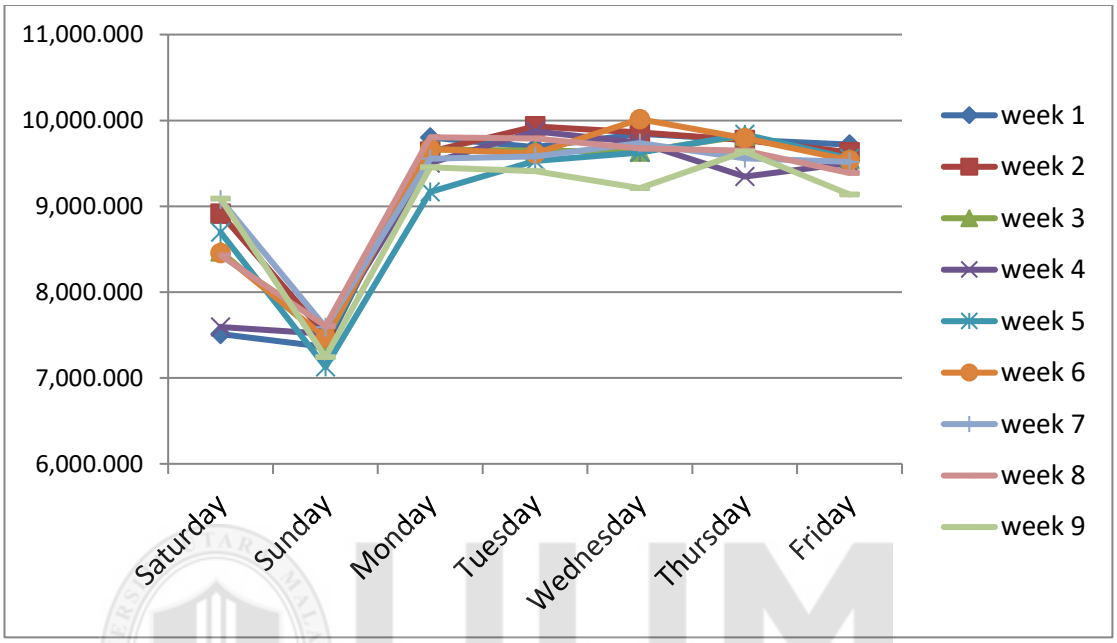


Figure 1.2. Daily ELD for the financial year 2002 based on the days and weeks from week 1 to 9

Universiti Utara Malaysia

Here, Figure 1.3 reveals an irregular and low load pattern for week 16 (15 – 21 Dec 2001). This was due to the HRA celebration, which started from the beginning of week 16 and was followed by Christmas (Tuesday) in week 17 (22 – 28 Dec 2001). Moreover, other low and irregular patterns identified were seen in week 11 due to Deepavali (Wednesday), week 12 due to the King's birthday celebration (Thursday), and week 18 due to New Year celebration (Tuesday, 1st Jan 2002).

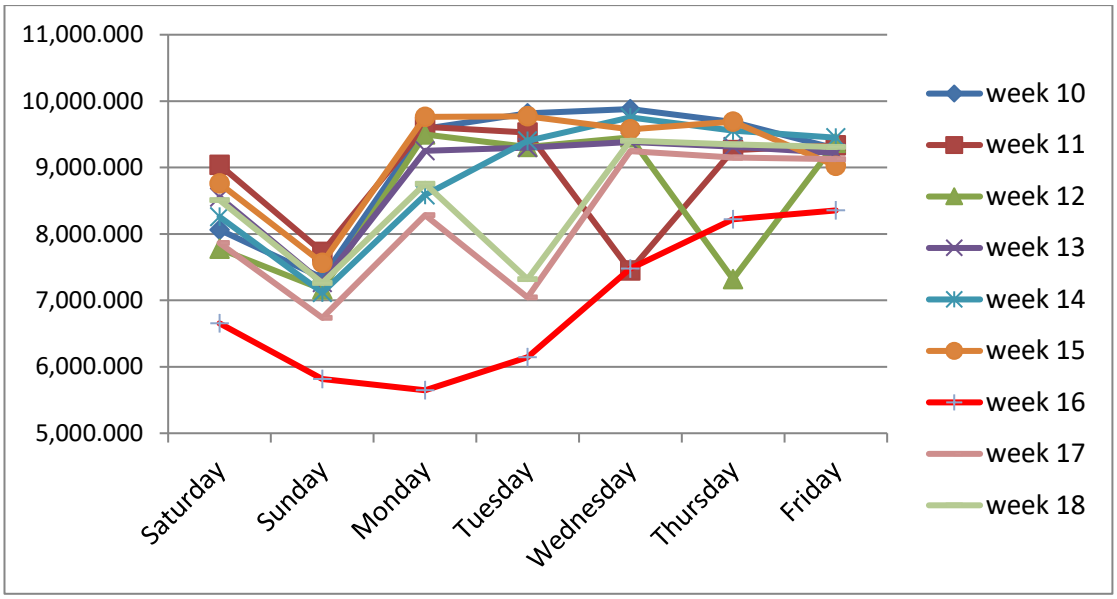


Figure 1.3. Daily ELD for the financial year 2002 based on the days and weeks from week 10 to 18

As depicted in the Figure 1.3, the moving holiday affects the ELD for the whole week. However, such moving holiday effect will differ if the holiday falls on a different type of day as those celebrating the events will take up the opportunity for a longer leave, such as in the case of a holiday occurring in the middle of the week. This situation may be different if the holiday falls on the weekend. Therefore, a utility company should take this matter seriously towards planning and maximising their profits via an efficient operation. Additionally, customer satisfaction is another element requiring much care for their reputation's purposes. Therefore, the importance of a MH-ELD forecasting model is undeniable as it can be used to predict the ELD values of MH in order to prevent any shortage or excess of electricity.

1.1.3 Electricity Load Demand (ELD) Forecasting

Forecasting is underlined as the process of making predictions of a future value or making a statement about future events based on historical and current data available, which is carried out by generating an analysis of trends and other factors (Chen, 1996;

Gahirwal, 2013). To this end, ELD forecasting is henceforth the process of predicting the future maximum amount of power demand value and future statement based on historical data available, which is done via an analysis of trends, relationships, and other factors.

Predicting future ELD in various ELD management and operational areas is a crucial issue for several reasons. First, the utility management is required to decide on the matters of energy purchasing, transmission, and distribution planning (Hong et al., 2010), as well as in operation and maintenance scheduling (Kamel & Baharudin, 2007; Khamis et al., 2011; Tiwari et al., 2015). In the electricity sector, the decision-makers will typically undergo a complex decision-making process and must consider some levels of processes before making one.

An example of this is the planning of facilities and optimal operation of a power plant across different time horizons. To accomplish these tasks, ELD forecasting is highly pertinent as finding an appropriate approach and model is the core of the decision process itself (Hahn et al., 2009). Besides, the decision-makers will need meaningful information to illustrate the ELD data. To achieve this, the ELD data should be analysed and converted into meaningful information necessary via statistical and mathematical forecasting approaches.

To date, several statistical forecasting methods have been developed for ELD data analysis purposes (Khuntia et al., 2018; Nguyen & Hansen, 2017; Qiu et al., 2017). For example Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) (Nguyen & Hansen, 2017), autoregressive conditional heteroscedasticity (ARCH) by multiplicative error model

Universiti Utara Malaysia

(Khuntia et al., 2018) and Empirical Mode Decomposition (EMD) algorithm and deep learning approach (Qiu et al., 2017). Although the analyses give promising results, however, they direct much of the efforts on building more statistically sophisticated forecasting methods without considering the ability of such methods to accurately predict real-life data (Jarrett & Plouffe, 2011). Therefore, this study takes the opportunity to explore a novel linguistic ELD model, which implements linguistic variables that capable of generating a meaningful and easier ELD model for ordinary people to understand to interpret it.

1.1.4 Moving Holiday Electricity Load Demand (MH-ELD) Forecasting

Most of the previous studies have classified MH-ELD forecasting methods into two main broad categories, namely statistical and AI-based methods (Buitrago & Asfour, 2017; Hong et al., 2010; Nowicka-Zagrajek & Weron, 2002; Wi et al., 2012). However, the past few years have been associated with forecasting models based on linguistic variable time series with rising attraction. Therefore, their role has been considered in various types of forecasting applications, such as in ELD (Lee et al., 2009; Mansor et al., 2017; Pei, 2015), sugar production (Kaushik & Singh, 2013), stock exchange (Chen & Kao, 2013; Chen & Chen, 2015), student enrolment (Kumar & Gangwar, 2015; Mansor et al., 2016; Tinh et al., 2016; Wang & Wang, 2014; Wang et al., 2016; Zhang et al., 2015), passenger in public transportation (A'yun et al., 2015), and crop production (Shrivastava & Sharma, 2014). Overall, these researchers have implemented the concept of fuzzy set theory (FST) in their respective studies due to its capability to employ data that are highly complex, nonlinear, and full of uncertainties (Kaushik & Singh, 2013; Selim & Elanany, 2013; Zadeh, 2008).

Universiti Utara Malaysia

Since the MH-ELD is in the form of a time series and the data are complex, nonlinear, and full of uncertainties (Khamis et al., 2011; Singh, 2016), time series modelling has been deemed as a potential method capable of solving the problems. Moreover, MH-ELD data are problematic due to a limited volume of recent historical data as such events typically occur annually only.

In particular, complex data indicates that the ELD data may contain multiple seasonal patterns, such as daily, weekly, monthly, workday, and weekend seasonal series. Additionally, the dual-calendar seasonal effect further contributes to data complexity (De et al., 2011).

Another example of uncertainty in ELD is any sudden variation in its data, thereby suggesting that these events are very uncertain and erratic. As a result, their characteristics cannot be described accurately. Besides, Singh (2016) has referred to these events as "imprecise knowledge" or "incomplete knowledge", which cannot be handled using conventional mathematical or statistical time series models. Thus, the need to yield precision unto such imprecise knowledge in time series data is very significant.

Universiti Utara Malaysia

Furthermore, some research works have revealed that forecasting errors encountered in moving holiday are higher than a normal day. In fact, a 20% increment of forecasting error has been noted on moving holiday when compared with a normal day (Wang et al., 2005). If the moving holiday falls on a Saturday or Monday instead of other weekdays, then there is a chance for the occurrence of a big load forecasting error (Song, et al., 2005). Moreover, Bunn and Farmer (1985) have divulged on an estimated increment of 10 million pounds per year in operating cost and associated with only a

1% increase in forecast error. Thus, this work is focused on the MH effect on ELD to forecast the ELD on MH, along with the aims of reducing the forecasting error and increasing the accuracy of ELD forecasting.

Unfortunately, carrying out the forecasting with MH effect in place while maintaining an equivalent balance between electricity generation and demand is not as simple as in other markets. This is attributable to the effect of MH in the ELD being a reflection of any shortage or wastage (Shukur et al., 2014) as long-term electricity storage is not possible. Therefore, any relatively small changes in the electricity load or generation can result in a large price difference, which may collectively occur in the matter of hours or minutes (Nowicka-Zagrajek & Weron, 2002).

1.1.5 Fuzzy Time Series (FTS) Forecasting

Future prediction of time series events has attracted people from the beginning of times until today. Forecasting these events with 100% accuracy may not be possible; however, the forecasting accuracy and forecasting process speed can be consistently improved. To resolve this problem, Song and Chissom (1993) have developed a model based on the uncertainty and imprecise knowledge accommodated within time series data, whereby the FST concept is initially implemented to represent or manage these uncertainties. This is conceptually referred to as the “Fuzzy Time Series”.

Over time, FTS modelling has emerged as increasingly popular in recent years due to its advantage: it is capable of dealing with time series data without requiring any theoretical assumption validation (Selim & Elanany, 2013). This is in contrast to statistical time series modelling (e.g. time series regression), which renders it

compulsory for all assumptions and fitness tests to be fulfilled. If this criterion is not met, the results may be biased.

However, issues also inevitably present in FTS algorithm either in One-factor or M-factor fuzzy time series forecasting algorithm. One-factor FTS is where only one factor is considered in FTS forecasting. Meanwhile, if the FTS forecasting considers more than one factor, this type of forecasting is known as M-factor FTS forecasting. This has led to various previous research works focusing on this type of forecasting as it motivates researchers to upgrade the algorithm and make it better (Ngoc & Nguyen-trang, 2018; Ye et al., 2016). The six principles in FTS algorithm are:

i. Defining and partitioning the universe of discourse.
ii. Defining fuzzy sets on the universe of discourse.
iii. Fuzzifying historical data.
iv. Identifying fuzzy logical relationships.
v. Identifying fuzzy logical relationship groups.
vi. Defuzzifying the forecasted output.

Universiti Utara Malaysia

Nevertheless, prior research works have emphasised on certain step(s) only in their respective studies, such as to improve FTS forecasting. This is seen in the works by Abdullah and Ling (2012) and Huarng (2001), which have detailed the length of intervals in Step (i). Meanwhile, some studies have executed the FTS algorithm without forecasting, whereby they are more in line with fitted FTS model only (Shrivastava & Sharma, 2014). Unfortunately, previous works on FTS algorithm have yet to execute it on MH-ELD forecasting problems. Therefore, this study opts to modify the principles of FTS algorithm by presenting a complete algorithm spanning

from the pre-processing phase to evaluation phase so as to significantly contribute in modelling MH-ELD in Malaysia and provide a meaningful FTS model interpretation in One-factor and M-factor FTS.

1.1.6 Segmented FTS

Segmented FTS refers to the FTS data that has undergone the process data segmentation process, whereas FTS segmentation is the process of separating FTS data into subseries based on certain criteria. As of today, there is no standard procedure employed for the purpose of FTS segmentation and time series segmentation (Crone & Kourentzes, 2011). In the case of ELD FTS data, different procedures are applied to segment the data into subseries with homogeneous load patterns, which are selected based on the FTS frequency and load pattern heterogeneity. For example, FTS data within a year can be segmented into two classes based on the criterion of different types of day, namely working and non-working days. Besides, the same data can be segmented into four classes based on annual seasonality, which consist of summer, winter, spring, and autumn.

The objective of segmentation is geared towards designing multiple local models for each homogeneous subseries, which will require a simpler construction by eliminating multiple levels of seasonality and necessitating less data and computational resources. Furthermore, segmentation of time series forecasting is capable of reducing the presence of forecasting errors (Bessec et al., 2016; Crone & Kourentzes, 2011).

Different researchers have typically formulated varying models to cater to dissimilar classes, whereas an FTS model has yet to be constructed based on segmented FTS. Based on the advantages of segmented FTS, however, this study separates the ELD

time series into the new week of the year series and causes breaks in the trend vectors of two big events celebrated in Malaysia, namely HRA and the CNY. The new big event series is thus named as the segmented FTS data, whereby the modified FTS algorithm is then executed into the segmented FTS data.

1.2 Gap in Moving Holiday Electricity Load Demand Forecasting

Proper forecast decision and planning may result in the minimization of cost of electricity and power loss. According to Bunn and Farmer (1985), a one percent (1%) reduction of mean absolute percentage error (MAPE) in load forecasting saves 10,000 MegaWatt (MW) in electricity load which may lead to savings of approximately £1.6 million (around RM9 million at current exchange rates) per year. This means that a 1% reduction in MAPE in 2020 essentially results in savings of more than £1.6 million per year since the price of electricity has increased annually in real terms.

Moreover, the existence of holiday periods in the calendar contributes significantly to uncertainties in the load data pattern, especially MHs. A moving holiday is a "non-fixed" holiday based on the Gregorian calendar. The presence of MHs also contributes to an increase in ELD forecasting error. The forecasting error may increase in excess of 20% on a MH compared to a normal day (Wang et al., 2005a). The error may worsen when the MH falls on a Saturday or Monday (Song et al., 2005). When this happens, the sudden variation in data pattern indicates that the event is highly uncertain and contributes to a nonlinear data pattern (Khamis et al., 2011; Singh, 2016). The variation will become an outlier in the data pattern. Moreover, when the data pattern is nonlinear, statistical forecasting approaches are difficult to implement since most of the approaches need verification that the data is linear. Otherwise, the forecasting results may possibly be biased.

Universiti Utara Malaysia

Therefore, one of the efforts to reduce the error, especially in the MAPE, is using MH-ELD forecasting and considering the holiday effect in the forecasting model (Çevik & Çunkaş, 2016; Sulandari et al., 2020). However, making an accurate MH-ELD model is a difficult task (Çevik & Çunkaş, 2016). Therefore, this study focuses on the MH-ELD forecasting algorithm that can be used to guide other forecasters in forecasting activities in order to reduce the difficulty of MH-ELD modelling and forecasting process.

One of the difficulties in the MH-ELD forecasting process is the data complexity since various factors can influence next day load forecasting and these factors cause variety and multiple patterns in the data. Two of them are time (Hongbin & Li, 2009) and weather (Kown et al., 2014; Papalexopoulos & Hesterberg, 1990). Usually, factors related to time are holidays, day type, and calendar, while factors related to weather are temperature and humidity. The temperature factor shows a significant contribution to forecasting error issues especially in temperate countries. However, the temperature in Malaysia averages 30°C (or 86°F) every day. Therefore, the weather is considerably fairly hot throughout the year in Malaysia. In this research, considering the stability of temperatures in Malaysia (hot throughout the year) and the fact that Malaysia's daily temperature data is not easy available, the temperature information is omitted from the model factors studied in this research as it will not have a significant impact on the accuracy of data forecasting (Nagi et al., 2011).

It is well-established that Malaysia is a multicultural country. There are three main ethnic groups (i.e., Malay, Chinese, and Indian) who have different religions (i.e., Islam, Buddhism, and Hinduism) and celebrate different events at different times. A group of these events can be considered as MHs. The MHs will affect the fluctuation

of electricity data in Malaysia as during the festive seasons, Malaysians tend to use more electricity for their festival preparations. The MH seasonal effect will contribute to the complexity of ELD data. This is an example of time factors that can influence the ELD forecasting. Moreover, MH-ELD historical data are very limited due to the events occurring only once a year.

Therefore, the effects of fixed and non-fixed holiday (or moving holiday) is one of the input factors that should be included in the electricity load forecasting (Razak, Hashim, Abidin, & Shitan, 2010). To date, very few research have been done on MH-ELD forecasting (Ebrahimi & Moshari, 2013; Kim et al., 2000; Kim, 2013; Razak et al., 2010; Song et al., 2005; Wang et al., 2005). Most of the research on electricity utilization and planning system focused on the non-fuzzy approach (Kim, 2013; Wang et al., 2005) and little attention has been given to the fuzzy approach (Çevik & Çunkaş, 2016; Song et al., 2005; Srinivasan et al., 1995). One should understand that using different approaches for the input factors in any forecasting model most probably will produce different results. Therefore, one should believe that systems that use fuzzy logic can produce more realistic results, where this type of system can handle the uncertainty, subjectivity, and imprecision of the data and its assessment process (Tóth-Laufer et al., 2014). Furthermore, the use of fuzzy logic can effectively handle the variation of the electricity load due to special events or festive holidays (Srinivasan et al., 1995).

1.3 Problem Statement

A forecasting algorithm should be able to guide a reader in its execution optimally; the reader should be capable of following the steps of the algorithm to reduce forecasting errors. Furthermore, it should be easy to implement, interpret, and explain the

forecasting model. The main issue related to MH-ELD forecasting is the higher forecasting error seen on MHs compared to a normal day and its nature of data that are complex, nonlinear, and filled with uncertainty. Moreover, MH-ELD historical data are very limited due to the events occurring only once annually.

As a result, the conventional statistical forecasting methods are found to be less appropriate in solving the problems, whereby some methods are required to fulfil a number of assumptions and with sufficient data. Although linear models are advantageous in the way that they can be understood and analysed in great detail, and easy to explain and implement, they may be completely inappropriate if the underlying process is non-linear. The reality in real-world may be associated with non-linear correlations, which cannot be modelled by forecasting techniques such as the Box-Jenkins model.

Universiti Utara Malaysia

Furthermore, violations of these statistical assumptions will result in biased and misleading results, which further underline the limitation of conventional statistical forecasting methods when faced with the above problem. In contrast, the FTS method can solve these problems since it does have any requirement of assumptions as compared to many other statistical techniques. Moreover, it offers the advantage of dealing with forecasting problems wherein the historical data are linguistic values representing how humans are thinking naturally.

Although they can overcome the MH-ELD forecasting problem, most of the current FTS methods yield less interpretability in terms of relationship strength between the linguistic term independence and dependence variables. For example, FTS model by Chen (1996) and Efendi et al. (2016) show fuzzy logical relationship between

linguistic terms in past and present linguistic time series but without any relationship strength information in their results since their aim is more on reducing the forecasting error. As a result, their FTS models may generate a meaningful but lacking of final model interpretation. Besides, the lack of explanation about the relationship strength will further reveal less information about the correlation naturally representing the manner in which humans make judgements and decisions. This may be attributable to the absence of any measurement available to measure the relationship strength between the left-hand side (LHS) and right-hand side (RHS) linguistic term in the steps of the fuzzy logical relationship. However, suggestion by Rasmani and Shen (2004) by adding weights based on subsethood values in the FTS forecasting model will produce meaningful model interpretation especially about the strength relationship between LHS and RHS in fuzzy logical relationship group (FGLR).

Moreover, the current FTS algorithm does not provide a standardised or complete FTS forecasting procedure as a guideline or suggestion to its practitioners or users in conducting analyses for forecasting purposes. For example, previous studies have depicted the accuracy of FTS forecasting model using in-sample data set in which only the fitted FTS model is evaluated using such data, while the FTS forecasting model is not subjected to the same treatment. As a result, the algorithm fails to yield the correct FTS forecasting process. Accordingly, the assumption obtained here highlights that a good generalisation is indicative of a model fitted to one data set, which will yield a good performance on another data set sourced from the same process.

Additionally, some challenges have been encountered in order to increase the accuracy of ELD forecasting for MH, specifically due to the relatively small amount of recent historical data available for it in comparison with those available for normal weekdays

and weekends. Numerous past researches have excluded the moving holiday effect from their data and some researchers state that the moving holiday is an outlier or a missing value and has been replaced with other value (Taylor et al., 2006). In other researches, the moving holiday effect has been handled separately so that researchers could predict the two data series separately (Darbellay & Slama, 2000; Kim, 2013; Shayeghi et al., 2009). This indicates the dismissal of MH-ELD's real values in their analyses, thus necessitating a pre-processing phase that capable of catering this problem. This may be achieved by segmenting the data set into the MH dataset. In this research, segmented FTS data is employed in the modified algorithm, which the focus is mainly on MH week only.

However, to measure the accuracy of FTS model with fuzzy outputs, there is a need of defuzzification process to defuzzify these forecasting results. Since the weighted subsethood is new in FTS forecasting, and the application of the method were in previous clustering research, therefore defuzzification process were not discussed in the previous researches due to the final clustering result is not compulsory crisp value. Compared to FTS in MH-ELD, the final result as crisp values are required for accuracy measurement. Although there are some defuzzification methods previously in fuzzy forecasting, the defuzzification methods are not suitable for weighted subsethood forecasting model. Therefore, there is a need for defuzzification method, which is able to defuzzify the fuzzy output from the weighted subsethood forecasting model.

In conclusion, the abovementioned problems require the development of a practical approach. This study focuses on modfying FTS algorithm to forecast the segmented MH-ELD time series, which is based on the weighted subsethood fuzzy logical

relationship and fuzzy reasoning. Figure 1.4 shows the summary of the problem statement in this study.

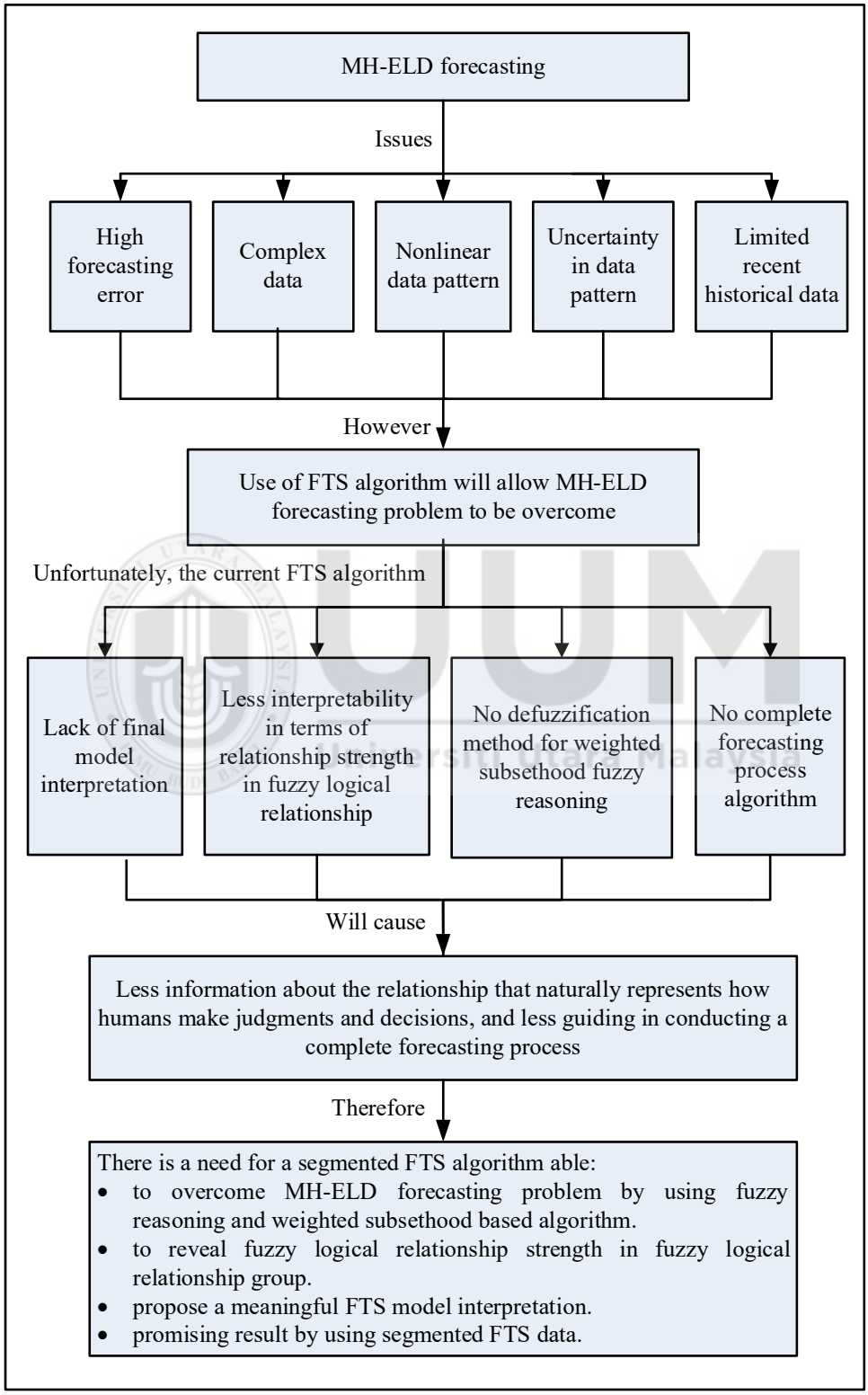


Figure 1.4. Problem statement of the research

In the process of discovering a resolution for the identified gap, several research questions are formulated and listed accordingly in the following section.

1.4 Research Questions

Various gaps have been identified in existing studies in the context of forecasting modelling for MH-ELD problem, which is attributable to FTS as the possible forecasting method for such issue. Therefore, the primary research question in this research is concerning the technique to modify the current FTS forecasting algorithm so that it can be used to predict MH-ELD in Malaysia. The research questions are as follows:

1. How does the scenario of MH affect the ELD in Malaysia?
2. How can FTS models be generated from segmented data using the modified forecasting algorithm?
3. How is the performance of the proposed modified forecasting algorithm?

Universiti Utara Malaysia

1.5 Research Objectives

The main objective of this research is to enhance the current FTS forecasting algorithm in order to predict MH-ELD, which is to be achieved specifically by considering a weighted fuzzy subsethood algorithm and fuzzy reasoning. To achieve this, the sub-objectives that must be fulfilled are as follows:

1. To develop the One-factor and M-factor weighted subsethood segmented fuzzy time series (WeSuSFTS) forecasting algorithms.
2. To introduce an alternative defuzzification method for WeSuSFTS.
3. To validate the WeSuSFTS forecasting model.

1.6 Significance of the Study

Several positive significances in the fields of FTS and MH-ELD forecasting in Malaysia are identified in this research. The major significance can be simplified as application aspect and theoretical aspect.

1.6.1 Application Aspect

Based on the aforementioned issues in previous sections, forecasting the ELD is very important, especially when the holiday is non-fixed holiday. Therefore, this study modified a forecasting approach, where this modified approach not just able to forecast the total electricity on weekdays but will also predict the amount of electricity load demand on the moving holidays. In Malaysia, ELD forecasting is needed in the decision-making process of how much load needs to be supplied to the grid system and how to prepare for generating electric energy. Information obtained from forecasting can help the utility company to develop cost effective risk management plans, such as operation planning, real time planning, electricity price and electricity power plan. It is crucial to emphasis the importance of demand forecasting at all levels. The adverse effects of error from forecasting the demand are serious and will directly give a negative effect to stakeholders in the electricity supply industry.

Universiti Utara Malaysia

1.6.2 Theoretical Aspect

i. In general, this research offers a new FTS algorithm which is a hybrid with weighted subsethood based algorithm (WSBA) that can forecast daily electricity load in Malaysia. Specifically, this WeSuSFTS procedure provides an alternative way to forecast MH-ELD when dealing with uncertainty in electricity load data which has been discussed in previous section.

ii. This research introduces fuzzification mechanism in constructing the input and output membership function for moving holiday electricity load demand. This mechanism can be an alternative approach to reduce the dependency on human experts in this electricity load research area.

iii. Data driven rule generation that is proposed in this research could be an alternative approach and can be very useful under the situation where there are no human experts and also can provide information which are not acknowledged by the experts.

iv. The rules generation method that is used in this research, namely Weighted Subsethood-Based Algorithm (WSBA) is a quite new algorithm in the forecasting research area. This alternative method can contribute to the knowledge of forecasting rule generation. Furthermore, this method is more transparent as compared to the other methods in terms of knowing the calculation behind the process.

v. The procedure in WeSuSFTS algorithm is not limited to time series data only. The procedure can also be used for non-timeseries types of data because of its fuzzy reasoning characteristic.

vi. The defuzzification method introduced in the proposed algorithm is also significant because it can be used as an alternative defuzzification method to transform fuzzy output to crisp output.

Universiti Utara Malaysia

1.7 Scope of the Study

In general, research in ELD forecasting can be categorised into four different time horizons based on forecast horizon planning, which is explained in Section 1.1. They are: very-short-term, short-term, medium-term, and long-term forecast horizons.

Accordingly, this research opts for the short-term ELD forecasting approach. Furthermore, it focuses on the development of a Weighted Subsethood Segmented Fuzzy Time Series algorithm, which is later known as WeSuSFTS.

The modified algorithm in this research is based on a modification of FTS principle steps shown in Chen's (Saxena et al., 2012) and Cheng's algorithms, respectively (Cheng et al., 2008). Both algorithms are well-known in the field and serve as a benchmark in many previous works (Efendi et al., 2016; Fathoni, 2017; Ngoc & Nguyen-trang, 2018; Tsai et al., 2019).

This research implements daily ELD data recorded in Peninsular Malaysia, which refers to the historical daily electricity load data spanning from the year 2017 to 2018. The empirical data are utilised to investigate the effect of MH on the forecasted electricity load in Malaysia, with an emphasis on the HRA and CNY celebrations. Additionally, two types of model are presented in this study, namely One-factor and M-factor WeSuSFTS.

Universiti Utara Malaysia

1.8 Thesis Organisation

This thesis is divided into five chapters: first, Chapter One presents an overview of the research work carried out, which contains a brief introduction and details the background, problem statement, research questions, objectives, and scope of the current study. Then, an overview of FTS and ELD forecasting is highlighted in the Chapter Two, as well as previous studies of significance regarding MH-ELD forecasting and FTS. Following this, Chapter Three elucidates the methodology implemented in this study by introducing the WeSuSFTS algorithm using a step-by-step approach, whereas the resulting outcomes and discourse on them are detailed in

Chapter Four. Finally, a conclusion and some of the recommendations and contributions of this research towards the body of knowledge and literary is delineated in Chapter Five, heavily emphasizing on the domain of MH-ELD forecasting problem.

Universiti Utara Malaysia

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter presents literature that are related to this research in order to justify the stated objective in the previous chapter. Firstly, some definition related to fuzzy time series (FTS) and fuzzy subsethood-based algorithm are presented in Sections 2.2 and 2.3 respectively. Then, related literature on previous studies on FTS forecasting and weighted FTS methods are presented in Section 2.4 and 2.5 respectively followed by segmented FTS in Section 2.6. Subsequently, discussion on time series forecasting model validation is presented in Section 2.7. Section 2.8 addresses the importance of electricity load demand (ELD) forecasting, while Section 2.9 deliberates on moving holiday electricity load demand (MH-ELD) forecasting. Section 2.10 focuses on factors affecting MH-ELD, while Section 2.11 provides the summary of the chapter.

Universiti Utara Malaysia

2.2 Fuzzy Time Series (FTS)

According to Fernandez and Herrera (2012), fuzzy system is a significant area of interest for researchers to apply the fuzzy logic and fuzzy set theory. When the fuzzy data is formed in a time series format, the model structure is named a fuzzy time series. Therefore, related literature on the fuzzy set and FTS and some definitions in FTS is discussed in detail in this section.

A time series is a collection of values of certain events or tasks which is obtained with respect to time. Advance prediction of some significant time series events such as prediction of next ELD for a day which falls on a MH is a major scientific issue in the domain of ELD forecasting (Ebrahimi & Moshari, 2013; Ismail et al., 2016). Because

of the nature of the ELD time series data, which is highly non-stationary and uncertain, the decision-making process becomes very challenging. For example, a sudden decrease in weekday ELD when the moving holiday falls on a weekday due to people leaving work earlier or extending their holiday or the MH falls in the school holidays indicates that these events are very uncertain. The characteristic of how much the load increases and decreases cannot be described accurately. Therefore, it is referred to as "imprecise knowledge" or "incomplete knowledge" (Singh, 2016). To solve this problem, Song and Chissom (1993) developed a model in 1993 based on uncertainty and imprecise knowledge contained in time series data. They initially used the fuzzy set concept to represent or manage all these uncertainties and referred to this concept as Fuzzy Time Series (FTS).

FTS forecasting in this study is based on fuzzy logical relationship. One of the interesting features of FTS modelling is the assumptions regarding the data that are not required, which differentiates it from the statistical forecasting model approaches. For example, the number of observations does not need to be limited and linearity assumption does not have to be considered (Ismail et al., 2015). Besides, FTS modelling can be used if the time series data is not limited to numerical values but also has linguistic values. This section explains briefly the basic concepts and definition of Fuzzy Set Theory (FST), FTS and fuzzy subsethood algorithm. The basic definitions of FTS are given as follows.

2.2.1 Fuzzy Time Series

Let $Y(t), (t = 0,1,2, \dots)$, a subset of real numbers, be the universe of discourse by which fuzzy sets $f_i(t), (i = 1,2,3, \dots)$ are defined. If $F(t)$ is a collection of

$f_1(t), f_2(t), \ldots$ then $F(t)$ is called a FTS defined on universal of discourse $Y(t)(t = 0,1,2, \ldots)$ (Yusuf et al, 2017).

2.2.2 Linguistic Variable

Linguistic variables refer to variables whose values are not numbers, but words or sentences in a natural or artificial language. This concept is a complement to the concept of a numerical variable. Numerically, a linguistic variable, is defined as a *quintuple*, (X, A, U, G, M), where *X* is the name of the variable, $A = \{A_1, A_2, \ldots, A_N\}$ is the set of *linguistic terms* of *X* (called *termset*), *U* is a universe of discourse, G is a syntactic rule for generating linguistic terms, and *M* is a semantic rule for associating its meaning with *X* (a fuzzy set in *U*) (Zadeh, 1975). For a better understanding, an example of a linguistic variable *Temperature* with three linguistic terms of "Low", "Medium", and "High" is illustrated in Figure 2.1. From this figure (Fernandez & Herrera, 2012), the variable refers to the temperature that is given in appropriate physical units, where *a,b,c* and *d* are the trapezoidal membership function parameters.

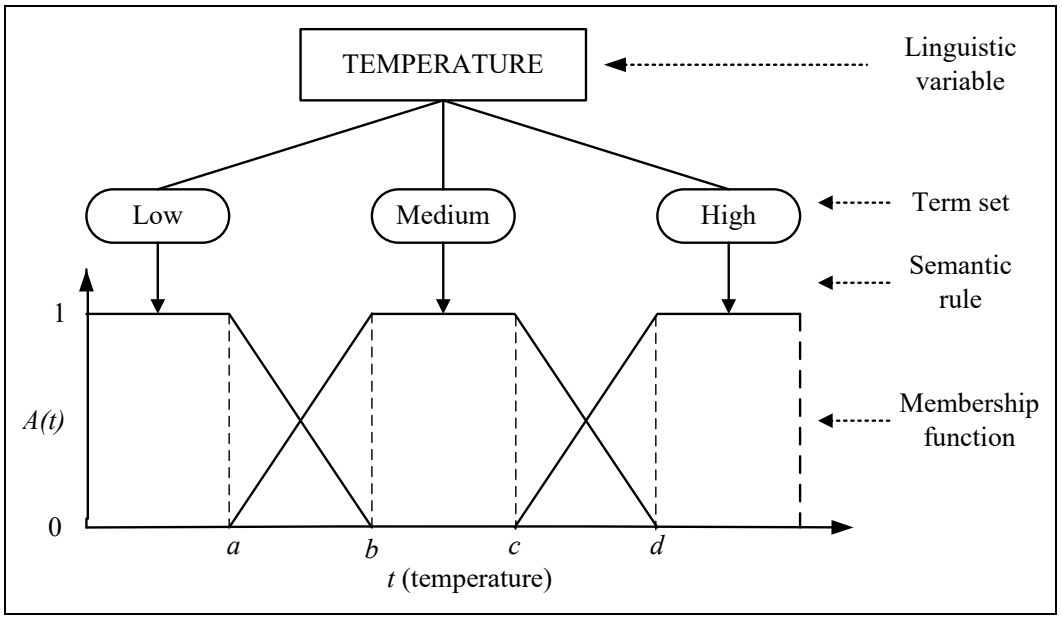


Figure 2.1. Linguistic variable of *Temperature*
Source: Fernandez & Herrera (2012)

2.2.3 Membership Function

Every fuzzy set can be represented by its membership function. The membership function is a generalization of the characteristic function of crisp sets, which for each fuzzy set assigns a physical value on the abscissa to a truth value which describes to which extent (between 0 and 1) this value belongs to the set.

A shape of membership function can be represented in trapezoidal form.The trapezoidal membership function, as shown in Figure 2.1, is a function with four parameters defined by Equation (2.1)

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq a \\ \dfrac{(x-a)}{(b-a)}, & a < x \leq b \\ 1, & b < x \leq c \\ \dfrac{(d-x)}{(d-c)}, & c < x \leq d \\ 0, & x > d \end{cases} \tag{2.1}$$

Or can be written as Equation (2.2)

$$\mu_{Medium}(x) = max\left\{0, min\left[\frac{(x-a)}{(b-a)}, 1, \frac{(d-x)}{(d-c)}\right]\right\} \tag{2.2}$$

Furthermore, the property of *Medium* for the linguistic variable of temperature can also be represented as triangular membership function as in Figure 2.2. In the example, if the measured temperature value is *x*, then the level of membership (also: grade of membership or degree of membership) of *x* in the fuzzy set *Medium* is given by $\mu(x)$ and is 0.7. It can be said that the level of truth for the proposition: *The temperature x is Medium,* with the degree of *Medium* is 0.7, or *x* is 70% belongs to *Medium temperature*.

Universiti Utara Malaysia

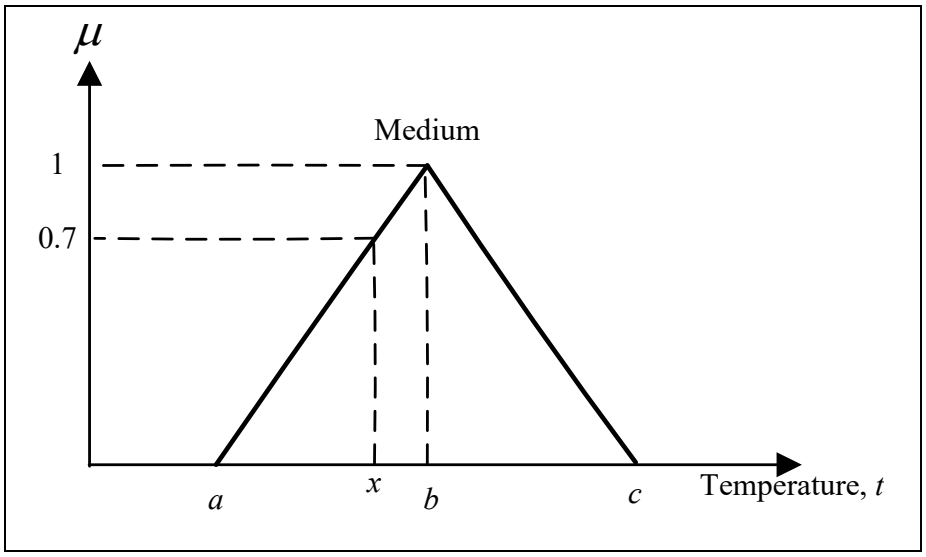


Figure 2.2. An example for membership function

Figure 2.2 shows a triangular membership function. Generally, the triangular membership function as shown in Figure 2.2 is a function with three parameters defined by Equation 2.3.

$$\mu_{Medium}(x) = \begin{cases} 0, & x \leq a \\ \dfrac{(x-a)}{(b-a)}, & a < x \leq b \\ \dfrac{(c-x)}{(c-b)}, & b < x \leq c \\ 0, & x > c \end{cases} \tag{2.3}$$

Or can be written as Equation (2.4)

$$\mu_{Medium}(x) = max\left\{0, min\left[\frac{(x-a)}{(b-a)}, \frac{(c-x)}{(c-b)}\right]\right\} \tag{2.4}$$

Uncertainty characterization is a broad theoretical subject studied in many diverse fields. In the context of fuzzy system design, uncertainties are represented by membership functions and their individual properties. The question that is always present is how to determine the exact shape of the membership function for a fuzzy set. Generally, a membership function provides a gradual transition from regions completely outside a set to regions completely inside the set. It approximates a smooth

transition between the two regions. A membership function can be designed in the following three ways (Padhy, 2005):

- Interview those who are familiar with the underlying concept and then adjust the membership function based on a tuning strategy.
- Construct the membership function automatically from the data.
- Design the membership function based on feedback from the system performance.

In general, the number of membership functions and their locations within the universe of discourse affect the performance of the basic fuzzy inference algorithm relatively more severely than shape variations among membership functions. The parameterisable membership function most commonly used are the triangular membership function and trapezoidal membership function (Padhy, 2005):

Universiti Utara Malaysia

2.2.4 Fuzzy Logical Relationship

Let fuzzy time series be $F(t)$ and $F(t-1)$. FTS relationships assume that $F(t)$ is caused only by $F(t-1)$, then the relationship can be expressed as in Equation (2.5):

$$F(t) = F(t-1) * R(t, t-1), \tag{2.5}$$

which is the fuzzy relationship between $F(t)$ and $F(t-1)$, where * represents the max-min composition operator on fuzzy sets. A fuzzy relation, R is a mapping from the Cartesian space $X \times Y$ to the interval [0,1], where the strength of mapping is expressed by the membership function of the relation $\mu_R(x, y): A \times B \rightarrow [0,1]$ and defined as in Equation (2.6) (Abhishekh & Kumar, 2019)

$$R = \{((x, y), \mu_R(x, y)) | \mu_R(x, y) \geq 0, x \in A, y \in B\} \quad (2.6)$$

To sum up, let $F(t-1) = A_i$ and $F(t) = A_j$. The fuzzy logical relationship between $F(t)$ and $F(t-1)$ can be denoted as $A_i \rightarrow A_j$ where A_i (current state) refers to the left-hand side (LHS) and A_j (next state) refers to the right-hand side (RHS) of the fuzzy logical relationship (FLR). Note that the RHS of the FLR represents the future fuzzy set (forecast). Its crisp counterpart is denoted as $Y(t)$.

2.2.5 Union and Intersection of Fuzzy Sets

Let A and B be two fuzzy sets of the universe of discourse U with membership functions μ_A and μ_B, respectively. The union of fuzzy sets A and B denoted as $A \cup B$, is defined by Equation (2.7)

$$A \cup B = max\{\mu_A(u), \mu_B(u)\}, \quad \forall u \in U \quad (2.7)$$

The intersection of A and B, denoted as $A \cap B$, is defined by Equation (2.8)

$$A \cap B = min\{\mu_A(u), \mu_B(u)\}, \quad \forall u \in U \quad (2.8)$$

2.2.6 Fuzzy Logical Relationship Group

This definition was introduced by Chen (1996). Relationships with the same fuzzy set on the LHS can be further placed into a relationship group. These relationship groups are also referred to as fuzzy logical relationship groups (FLRG). Suppose there are relationships such that

$$A_i \rightarrow A_{j1}$$
$$A_i \rightarrow A_{j2}$$

.

.

.

$$A_i \rightarrow A_{jn}$$

Then they can be grouped into a relationship group as follows:

$$A_i \rightarrow, A_{j1}A_{j2}, \ldots, A_{jn}$$

The same fuzzy set cannot appear more than once on the right-hand side of the relationship group.

2.2.7 Fuzzy Rules

A fuzzy rule is a conditional of the form "if *X* is *A*, then *Y* is *B*," where *A* and *B* are fuzzy sets. Fuzzy inference rules specify the relationships between fuzzy variables. A few fuzzy rules can encompass great complexity, compared to crisp rules. Fuzzy reasoning is a set of fuzzy rules.

Universiti Utara Malaysia

2.2.8 Fuzzification

Fuzzification is the process of converting crisp values into fuzzy values by identifying possible uncertainties or variations in the crisp values. This conversion is represented by the membership functions of fuzzy sets. In the fuzzification of FTS, determination of interval lengths is important in partitioning the universe of discourse. Then, the fuzzy sets constructed from the universe of discourse will be used as the base of the fuzzification process. There are various fuzzification approaches in FTS that can be carried out, for example fuzzification based on an intuitionistic approach (Kumar & Gangwar, 2015), equal lengths of triangular membership function (Chen, 1996; Joshi & Kumar, 2013; Song & Chissom, 1994), different lengths of triangular membership

function (Huarng, 2001; Cheng et al., 2008; Tinh & Duy, 2019), non-symmetrical triangle membership function (Ningrum et al., 2019), and picture fuzzification (Egrioglu et al., 2020). Fuzzification is highly related to the length of intervals in the FTS algorithm. Huarng (2001) pointed out that the different lengths of intervals in the universe of discourse can affect the forecasting result and a proper choice of length of each interval can greatly improve the forecasting accuracy rate.

2.2.9 Fuzzy Subsethood Value

Let A and B be two fuzzy sets of the universe of discourse U with membership functions μ_A and μ_B, respectively. The fuzzy subsethood value $S(A,B)$ measures the degree to which A is a subset of B can be expressed as in Equation (2.9) (Chen et al., 2001; Kosko, 1986):

$$S(A_i, B_j) == \frac{\sum_{u \in U} min\{\mu_A(u), \mu_B(u)\}}{\sum_{u \in U} \mu_A(u)} \tag{2.9}$$

where $S(A,B) \in [0,1]$.

Universiti Utara Malaysia

The Su-values is based on fuzzy subsethood based algorithm (SBA). The steps in SBA explained in Section 2.3.

2.2.10 Weighted Fuzzy Subsethood Value

Weighted subsethood based algorithm (WSBA) is the algorithm to find the relative weight created based on fuzzy subsethood value to provide multiplication factors for each independent linguistic variable's value. Then, in this study, the weight value based on WSBA as called as weighted fuzzy subsethood value (WeSu-value), and is defined as follows: For a classification problem with s classes and k input linguistic variables' values (or attributes), the weight $W(A_i, B_j) \in [0,1]$ between the j^{th}

independent linguistic value of linguistic variable $B_j, j = 1,2, \dots, k$ and class $A_i, i = 1,2, \dots, s$ can be estimated by Equation (2.10) (Boongoen et al, 2011; Nivetha & Samundeeswari, 2016; Soria et al., 2013)

$$W(A_i, B_j) = \frac{S(A_i, B_j)}{\max\limits_{j=1,2,3,\dots,k} S(A_i, B_j)} \tag{2.10}$$

These WeSu-value represents the degree of "importance" of input linguistic value B_j to the corresponding A_i.

2.2.11 *k*-means Clustering

The *k*-means clustering algorithm by Macqueen (1967), was developed five decades ago and is one of the most popular clustering algorithms used in a variety of domains. A prior knowledge of the number of clusters are a must for the *k*-means clustering algorithm. *k*-means is defined over continuous data and calculates its centers iteratively (Tinh, 2019). Let $X = \{x_i | i = 1,2,3, \dots, n\}$ be a data set having k cluster; $C = \{c_j | j = 1,2,3, \dots, k\}$ be a set of k centers and $E = \{x | x \text{ is the number of cluster } k\}$ be the set of samples that belong to the k^{th}cluster. *k*-means algorithm minimizes the following function (Equation (2.11)) which is defined as an objective function.

$$J(C) = \sum_{j=1}^{k} \sum_{i}^{n} \|x_i - \mu_j\|^2 \tag{2.11}$$

With $\mu_j$being the mean of cluster c_j

The main steps of *k*-means algorithm are as follows (Tinh, 2019):

Step 1. Select an initial partition with *k* clusters.

Step 2. Generate a new partition by assigning each pattern to its closest cluster center.

Step 3. Compute new cluster centers.

Step 4. Repeat Steps 2 and 3 till there is no change in cluster centers.

This study applies the *k*-means clustering technique to classify the collected data into clusters and adjust these clusters into intervals for generating intervals from numerical data. This study uses the *k*-means clustering algorithm because the aim is to avoid a zero value of denominator in the fuzzy subsethood calculation. A zero value means that the calculation cannot proceed and the process must stop. The intervals must then be revised (Mansor et al., 2018).

2.2.12 Defuzzzification

Defuzzification is a process of transforming the fuzzy output values to crisp output values for getting the forecasted values. In the FTS area, some defuzzification methods use intuitionistic defuzzification from fuzzy inference. For example, the fuzzy inference system (FIS) is a fuzzy rule-based system that contains a set of linguistic if-then rules and an inference engine for the interpretation of a set of rules using a certain inference mechanism. Defuzzification process is also required for transforming a fuzzy output of a FIS into a crisp output.

One of defuzzification type approaches is distribution method. The most extensively used defuzzification approach in FIS is the center of gravity (COG) or center of area defuzzification (Wang et al., 2009). It is a basic general defuzzification method that computes the center of gravity of the area under the membership function. As a consequence, it can only be used for fuzzy sets on R^4 (Leekwijck & Kerre, 1999). The formula of COG is shown in Equation (2.12) (Ahmed et al., 2017; Leekwijck & Kerre, 1999):

$$COG(A) = \frac{\sum_{x_{min}}^{x_{max}} x.\mu(x)}{\sum_{x_{min}}^{x_{max}} \mu(x)} \quad (2.12)$$

Where A is a linguistic variable, $\mu(x)$ is the degree of membership of x in A. The formula shows that COG calculates the forecasted value when A is considered to be a probability distribution. Leekwijck and Kerre (1999) classify COG as a general distribution defuzzification method. From the formula, the WSBA fuzzy reasoning parameter (numeric value from reasoning rules) is not considered in the formula.

The other type of defuzzification distribution method is specific distribution defuzzification method (Leekwijck & Kerre, 1999). Fuzzy Mean (FM) is one of them that considers the numeric value of output. The difference between COG and FM is that FM uses pre-calculated numerical values a_i for each of the fuzzy sets of the output universe (Leekwijck & Kerre, 1999). The formula is shown in Equation (2.13) (Leekwijck & Kerre, 1999):

Universiti Utara Malaysia

$$FM(\mathrm{A}) = \frac{\sum_{i=1}^{N_A} \alpha_i a_i}{\sum_{i=1}^{N_A} \alpha_i} \quad (2.13)$$

where N_A represents the number of fuzzy output sets, α_i, the degree of each output set (as a result of the inference), and a_i the numerical value of output set i. Therefore, based on the idea of COG and FM, this study introduced Average Rule (AR) defuzzification method as an effort to consider. Basically, the AR method is presented in Chapter Three considers the WSBA fuzzy reasoning parameter (numeric value from reasoning rules) to be multiplied with the corresponding peak point of output fuzzy set.

By focusing on defuzzification methods in FTS forecasting area, Chen (1996), Liu and Zhang (2019) and, Tinh and Duy (2019) implemented the defuzzification step using the midpoint of linguistic fuzzy interval but in a different mechanism. However, the defuzzification methods used did not consider the numeric value of weighted subsethood fuzzy reasoning rule. Chen's model defuzzification method is based on the average of the respective midpoints of intervals as presented in Equation (2.14) (Chen, 1996).

$$\text{Forecasted crisp value} = \frac{\sum_{i=1}^{n} m_i}{n} \tag{2.14}$$

Where m_i is the midpoints of corresponding intervals i and n is the number of corresponding intervals.

Tinh and Duy (2019) produced the forecasted output by introducing a new defuzzification method based on the midpoints of the corresponding intervals and the master voting scheme as shown in Equation (2.15). In this equation the symbol w_h represents the highest votes predefined by the user, m is the order of the FLR, M_{t1} and M_{ti} denote the midpoints of the corresponding intervals of the latest past and other past respectively in linguistic values of the current state.

$$\text{forecasted crisp value} = \frac{(M_{t1} * M_{t2}) + M_{ti} + \cdots + M_{tm}}{w_h + (m-1)} \tag{2.15}$$

Liu and Zhang (2019) defuzzified the data from a neural network result using Equation (2.16). They then calculated the forecasted change rate using Equation (2.15). Let m_{i-1}, m_i, m_{i+1}, be the midpoints of the fuzzy sets A_{i-1}, A_i, A_{i+1}, respectively. The corresponding membership functions are $\mu_{i-1}, \mu_i, \mu_{i+1}$, respectively. Let b_i represents the forecasted change rate. By using the adaptive forecasting formula in Equation

(2.17), the forecasted value of percent changes, p_{t+1} could be calculated. Where x_t is the original data of *t* .

$$b_i = \begin{cases} \dfrac{1+\mu_{i+1}}{\dfrac{1}{m_i}+\dfrac{\mu_{i+1}}{m_{i+1}}}, i = 1 \\ \dfrac{\mu_{i-1}+1+\mu_{i+1}}{\dfrac{\mu_{i-1}}{m_{i-1}}+\dfrac{1}{m_i}+\dfrac{\mu_{i+1}}{m_{i+1}}} 2 \le i \le n-1 \\ \dfrac{\mu_{i-1}+1}{\dfrac{\mu_{i-1}}{m_{i-1}}+\dfrac{1}{m_i}}, i = n \end{cases} \tag{2.16}$$

$$p_{t+1} = x_t.(1 + b_{t+1}\%) \tag{2.17}$$

However, Musleha et al., (2019) declared that their FTS algorithm does not involve a defuzzification step. They forecasted using heuristic rules (Musleha et al., 2019). This means that there is no standard FTS algorithm in the forecasting process.

Some FTS forecasting algorithms with triangular membership functions (TMF) usually use symmetrical triangular shapes, because they make it easier to calculate a forecast (Ningrum et al., 2019). Forecasting based on the FTS algorithm with TMF makes predictions based on the maximum value of membership degrees, or in other words the forecasting value is the value with a degree of membership equal to one or $\mu(x) = 1$. If the triangle member's function used is a symmetrical triangle, the forecasting value is the middle or midpoint value of the cluster. However, this is not entirely appropriate depending on the characteristics of the data (Ningrum et al., 2019). The use of TMFs is generally only to simplify the forecasting calculation process, because it only uses the midpoint value in the specified cluster in the fuzzification process.

Universiti Utara Malaysia

Since this study uses *k*-means clustering to identify the center of each cluster, the use of the center value as a peak value in the membership function is preferred. This is because in the *k*-means clustering algorithm, the data in a particular interval are closest to the cluster center's particular interval. Therefore, this study modifies the defuzzification process where the TMF used is a non-symmetrical triangle for defuzzification calculation.

In the scope of WSBA implementation in some research, Rasmani and Shen (2004) and Othman et al. (2013), implemented WSBA in the clustering of student performance and flood warning system. They did not use the defuzzification process because the researches focused on clustering only, that is the researchers forecasted the cluster and the crisp value. The final output of these researches were student performance cluster and warning cluster, respectively.

Universiti Utara Malaysia

2.2.13 One-factor and M-factor FTS

Let fuzzy time series $A(t), B(t), C(t), \dots, M(t)$ be the factors of the forecasting problems. If only $A(t)$ is used to solve the forecasting problems, then it is called One-factor FTS. If the remaining secondary-factors $B(t), C(t), \dots, M(t)$ are used with $A(t)$ to solve the forecasting problems, then it is called the M-factor FTS (Singh & Borah, 2014).

2.2.14 First and High-Order FTS

Given the FTS data *F*, the first order models use $F(t-1)$ data to predict $F(t)$. Then, fuzzy logical relationship between them can be represented by $F(t-1) \rightarrow F(t)$. Since one factor, $F(t-1)$ is only used to solve the forecasting problem, then it is called as One-factor first-order FTS model. The high-order models use $F(t-1), F(t-$

$2), \ldots, F(t-k)$ data to predict $F(t)$, then it can be called as One-factor high-order FTS model or One-factor *k*th-order FTS model. Then, fuzzy logical relationship between them can be represented by $F(t-1), F(t-2), \ldots, F(t-k) \rightarrow F(t)$ (Abhishekh & Kumar, 2019; Silva et al., 2017).

2.3 Fuzzy Subsethood-based Algorithm

Fuzzy subsethood-based algorithm (SBA) is the fuzzy rules extraction from historical data where the fuzzy rules consist of a subsethood value as a multiplicative factor in IF-THEN fuzzy reasoning rules. Fuzzy rule determination is one of the most important things to be considered in fuzzy forecasting. The use of these rules implemented in the FTS increases the accuracy of the results produced in forecasting situations that involve subjective, vague, and imprecise information (Rahim et al., 2018).

The SBA comprises three main steps.

Universiti Utara Malaysia

Step 1: Classify data in modelling part into subgroups according to the underlying linguistic terms of dependent variable.

Step 2: Calculate fuzzy subsethood values for each linguistic term of dependent variable in each subgroup by using Equation (2.9) in Section 2.2.9.

Step 3: Create fuzzy rules based on fuzzy subsethood values.

The initial SBA was from Rasmani and Shen (2003). However, the above SBA steps were simply modified to fit the FTS forecasting algorithm since Rasmani and Shen (2003) implemented SBA into a clustering problem. To illustrate the general fuzzy forecasting model based on SBA, let the elements $A_1, A_2, \ldots, A_s$ are the linguistic fuzzy

terms in dependent variable, A. While, $B_1, B_2, \ldots, B_k$ refer to the linguistic fuzzy terms in dependent variable, B. Table 2.1 represents the SBA values where $S(A_s, B_k)$ is the SBA value for linguistic fuzzy terms A_s and B_k.

Table 2.1

SBA Values

		$\boldsymbol{B}$			
		$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	...	$\boldsymbol{B_k}$
$\boldsymbol{A}$	$\boldsymbol{A_1}$	$S(A_1, B_1)$	$S(A_1, B_2)$	...	$S(A_1, B_k)$
	$\boldsymbol{A_2}$	$S(A_2, B_1)$	$S(A_2, B_2)$	...	$S(A_2, B_k)$
	⋮	⋮	⋮	...	⋮
	$\boldsymbol{A_s}$	$S(A_s, B_1)$	$S(A_s, B_2)$	...	$S(A_s, B_k)$

Hence, the general fuzzy forecasting model based on SBA is presented in Figure 2.3.

Universiti Utara Malaysia

Rule 1: IF B *is* $S(A_1, B_1)B_1$ OR $S(A_1, B_2)B_2$ OR ... OR $S(A_1, B_k)B_k$

THEN A *is* A_1.

Rule 2: IF B *is* $S(A_2, B_1)B_1$ OR $S(A_2, B_2)B_2$ OR ... OR $S(A_2, B_k)B_k$

THEN A *is* A_2.

.

.

.

Rule s: IF B *is* $S(A_s, B_1)B_1$ OR $S(A_s, B_2)B_2$ OR ... OR $S(A_s, B_k)B_k$

THEN A *is* A_s.

Figure 2.3. General fuzzy forecasting model based on SBA

Then the forecasted value could be identified by the min-max operator based on the fuzzy IF-THEN rule constructed in Figure 2.3. However, the final fuzzy model based on SBA is subjected to a pre-specified threshold value $\alpha \in [0,1]$. Therefore, the weighted subsethood based algorithm (WSBA) was introduced to overcome the SBA limitation (Rasmani & Shen, 2005, 2003).

Based on previous studies as summarized in Table 2.2, SBA was implemented in clustering of student performance problem (Othman et al., 2013; Rasmani & Shen, 2005), Iris-plant (Rasmani & Shen, 2003, 2004), Wisconsin breast cancer (Rasmani & Shen, 2004), Perlis rivers water level during the flood season (Othman et al., 2013) Malaysia crude palm oil price (Rahim et al., 2018); and forecasting of Malaysia crude palm oil price (Rahim et al., 2018). However, only one previous study considers defuzzification step in their algorithm (Rahim et al., 2018) since the others did not produce any forecast value but only to provide the clustering results. The Rahim's defuzzification is based on rule's terms and conditions corresponding to $Rule_i$ where $Rule_i$ is the Rule that produces highest value from rules calculation. However, the rule's terms and conditions were limitedly discussed in their work. This implies that defuzzification method is required to be used in WSBA forecasting.

Meanwhile, most of the previous studies contribute in modifying SBA in their research to produce better results and interpretation such as extending the SBA to WSBA (Othman et al., 2013; Rahim et al., 2018; Rasmani & Shen, 2003), modifying WSBA to fuzzy quantifier SBA (Rasmani & Shen, 2004, 2005) and extending the weighted subsethood value based on fuzzy multi-criteria decision-making (Othman et al., 2013). Therefore, this indicates that SBA has the potential to be established from various aspects that can lead to forecasting error reduction especially in FTS forecasting

algorithm. Although Rahim et al. (2018) conducted WSBA in FTS forecasting algorithm, there are some limitations of their FTS algorithm. For example, no independent variable selection step available which could lead to complexity of the model if many independent variables are considered in the analysis. Besides, partitioning the selected data cases randomly will not mimic the real forecasting data process since a number of last cases in time series data should be as a validation part.

Universiti Utara Malaysia

Table 2.2

Some Previous Studies using SBA and WSBA

Method	Description of method	Contribution	Limitation
Weighted linguistic modelling based on fuzzy subsethood values. (Rasmani & Shen, 2003)	Weights are created from the subsethood values to provide a multiplication factor for each linguistic variable. A resulting model is represented in the form of weighted fuzzy general rules, employing relative weights generated from fuzzy subsethood values. These weights are adjustable according to the datasets available for learning.	Produce high accuracy and high degree of transparency of fuzzy systems. Simplicity model by creating default rules without using any threshold value. Solve the Iris-plant and Saturday morning classification problem.	No defuzzification since the objective is to classify only. Therefore, the end result not in numeric real value. Then, the algorithm not suitable for point forecast value. Attribute selection may be required to increase the comprehensibility of the resulting models and to decrease the model's run-time computational complexity.
Modifying WSBA-based rule models with fuzzy quantifiers (Rasmani & Shen, 2004).	Fuzzy quantification to replace crisp weights in subsethood-based fuzzy rule models. Four types of quantifiers in WSBA model were compare in this study: continuous quantifiers, multi-valued quantifiers and two-valued quantifiers.	Applying fuzzy quantifiers to a fuzzy model does not necessarily make the existing model more complicated. The uses of continuous fuzzy quantifiers produce better results compared to the use of multi-valued quantifiers or two-valued quantifiers. Solve the Iris plant, Glass Identification and Wisconsin Breast cancer classification problems.	No defuzzification since the objective is to classify only. Therefore, the end result not in numeric real value. Then, the algorithm not suitable for point forecast value. Attribute selection may be required to increase the comprehensibility of the resulting models and to decrease the model's run-time computational complexity.

Table 2.2 continued.

Subsethood-based fuzzy rule models (Rasmani & Shen, 2005)	WSBA induces a fixed number of rules according to the number of possible classification outcomes. Fuzzy quantifier SBA (FuzzyQSBA) where fuzzy quantifiers are applied to replace the crisp weights within the rules learned by WSBA to improve the transparency of the systems.	Fuzzy rule-based models which combine expert knowledge with knowledge extracted from data. The model more interpretable and provides additional information that can be used for decision-making, whilst helping the user understand why the new grade was awarded. Solve the student performance problem.	No defuzzification since the objective is to classify only. Therefore, the end result not in numeric real value. Then, the algorithm not suitable for point forecast value.
Hybrid subjective evaluation method using WSBA rule generation algorithm (Othman et al., 2013)	Subjective student performance evaluation using fuzzy technique for ranking the attributes of different types of datasets under a multi-criteria environment. The method is based on fuzzy multi-criteria decision-making that consists of fuzzy rules which were extracted directly from input data through WSBA.	This method involves the simplicity with reducing in number of rules used and can be apply in different level of student evaluation. The method had consistency in accuracy in ranking with shorter rule properties and efficiency in the desired function at minimum effort, time and cost. Solve the student academic performance evaluation.	No defuzzification method explained in the paper. The outcome is the classification outcome. Then, the algorithm not suitable for point forecast value.

Universiti Utara Malaysia

Table 2.2 continued.

Fuzzy forecasting model using the SBA and WSBA. (Othman et al., 2013)	Forecast the classification of water level for flood warning system using the SBA and WSBA.	Identification of water levels from the expertise and the testing dataset match very well. The model able to forecast more accurately whether the area related is flooded or not. Solve the Perlis rivers water level classification during the flood season in Perlis.	No defuzzification since the final outcome of the analysis results were fuzzy term.
Fuzzy time series forecasting model using WSBA (Rahim et al., (2018)	Data driven Fuzzy Rule-Based System in the time series forecasting using WSBA in forecasting crude palm oil prices using FTS algorithm.	Defuzzification procedure is based on Rule of forecasting based on rule's terms and conditions corresponding to $Rule_i$ that produce highest value from rules calculation. Solve the crude palm oil price forecasting by producing forecasted classification and point forecast value.	No independent variables selection procedure in the algorithm. Data partition is based on randomly selection for modeling and evaluation part. This does not mimic the real forecasting process.

2.4 Previous Studies in Fuzzy Time Series Forecasting

Fuzzy time series (FTS) forecasting is one of the algorithm-based forecasting models. The enhancement of the FTS forecasting algorithm is by the modification of the previous FTS set of steps or procedure to increase or improve its quality, value, or extent. Basically, most of the previous studies elaborated the FTS algorithm enhancement as FTS modelling enhancement by proposing changes or modifying at least one step in the previous FTS algorithm. The enhancement of the FTS forecasting algorithm was also discussed in other previous studies (Cheng & Yang, 2015; Garg & Garg, 2016; Li & Cheng, 2009; Vovan, 2018; Yolcu et al., 2014). Most of the discussion mainly aimed to improve some issues in the FTS algorithm such as the heavy computational overhead (Li & Cheng, 2009), determination of the intervals (Huarng, 2001; Vovan, 2018; Yolcu et al., 2014), data preparation in the pre-processing part (Vovan, 2018), assigning weight in the FTS model (Garg & Garg, 2016) fuzzy reasoning in FTS (Cheng & Yang, 2015) and also focused on the defuzzification step. This shows the variety in FTS algorithm enhancement studies.

Universiti Utara Malaysia

Since every FTS forecasting model is algorithm-based, the performance of a FTS forecasting model can be affected by the modification of the steps. For example, Song and Chissom (1994, 1993) proposed a novel FTS definition and FTS algorithm. Chen (1996) then modified certain steps in the Song and Chissom's algorithm. Huarng (2001) polished Chen's model to produce a higher FTS forecasting model accuracy. Subsequently, Cheng et al., (2008) proposed a weighted FTS forecasting model by modifying certain steps in Chen's model. Research into the enhancement of the FTS algorithm have continued until now using many angles of step modifications.

Sadeei (2013) classified the attempts at enhancing the FTS algorithm in previous studies into five categories. The categories are enhancing FTS algorithm by (1) certain steps of the FTS algorithm, (2) when the time series data have a trend with no specific pattern, (3) hybridisation with other technique, (4) to specify the FTS algorithm to be more suitable for specific applications, and (5) proposing computational procedures rather than a pure FTS algorithm. The enhancement of the FTS forecasting algorithm in this thesis involves categories (1) and (4) only.

The first category is based on the enhancement of certain steps of the FTS algorithm by the pioneers of FTS, Song and Chisson (1993), then extended to other modifications by Chen (Chen, 1996) and Cheng (Cheng et al., 2008) and continued until now. The following are the three well known FTS algorithms which are the Song and Chissom, Chen, and Cheng algorithms.

- **Song and Chissom FTS algorithm**

  Song and Chissom proposed the FTS algorithm as follows (Song & Chissom, 1993b):

  Step 1: Define the universe of discourse, *U*, in which some fuzzy sets will be defined.

  Step 2: Collect historical data.

  Step 3: Define fuzzy sets in the *U* using the historical data.

  Step 4: Set up fuzzy relationship using historical data.

  Step 5: Sum up all the relationships defined in Step 4 (the summation will be the FTS model).

Universiti Utara Malaysia

Step 6: Apply the input to the model and calculate the output for forecast. The output will be the forecasted value.

Step 7: Defuzzify the output of the model (sometimes this step is not necessary)

- **Chen FTS algorithm**

Chen (1996) resolved the drawback of FTS models which were proposed by Song and Chissom (1993a, 1993b). Their solution was aimed at reducing the computation overhead of the time-variant and time-invariant models by using a simplified model including only simple arithmetic operations as listed in the following Chen model (Chen, 1996; Cheng et al., 2008).

Step 1: Define the *U* and intervals for rules abstraction. Based on the issue domain, the *U* can be defined as: $U[starting, ending]$. As the length of interval is determined, *U* can be partitioned into several equal length intervals.

Step 2: Define fuzzy sets based on the *U* and fuzzify the historical data.

Universiti Utara Malaysia

Step 3: Fuzzify observed rules. For example, a datum is fuzzified to A_j if the maximum degree of membership of that datum is in A_j.

Step 4: Establish fuzzy logical relationships.

Step 5: Establish FLRG based on the current states of the data of the fuzzy logical relationships. For example, $A_1 \rightarrow A_2, A_1 \rightarrow A_1, A_1 \rightarrow A_3$ can be grouped as: $A_1 \rightarrow A_1, A_2, A_3$.

Step 6: Defuzzifying.

- **Cheng FTS algorithm**

Cheng et al., (2008) proposed an enhanced algorithm by considering the weight component in the defuzzification process. The steps are:

Step 1: Define the *U* and partition the interval that has data amount less than or equal to the average.

Step 2: Define fuzzy sets in the *U.*

Step 3: Fuzzify crisp value into fuzzy value.

Step 4: Identify FLR.

Step 5: Establish FLRG.

Step 6: Assign weights based on occurrence of FLR.

Step 7: Calculate forecast result by matrix multiplication of defuzzified matrix and weighting matrix.

Step 8: Employ the adaptive forecasting equation to produce conclusive forecast.

By referring to the first step in all the FTS algorithms that have been previously explained, the *U* can be partitioned into equal or not equal length of intervals. One of the popular methods to find the cluster in the data is the *k* means clustering method. In the ELD area, *k*-means clustering was also applied to ELD data to create load pattern classes (Farfar & Khadir, 2018). The method has a simplicity of implementation and fast execution (Davidson, 2002) and able to identify the fuzzy interval in FTS (Mansor, et al., 2016a; Tinh et al., 2016; Tsekouras et al., 2008). Another method from previous studies in FTS is Fuzzy C-means clustering (Yusuf et al., 2017).

Table 2.3 shows the overview of the recent FTS forecasting implementation in studies in various fields, nature of data, and the diversity of FTS approaches. Most of the FTS previous studies were from Asian countries such as Taiwan, India, Malaysia, Turkey, and Indonesia. The FTS studies conducted in various area such as in stock exchange forecasting problem (Abhishekh et al., 2019; Gupta & Kumar, 2019; Liu & Zhang, 2019; Musleha et al., 2019; Tsai et al., 2019), electricity (Chang et al., 2019; Javedani

et al., 2019; Sulandari et al., 2020), and university student enrolment (Gupta & Kumar, 2019). Interestingly, the study of FTS forecasting approaches is still relevant currently based on the growth of FTS research papers published in recent years. Many suggested FTS approaches such as hybridisation or combining FTS with other methods (Javedani et al., 2019; Sulandari et al., 2020; Tinh & Duy, 2019), and enhancing the FTS algorithm (Chang et al., 2019; Musleha et al., 2019).

Besides, based on recent previous studies as summarized in Table 2.3, all the approaches aimed to increase the forecasting accuracy by proposing different FTS forecasting algorithm to solve the complex, uncertainty and nonlinear data series. Most of them proposing modified versions of the conventional FTS algorithm such as Chen FTS algorithm (Javedani et al., 2019; Musleha et al., 2019; Ningrum et al., 2019; Tinh & Duy, 2019; Tsai et al., 2019), Chang FTS algorithm (Chang et al., 2019), Cheng FTS algorithm (Sulandari et al., 2020) and Song and Chissom FTS algorithm (Musleha et al., 2019). All these studies produce promising new FTS algorithms by modifying the conventional FTS algorithm. Therefore, this study also takes the same action that is to modify the FTS algorithm based on Chen and Cheng conventional FTS algorithm, and focuses on the interpretation of FTS model as previous modified FTS algorithms did not consider this important issue. Their effort is to achieve research objective to reduce forecasting error. Basically, the model interpretation is useful for users of the model to understand about the model and also to be able to explain the nature of relationship in the data. Lack of final model interpretation will cause less information about the relationship that naturally represents how human make judgement and decision.

Universiti Utara Malaysia

Table 2.3

Some FTS Previous Studies

Method	Description of method	Contribution	Limitation
Singular Spectrum Analysis and Linear Recurrent Formula with FTS (SSA-LRF-FTS) (Sulandari et al., 2020).	Calculate the final forecast values by adding the SSA-LRF forecast values and the weighted FTS forecast values.	The combing model SSA-LRF-FTS produce less forecasting error than SSA-LRF. Forecast hourly electricity load consumption in Indonesia (year 2015) with MAPE 0.63% (SSA-LRF-FTS Cheng's model).	SSA-LRF-Fuzzy is not as good as when the method was implemented to the series year 2016, which associated to the effect of the holidays in the Islamic calendar in October 2014 and 2015. Limited to first order FTS only and no forecasting model interpretation.
Picture fuzzy time series (PFTS) (Egrioglu et al., 2020).	PFTS and a single variable high order PFTS forecasting model are defined based on picture fuzzy sets. PFTS is implemented using window approach.	Solves the issues inherent in the high order single variable picture fuzzy time series forecasting model. Forecast daily minimum temperature in Turkey with mean RMSE 0.78.	The method uses single variable only and no forecasting model interpretation.
Firefly-Chen fuzzy time series (Ningrum et al., 2019).	Modification of triangular member's function (TMF) based on Firefly-Chen FTS. The firefly-Chen FTS is the combination of Chen method and Firefly Algorithm.	The error value for the symmetrical TMF is still better compared to the non-symmetrical TMF.	Numerical value of the effect of TMF modification only and no forecasting model interpretation.

Table 2.3 continued.

Hybrid model of convolutional neural network and FTS (FTS-CNN) (Javedani et al., 2019) .	Combined method of CNN and Chen's FTS algorithm. Chen FTS algorithm was used in converting multi-variate time series into images and then using CNNs for forecasting purpose.	FTS from the original load data helped to decrease the negative effect of over-fitting in CNN. Forecast hourly electricity load demand in year 2019 Malaysia (Johor) with MAPE 2.89%.	No forecasting model interpretation.
Multifactor Fuzzy Time-Series Fitting Model (Tsai et al., 2019).	The model is based on the adaptive expectation Kmenta's model and the multi-period adaptation Chen's model which contains three significant factors. The model constructed using sliding window method.	Multi factor FTS model. The model parameters represent the degree of influence of factor in the linear multifactor forecasting model. Forecast (Taiwan Stock Exchange Capitalization Weighted Stock Index) TAIEX with average of RMSE is 101 (six-month moving window approach).	The selection of significance factors is based on previous study only, not from numerical approve. The forecasting model is not explained in linguistic form.
High-order fuzzy time series with Particle Swam Optimization (FTS-PSO) (Tinh & Duy, 2019).	Combining the high-order FTS with Particle Swam Optimisation (PSO). PSO is used to get the optimal partition of the interval in the universe of discourse in Chen FTS algorithm.	MSE value of 583.23 based on 7th-order for forecasting Gasoline in Vietnam and 1678.5 for forecasting student enrolment of University of Alabama.	No forecasting model interpretation.
Fuzzy time series with trapezoidal fuzzy numbers and (TrFNs) center of gravity (COG) similarity measure approach. (Musleha et al., 2019)	The TrFNs is used to represent the linguistic values and the similarity measure based on COG is selected to calculate the forecasting performance. FTS algorithm based on Jilani, Chen and; Song and Chissom algorithm.	Provide the forecasted range under different degree of confidence. The forecasting performance is evaluated based on similarity measure of COG type to replace the common accuracy. The average degree of similarity for the TAIEX data is 0.99634.	No forecasting model interpretation.

Table 2.3 continued.

Weighted fuzzy time series model of N-th Quantile Discretisation Approach method (NQDA)(Chang et al., 2019)	The NQDA is used in partitioning the universal of discourse in Chang FTS algorithm.	The method can objectively consider the distribution of training data and establish semantic cuts, which can improve the shortcomings of subjective semantics of traditional fuzzy time series. Forecast Taiwan Yearly total electricity consumption with RMSE is 13.4.	No forecasting model interpretation and data partition.
High-order fuzzy time series forecasting method based on probabilistic fuzzy sets (PFS) (Gupta & Kumar, 2019)	Gaussian probability distribution function is used to associate probabilities to membership grades.	Forecast University of Alabama enrolments and Taiwan Future Exchange (TAIFEX) with RMSE 137.68 and 30.88 respectively.	No forecasting model interpretation
Type 2 fuzzy time series forecasting model based on three-factors fuzzy logical relationship groups (Abhishekh et al., 2019)	The method uses type-2 fuzzy set in FTS algorithm.	Forecast India Bombay Stock Exchange (BSE) Sensex with RMSE 65.5 using type-2 FTS.	No forecasting model interpretation
second-order fuzzy time series model (Liu & Zhang, 2019)	Three-layer back propagation (BP) neural network is established in this FTS algorithm where the second-order fuzzy relation is established applying three-layer BP neural network.	Forecast stock price of State Bank of India (SBI) and Dow-Jones Industrial Average (DJIA) with RMSE 6.7	No forecasting model interpretation

Universiti Utara Malaysia

Although Tsai et al., (2019) produce a model with coefficient factor in their FTS model, the coefficient can only represents the degree of influence of factor in the linear multifactor forecasting model, but not in linguistic term model.

Basically, the previous studies as stated in Table 2.3 contributed to enhance the FTS algorithm to reduce the forecasting error. Some of them partitioned the universal of discourse and defining fuzzy set using different approach such as Gaussian probability distribution function (Gupta & Kumar, 2019), type-2 fuzzy set (Abhishekh et al., 2019), quartile discretization approach (Chang et al., 2019), trapezoidal fuzzy number (Musleha et al., 2019), particle swarm optimization (Tinh & Duy, 2019), and firefly algorithm (Tinh & Duy, 2019). All the approaches give less error in forecasting.

2.5 Weighted Fuzzy Time Series Methods

This section discusses some previous studies focusing on weighted FTS algorithms. In time series model, when unexpected conditions happen, the historical data cannot respond to the fluctuations immediately. This would probably result in a terribly inaccurate forecast. To deal with the problem, a group decision-making method is employed to integrate the subjective forecast values of all decision makers. Therefore, the weighted method is the one of the solutions (Cheng et al., 2008).

Table 2.4 shows several previous weighted FTS studies with different FTS algorithm architectures and a variety of weight schemes with different datasets. Some studies applied the FTS algorithm to more than one factor FTS modelling (Abhishekh & Kumar, 2019; Rahim et al., 2018; Tsai et al., 2019) and one factor or first order FTS modelling (Cheng et al., 2006; Yu, 2004).

This study names the various FTS algorithm architectures introduced previously as enhanced FTS algorithms since the algorithms are basically enhanced or modified from previous FTS algorithms by at least one step from the pioneer of FTS definition, the Song and Chissom algorithm. Most of them proposed the trend-weighted type (Abhishekh & Kumar, 2019; Cheng et al., 2006; Tsai et al., 2019; Yu, 2004). However, different FTS algorithms proposed different trend-weighted schemes. Similarly, Efendi et al. (2015) proposed an index number weighted scheme. However, technically, the index number weighted scheme could be considered as an in trend-weighted type since the index number is the chronology of linguistics series and the weights are assigned by using the index number of close relationships in the FLRG.

Interestingly, Rahim et al. (2018) in their study applied a weighted subsethood based algorithm (WSBA) using the FTS algorithm which was proposed by Mansor et al. (2016) but in a different defuzzification scheme. Since the novel weighted mechanism was introduced in the FTS algorithm, the researchers have declared that defuzzification based on weighted results is a new defuzzification method (Abhishekh & Kumar, 2019). From Table 2.4, the defuzzification scheme used in the FTS algorithms were based on the midpoint linguistic interval (Chen, 1996; Cheng et al., 2006, 2008; Efendi et al., 2015; Suhartono & Lee, 2011; Tsai et al., 2019; Yu, 2004), and on certain forecasting rules (Abhishekh & Kumar, 2019; Rahim et al., 2018). However, all the weighted FTS algorithms were not considering the weights as the degree of importance of linguistic terms in the forecasting model. Therefore, this study proposes the weights that can explain the degree of importance of linguistic term in FTS model. The model interpretation can be meaningful with the existence of the weighted value. So, this study focuses on the development of the weighted subsethood FTS (WeSuSFTS), but with the provision of the model interpretation.

Table 2.4

Some Previous Studies on Weighted FTS

Method	FTS algorithm	Weighted approach	Defuzzification	Limitation
First-order One-factor FTS model. Trend-Weighted Fuzzy Time-Series (Cheng et al., 2006).	**Seven steps:** Step 1: Defining U and partitioning it into intervals. Step 2: Establishing fuzzy sets Step 3: Establishing fuzzy relationships. Step 4: Establishing FLRG. Step 5: Assigning trend weights. Step 6: Aggregating weight. Step 7: Employing the adaptive forecasting equation to produce a conclusive forecast.	Frequency-weighted based on counts of fuzzy relationship trends	$F(t+1) = L(t)W(t)$ Where $L(t) = [m_1\ m_2\ \ldots\ m_i]$ Where $F(t+1)$ is the defuzzified forecast, $L(t)$ is the defuzzified matrix, $W(t)$ is the normalized weighted matrix and m_i is the midpoint of each linguistic interval	The weighted not explain the degree of importance linguistic term of the factors in the model. No forecasting model interpretation.
First-order One-factor FTS model. Fuzzy time-series based on adaptive expectation model (Cheng et al., 2008).	**Eight steps:** Step 1: Defining the universe of discourse and partitioning it into intervals. Step 2: Defining fuzzy sets on the U. Step 3: Fuzzifying crisp value into fuzzy value. Step 4: Establishing fuzzy relationships. Step 5: Identifying fuzzy logical relationship (FLR). Step 6: Assigning weights. Step 7: Calculating forecast results. Step 8: Employing the adaptive forecasting equation to produce a conclusive forecast.	Frequency-weighted based on counts of fuzzy relationship trends	$F(t+1) = L(t)W(t)$ Where $L(t) = [m_1\ m_2\ \ldots\ m_i]$ Where $F(t+1)$ is the defuzzified forecast, $L(t)$ is the defuzzified matrix, $W(t)$ is the normalized weighted matrix and m_i is the midpoint of each linguistic interval	The weighted not explain the degree of importance linguistic term of the factors in the model. No forecasting model interpretation.

Universiti Utara Malaysia

Table 2.4 continued.

First-order two-factor FTS model. Modified weighted fuzzy time series model for forecasting based on two-factors fuzzy logical relationship groups (FLRG) (Abhishekh & Kumar, 2019)	**Nine steps** Step 1: Define the universe of discourse *U*, of main factor. Step 2: Define membership grade datum of main factor. Step 3: Fuzzify datum of the main factor. Step 4: Define the universe of discourse, *V,* of the second factor. Step 5: Define membership grade datum of second factor. Step 6: Fuzzify datum of the second factor. Step 7: Establish the two-factors FLRG. Step 8: Establish the weighted function and compute forecasted output. Step 9: Analysis error performance.	This study introduces two rules to establish a weight function depending on two-factors FLRG and based on parameter α. The α value is set as -1, 0, and 1 depend upon the time increase, decrease and no change (based on trend).	This study introduces a new defuzzification technique based on the weighted function defined on two-factors FLRG.	The weighted not explain the degree of importance linguistic term of the factors in the model. No forecasting model interpretation.
First-order three-factor FTS model. Multifactor FTS model based on stock volatility to forecast a stock index. (Tsai et al., 2019)	**Eight steps:** Step 1. Collect the datasets. Step 2. Fuzzify and defuzzify $F(t)$ to obtain an initial forecast. ● Determine the range and linguistic values ● Build fuzzy sets and fuzzify. ● Build FLR. ● Merge all FLR. ● Give weights to all FLRG. ● Defuzzify Step 3: Transfer the trading volume into market signals. Step 4: Compute the daily differences of the two stock market indexes. Step 5: Propose a multifactor forecasting model. Step 6: Adapt the best model's parameters. Step 7: Forecast the stock index. Step 8: Evaluate the performance forecast	Trend-weighted approach by Cheng et al., (2006, 2008)	$F(t+1) = L(t)W(t)$ Where $L(t) = [m_1\ m_2\ \ldots\ m_i]$ Where $F(t+1)$ is the defuzzified forecast, $L(t)$ is the defuzzified matrix, $W(t)$ is the normalized weighted matrix and m_i is the midpoint of each linguistic interval, L_i Cheng et al., (2006, 2008)	The weighted not explain the degree of importance linguistic term of the factors in the model. No forecasting model interpretation.

Universiti Utara Malaysia

2.6 Segmented Fuzzy Time Series

The segmentation of time series is the separation of time series into smaller subseries with more homogeneous load pattern properties (Keogh et al., 2003; Crone & Kourentzes, 2011). The benefit of segmentation is that we can control the non-stationary time series where time series in the same segment will have the same pattern as smaller subseries with more homogeneous load pattern properties (Keogh et al., 2003). Moreover, segmentation of time series forecasting is also able to reduce forecasting error (Bessec et al., 2016; Crone & Kourentzes, 2011). Keogh et al., (2003) overview about the time series segmentation algorithm that can be grouped into one of the following three categories.

- Sliding Windows: A segment is grown until it exceeds some error bound. The process repeats with the next data point not included in the newly approximated segment.

- Top-Down: The time series is recursively partitioned until some stopping criteria is met.

- Bottom-Up: Starting from the finest possible approximation, segments are merged until some stopping criteria is met.

Keogh et al., (2003) proposes a combining of Sliding Window and Bottom-up segmentation algorithm (SWAB). By validation experiment using 10 different data sets, SWAB results are essentiality identical to Bottom-Up due to redundancy steps in both algorithms. Meanwhile, Crone and Kourentzes (2011) and Bessec et al., (2016) conducted segmentation time series in electricity data. Crone and Kourentzes (2011)

Universiti Utara Malaysia

perform the segmentation process to reduce the complexity of building electricity load forecasting model. The results show segmented series produce less forecasting error than complete series in naïve hourly, weekly and annually models; and multiplicative seasonality exponential smoothing daily and annually models. Meanwhile, Bessec et al. (2016) perform the segmentation process in building electricity spot price forecasting model. Four-year data in the study were segmented into four time series: winter, summer, spring and fall series as displayed in Figure 2.4. The results show the seasonal segmented series produce high accuracy for linear and non-linear forecasting model. However, some limitations are found in previous study that since they only consider the seasonal fix date in Gregorian calendar effect only. Therefore, this study proposed segmented series based on non-fixed date in Gregorian calendar as one of the efforts to reduce forecasting error.

In a nutshell, there are two types of time series segmentation; known segmentation break and unknown segmentation break. An example of known segmentation break is segmentation of time series based on type of seasons (Bessec et al., 2016; Crone & Kourentzes, 2011). Meanwhile, an example of unknown segmentation break is based on an automatic approach or based on the criteria of breakpoint (Keogh et al., 2003). Since MH is a seasonal type of holiday, this study generates the MH-ELD data by applying the fundamentals of known segmentation break based on seven days only in surrounding the moving holidays.

Some previous research continued the segmentation process to combine the segmented time series into new data of time series (Bessec et al., 2016; Gardner, 2006). Gardner (2006) also proposed a combined observation in their study with decision that if the

irregular time series component exists in the no trend and no seasonality data fluctuation, the data for several periods may be reported as a combined observation.

2.7 Time Series Forecasting Model Validation

Model validation provides a way to tell how useful the model is and should realistically represent the 'real' forecasting system. The model validation is measured by model evaluation. Several strategies in model evaluation have been proposed in the literature and currently there is no consensual approach (Cerqueira et al., 2020). However, in general there are two categories of time series validation model. These two methods are as follows (Cerqueira et al., 2020; Tiwari, 2020; Wang & Chaovalitwongse, 2011):

- Out-of-sample validation: This method has been traditionally used to estimate predictive performance in time-dependent data. Essentially, out-of-sample methods hold out the last part of the time series for testing. Although these approaches do not make a complete use of the available data for modelling process, they preserve the temporal order of observations. This property may be important to cope with the dependency among observations and accounts for the potential temporal correlation between the consecutive values of the time series. The example of approaches in this method are Single modeling-evaluation split and Multiple modeling-evaluation split.

- Time series cross-validation. The typical approach when using *K*-fold cross-validation is to randomly shuffle the data and split it in *K* equally-sized folds or blocks. Each fold is a subset of the data comprising *t/K* randomly assigned observations, where *t* is the number of observations. After splitting the data

into *K* folds, each fold is iteratively picked for modeling. A model is constructed on *K*-1 folds and its loss is estimated on the left out fold. The example of approaches in this method are Repeated random partition validation, K-fold cross-validation and Leave-One-out cross-validation.

Therefore, one of the main principles in modelling is forecasting accuracy for model validation purpose. For that purpose, after the time series data were generated in the earlier step, the next step is to divide the data into two parts; modelling and evaluation parts. The common procedure of the FTS application in previous studies tested the proposed model in a sample period for measuring forecasting accuracy. Most of the data used in the previous studies is the enrolment data of Alabama University (Joshi & Kumar, 2013; Mansor et al., 2017; Nurhayadi, 2014). A reason for evaluating the model in a sample period is because this data is widely used by many researchers in time series forecasting. However, the procedure is not for forecasting accuracy but more towards looking for the goodness of model fit where the process is measuring the estimation accuracy only (Duru & Yoshida, 2012).

Based on the previous related works, this study also takes the same move by partitioning the data into two parts, for modelling and for evaluation purposes. The following Figure 2.4 shows the partitioning of the data based on the experimental design of Bessec et al. (2016) by applying out-of-sample validation process. The way Bessec segmented and combined the data has been explained in the previous section, Section 2.6.

Universiti Utara Malaysia

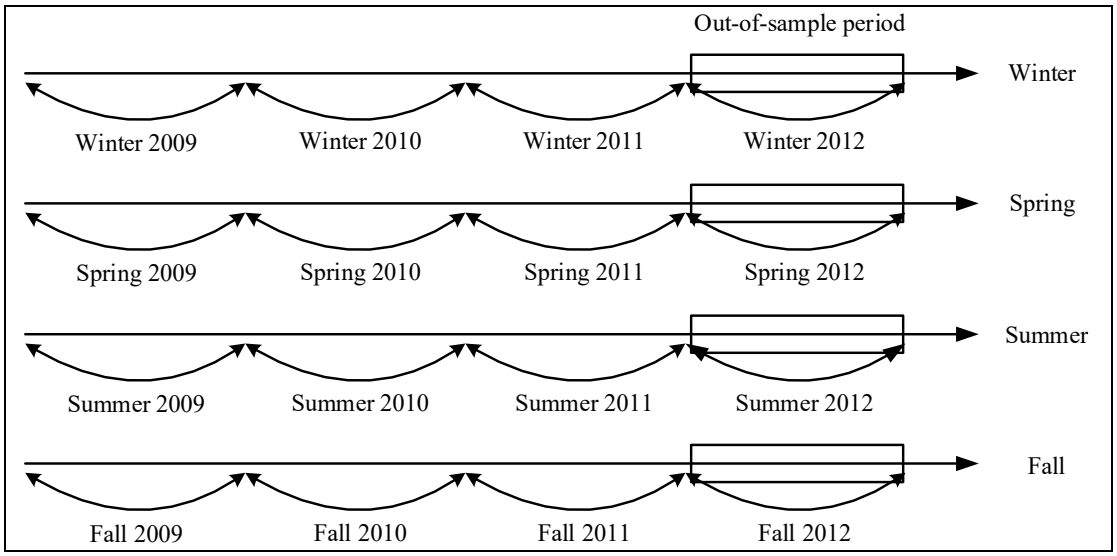


Figure 2.4. Partitioning data based on segmented time series

Therefore, data in the modelling part is used to construct the WeSuSFTS model in this study. Then this study forecasts the output using the model constructed in the modelling part based on data in the evaluation part. Consequently, this study calculates the forecasting error by comparing the actual data in the evaluation part with the forecasted value to measure the forecasting accuracy. The details of the evaluation process for model validation to be conducted in Phase 4 of proposed FTS algorithm is provided in Chapter Three. By doing this process it is argued that the forecasting process mimics the real process of forecasting.

2.8 The Importance of Electricity Load Demand Forecasting

As mentioned previously, FST approach able to solve the complex data, non-linear an uncertainty in data pattern. The ELD forecasting has all these problems. Therefore, this and subsequent sections describe the importance of ELD forecasting and some previous related researches.

Universiti Utara Malaysia

The process of observing ELD is a priority task for a power utility company who is responsible in ensuring that there is enough supply of electrical load to fulfil the demand. ELD forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Moreover, some previous researches stressed on the importance of forecasting ELD in their studies. For examples, load forecasts are extremely important for energy purchasing (Badar & Islam, 2011; Hong et al., 2010), transmission and distribution planning (Hong et al., 2010; Tiwari et al., 2015), operations and maintenance (Kamel & Baharudin, 2007; Khamis et al., 2011; Tiwari et al., 2015), and for demand side management (DSM) (Abogaleela et al., 2013; Energy Comission, 2016; Hong et al., 2010; Tenaga, 2011; Tiwari et al., 2015). The same situation in Malaysia, ELD forecasting is important for several reasons such as (Energy Comission, 2016; Hong et al., 2010; Tenaga, 2011):

- **Energy purchasing**. In this area, decisions such as how much power to purchase should be made based on the distribution of the load forecast. In Malaysia, the Single Buyer (SB) department prepares demand forecast reports and long-term capacity plant-up plans by optimising fuel type and resources to promote renewable energy to the system and ensure sustainability. SB is responsible for procuring electricity from Independent Power Producers (IPPs) and TNB Generation to meet demand at least cost. IPPs are private entities that are not classified as public utilities but own facilities to generate electric power for sale to utilities and end users. Therefore, SB plays an important role in planning and managing generator agreements to ensure that supply to the electricity industry is secured, reliable, and affordable with the collaboration of the IPPs and TNB.

- **Transmission and distribution planning**. In this planning area, the utility company needs to properly preserve and upgrade the systems towards satisfying the growth of demand in the service area and improve reliability. Furthermore, sometimes utility companies need to place new substations in the future based on the load forecasting result.

- **Operations and maintenance.** This area focuses on load forecasting methods to produce the energy load pattern which assists the system operators in making decisions on the processes of switching and loading as well as scheduling maintenance outages.

- **Demand side management (DSM).** In Malaysia, DSM is a unit in the Energy Management and Industry Development Department in Energy Commission. The unit was established to promote and regulate electrical energy efficiency in Malaysia. DSM requires the load forecast results by the utility company to encourage efficiency, economy, and safety in the generation, production, transmission, distribution, supply, and use of electricity.

Universiti Utara Malaysia

2.9 Previous Research on MH-ELD Forecasting

MH-ELD forecasting methods have been applied with either conventional or artificial intelligence (AI) forecasting techniques. The conventional techniques include Box-Jenkins methodology and regression models and AI techniques include fuzzy neural network, fuzzy linear regression, fuzzy reasoning, and fuzzy expert system. Table 2.5 shows a list of some researches who have used MH-ELD forecasting in their research.

One of the forecasting methods in conventional forecasting techniques is the statistical forecasting method. In this method, there is an assumption about data normality from the test of significant models where there exists linear relationships between load demand and several factors that might affect the demand. The obtained results may be biased if the data does not satisfy this assumption (Ismail & Mansor, 2011). However, it is hard to satisfy the assumption of linearity due to a great number of factors considered in the model (Hahn et al., 2009).

Table 2.5

Some Previous Research in Moving Holiday Electricity Load Forecasting

Technique		Author	Forecasting error
Conventional Technique	Statistical time series model (Box-Jenkin methodology)	Medeiros and Soares, (2008)	The results do not forecast MH day, but mention that the MAPE are higher on MH by using dummy variables for the effect of MH.
		Razak et al., (2010)	18.94% (H-ELD) 15.95 (H-ELD)
		Kim, (2013)	9.68% (MH-ELD)
	Statistical time series model (Exponential smoothing)	Kim, (2013)	11.27% (MH-ELD)
	Statistical time series model (Regression model)	Razak et al., (2010)	2.22% (H-ELD)
		Ding et al., (2005)	15.59% (MH-ELD) 8.98% (H-ELD) 1.92% (H-ELD)
		Fernandes et al., (2011)	1.88% - 6.00% (H-ELD) 3.05% - 6.38% (MH-ELD)
Artificial Intelligence Technique	Fuzzy neural network	Kim et al., (2000)	1.03% - 3.14% (H-ELD) 1.13% - 2.64 (MH-ELD)
		Srinivasan et al., (1995)	1.17% (MH-ELD)
	Fuzzy linear regression	Song et al., (2005)	1.79% - 5.53% (H-ELD) 3.09% - 4.85% (MH-ELD)

Universiti Utara Malaysia

Table 2.5 continued.

Fuzzy expert system	Ebrahimi and Moshari, (2013)	3.90% (H-ELD) 6.35% (H-ELD) 4.19% (MH-ELD) 6.08% (MH-ELD)
Fuzzy inference system	Ding et al., (2005)	2.72% (MH-ELD) 2.99% (H-ELD) 1.50% (H-ELD) 3.18% - 9.31% (H-ELD)
	Song et al., (2005)	4.01% - 6.53% (MH-ELD)
	Arora and Taylor, (2013)	Less than 4% (MH-ELD)
	Çevik and Çunkaş, (2016)	2.03% - 11.29% (H-ELD) 4.57% - 7.54% (MH-ELD)
Neural Network	Yap and Yap, (2012)	3.77% (MH-ELD) 5.69% (MH-ELD) 6.73% (MH-ELD)
	Kim et al., (2000)	1.16 % - 2.76% (H-ELD) 1.24% - 3.97% (MH-ELD)
	Ebrahimi and Moshari, (2013)	5.90% (H-ELD) 7.80% (MH-ELD)

Universiti Utara Malaysia

Some previous studies used statistical time series method in forecasting MH-ELD as in Table 2.5, but different with Medeiros and Soares (2008), since they do not forecast MH-ELD but use dummy variables instead, for the effect of MH in their short-term Brazil ELD model. They conducted some comparison of methods such as models from Box-Jenkins methodology, general linear model and neural network (NN). They found the best model was Two Level Seasonal Autoregressive model with Mean Absolute Percentage Error (MAPE) range from 2.86% to 3.56%. In the analysis, they also found that by considering more complex nonlinear models in the data, such as NN, does not bring any clear benefit in terms of forecasting performance (Medeiros & Soares, 2008). Razak et al. (2010), also considered MH as dummy variables in methodology their Malaysia ELD model but with Box-Jenkins methodology and Dynamic Regression model. However, they forecast for holiday-ELD (H-ELD) only but not

MH-ELD. The H-ELD that they forecast was on New Year's Eve (1st January) with 2.22% MAPE value by Dynamic Regression model. Kim (2013) also applied Box-Jenkins in his analysis of Korea ELD data. The results showed that seasonal autoregressive moving average with the exogeneous variable (SARMAX) with two types of special day model was the best model in forecasting MH-ELD with average lowest MAPE of 9.68%.

Ding et al., (2005) conducted MH-ELD and H-ELD of Beijing ELD by using linear regression and fuzzy inference methods. The best model was hybrid method of fuzzy inference and similar day model with MAPE 2.72% for MH-ELD, and 1.50% MAPE for H-ELD. Fernandes et al. (2011) also conducted ELD forecasting by using linear regression in Mumbai data. They proposed two separate models; Sunday and Holiday model using some modification on weighted linear regression. They found the MAPE for MH-ELD were from 3.05% to 6.38% including moving holiday of Holi, Eid, Diwali, Muharram, Ambedkar Jayanti, Maharashtra Day, Ganesh Chaturthi, Gandhi Jayanti. MAPE for H-ELD were from 1.88% to 6.00% including holiday of Good Friday, Christmas, Republic Day and Independence Day.

Other than the statistical method, some researchers have suggested a NN method in their ELD forecasting analysis. Benaouda and Murtagh (2006) forecast Australia ELD using NN trained from wavelet-transformed data. They found out that a hybrid forecasting method of multilayer perception NN and nonlinear multi-resolution autoregressive gave a better forecasting results with MAPE of 1.06%. Meanwhile, Mohamed and Ahmad (2012) forecast Malaysia ELD using multilayer feed-forward NN with the forecasting results MAPE 1.24%.

Universiti Utara Malaysia

Based on the general NN method, one of the methods in NN is the black-box neural network, which is suitable for handling a nonlinear model problem (Khosravi et al., 2011; Medeiros & Soares, 2008). Models with NN require less intellectual effort from the researchers. This is because they do not have to derive complicated linear equations as there is a reflection for the potential nonlinearities that can be associated with the problem of demand prediction. The complexity of a model with NN is in its optimisation equations, which require various tests on the NN architecture (i.e., number of neurons in the hidden layer and learning function) (Hernández et al., 2014). However, both mentioned previous studies did not forecast the MH scenario.

There are previous studies that applied NN, fuzzy NN and hybrid of both methods as AI technique to forecast MH-ELD. For instance, fuzzy NN (Kim et al., 2000; Srinivasan et al., 1995), fuzzy linear regression (Song et al., 2005), fuzzy expert system (Ebrahimi & Moshari, 2013) and fuzzy inference system (Arora & Taylor, 2013; Çevik & Çunkaş, 2016; Ding et al., 2005; Kim et al., 2000) and NN (Yap & Yap, 2012). Kim et al. (2000) conducted study of Korea ELD using fuzzy NN model, and adaptive linear element (ADALINE). They found that by using ADALINE and fuzzy NN, the MAPE were from 1.16 % to 2.76% and from 1.03% to 3.14% for H-ELD respectively. The H-ELD in this study were Independence Day, Arbor Day, May Day, Children Day, Memorial Day, Constitution Day, Liberation Day, National Foundation Day, Christmas and New Year's Day. Meanwhile, Buddha's Birthday, Korean Thank-giving Day and Lunar New Year's Day were for MH-ELD recorded MAPE from 1.24% to 3.97% and from 1.13% to 2.64% by using ADELINE and fuzzy NN respectively. Similarly, (Song et al., 2005) also conducted study to Korea ELD data. They found that the forecasting error for H-ELD were from 3.18% - 9.31% by using fuzzy inference system and from 1.79% to 5.53% by using fuzzy linear regression.

Meanwhile, the study also showed the forecasting error were from 4.01% to 6.53% by using fuzzy inference system and from 3.09% to 4.85% by using fuzzy linear regression in MH-ELD forecasting.

Srinivasan et al., (1995) proposed the Singapore forecasting model for Sunday and MH-ELD with MAPE 1.17% using fuzzy NN. Ebrahimi and Moshari (2013) proposed fuzzy improved similar day (FISDM) method in their fuzzy expert system model. They found the average forecasting error for H-ELD and MH ELD was the lowest by using FISDM as compared to modified similar day method (MSDM) and NN. Arora and Taylor, (2013) proposed incorporation rule-based approach into four statistical forecasting model; triple seasonal Holt-Winter-Taylor exponential smoothing, triple seasonal autoregressive moving average (SARMA), NN and triple seasonal intraweek singular value decomposition (SVD) in conducting study of Britain ELD data. The comparison of four type of rules were discussed in each statistical model. Each rule was about the different characteristic of holidays in the data. The analysis reveals by doing the corporation of rules-based able to reduce the forecasting error with MAPE less than 4%. Çevik and Çunkaş (2016) conducted Turkey ELD using Mamdani fuzzy inference system. The results show MAPE from 2.03% to 11.29% for H-ELD and from 4.57% to 7.54% for MH-ELD. Yap and Yap (2012) study on Malaysia ELD by using new NN approach with the name Multi-Agent System based on Online Sequential Extreme Learning Machine Neural Network with weighted average strategy (MAS-OSELM-WA). The experimental results for MH-ELD have shown that MAS-OSELM-WA has achieved a promising result which is better than Generalized Regression Neural Network (GRNN) and Support Vector Regression (SVR) with MAPE 3.77%, 5.69% and 6.73% respectively.

Universiti Utara Malaysia

Nevertheless, a conventional NN that is based on the short-term forecasting method has six limitations. First, there is no established method that can best approximate the function mapping of the inputs to the outputs in neural network architecture (Darbellay & Slama, 2000). Second, it is difficult to obtain sufficient data sets for learning the irregular load profiles, which refers to the anomalous load condition of the special day (or day of holiday). The third limitation is in this approach itself that cannot be used together with the experience and qualitative knowledge of the human forecasters who can provide comparatively accurate forecasting results for special days (or moving holidays) (Kim et al., 2000). The fourth limitation is in this method itself that profoundly depends on its learning capability (Khosravi et al., 2011). The fifth is NN has the properties of slow convergence time and poor ability to process a large number of variables at a time (Sachdeva & Verma, 2008). The last limitation is in its lack of interpretability and over-fitting issue in the research of electric load modelling and forecasting with NN (Hong et al., 2010).

Universiti Utara Malaysia

Due to the aforementioned reasons, a number of researchers have used the fuzzy inference system method to study the MH-ELD forecasting and produced good results for the holiday short term load forecast (Çevik & Çunkaş, 2016; Ding et al., 2005; Fernandes et al., 2011; Kim et al., 2000). From the results, the nature of the relationship between ELD and some independent variables such as the moving holiday factor is complex, and sometimes it is not possible to fit the load curve by using conventional statistical models.

Therefore, this research has considered the concept of FST that was proposed by Zadeh (1965), which can be used as an alternative approach in research areas that have to deal with data that has a feature of special day or holiday effect. The fuzzy logic

approach has the benefits of being easy and robust robust (Rizwan et al., 2012), and this approach has an advantage over a NN. FST can deal with the non-linear part of the forecasted load curve, as well as having the ability to deal with sudden variations in a system's load. Fuzzy logic allows everything to be granulated, where a granule is a clump for factor-values that are drawn together with their distinguishable ability, similarity, proximity, and functionality. A unique feature of fuzzy logic is graduated granulation, or known as an equivalently fuzzy granulation) (Zadeh, 2008). The transparent fuzzy logic models can simultaneously handle quantitative and qualitative information when it is compared with a neural network, thus this method is the best alternative for uncertainty modelling, prediction, and forecasting purposes (Khosravi et al., 2011).

In a nutshell, all the previous studies as previously mentioned, have similar main research objective, which is to find the H-ELD and/or MH-ELD forecasting models with small forecasting error either based on conventional forecasting techniques or hybrid techniques.

Universiti Utara Malaysia

2.10 Factors Affecting MH-ELD

One of the critical issues in the successful application of fuzzy models is the appropriate selection of input variables/independent variables (Zounemat-Kermani & Scholz, 2014). The study applied stepwise regression to select the significant independent variables in their fuzzy modelling. Stepwise regression is a routine statistical technique used to select variables. Other types of variable selection in regression are backward, forward, and enter variable selections. These four selection techniques are imbedded in the regression analysis tool in many well-known statistical

software such as Statistical Package for the Social Sciences (SPSS) and Statistical Analysis System (SAS).

Generally, in constructing a model, some selection variables do not have an important explanatory effect on dependent variables. Thus, this statistical selection technique is only a convenient simplification to keep the statistically significant variables in the model. Mansor et al. (2014) built manual and automatic simplification models to apply fuzzy modelling for electricity load demand forecasting. However, the analysis from the study was not specified to forecast MH-ELD.

MH-ELD forecasting is influenced by many factors. The following Table 2.6 is related to the previous Table 2.5 that shows a summary of some of the research with factors that influenced the input in their research regarding MH-ELD forecasting. From Table 2.6, it can be observed that almost all previous studies included *day types, past load*, and *past temperature* as the factors in their MH-ELD forecasting models. There were also some new factors used in their research such as standard deviation measure as the *load difference variation* (Ebrahimi & Moshari, 2013; Kim et al., 2000) and *load annual increment rate* (Ding et al., 2005). However, they did not verify the significant factors and also did not provide standard procedures in the study factor selection process in their MH-ELD modelling.

Universiti Utara Malaysia

Table 2.6

Summary of Factors in Moving Holiday Electricity Load Demand Forecasting

Author	Factor summary	Data	Forecasting time frame	Input variables selection method
Srinivasan et al., (1995)	● Daily minimum temperature ● Daily maximum temperature ● Daily minimum load ● Daily maximum load ● rain indication ● seasonal variation ● day of the week ● special day effect	Singapore (1991 – 1992)	a day ahead hourly	Not mention.
Kim et al., (2000)	● maximum variation of load difference of special day ● minimum variation of load difference of special day	Korea (1990 – 1995)	a day ahead hourly	Not mention
(Song et al., 2005)	● type of day ● maximum loads of the four weekdays before the holidays ● maximum loads of the holidays in past three years	Korea (1996 – 1997)	a day ahead hourly	No need because use fuzzy regression method.
Ding et al., (2005)	● daily minimum temperature of the holiday ● daily maximum temperature of the holiday ● daily minimum load of last year's holiday ● daily maximum load of last year's holiday ● annual increment rate of maximum load ● annual increment rate of minimum load	Beijing (1999 – 2004)	a day ahead hourly	Similar day method
Fernandes et al., (2011)	● load of the same day in previous week ● load profile of nearest Sunday	India (2010 – 2011)	a day ahead 15 minutes	Similar day method
Yap and Yap (2012)	● maximum daily load of past seven days. ● day of the week ● days before, during and after moving holiday.	Malaysia (2002 – 2004)	a day ahead daily	Similar day method

Universiti Utara Malaysia

Table 2.6 continued.

Author	Factor summary	Data	Forecasting time frame	Input variables selection method
Ebrahimi and Moshari, (2013)	● day of the week ● load standard deviation for the nearest weekend ● load average for the nearest weekend ● mean value of the difference between the average load of the holiday and the weekend in the previous year.	Isfahan, Iran (2002 – 2006)	a day ahead hourly	Modified Similar Day Method (MSDM)
Çevik and Çunkaş, (2016)	● holiday type ● previous week load ● previous year/holiday load	Turkey (2009 – 2011)	A day ahead hourly	Similar day method

Variable selection plays a critical role in building a good forecasting model. It is important to first analyse the data to ensure all essential variables are included (Setiawan et al., 2009). Therefore, the application of certain methods in identifying the suitable and significant variables is much more worthwhile. Hence, this study applies correlation analysis in the variable selection step to identify the variables for MH-ELD forecasting in the first phase of the FTS algorithm. This variable selection method presumes that the dependent variable behaves like a series of independent variables either correlated or independent from each other (Fallah et al., 2019). Zounemat-Kermani and Scholz (2014) conducted correlation analysis as a variable selection method in the pre-processing phase of neural network ELD forecasting approach.

Other studies have suggested other variable selection methods in ELD forecasting, such as rough set analysis (Mansor et al., 2016a), entropy mutual information feature selection (Samuel et al., 2020), and variable selection based on stepwise and Autometrics (Mansor et al., 2014). Although the correlation analysis does not guarantee an optimal solution, it can be used as a guide to the forecaster to implement

the variable selection step in their forecasting process if necessary, especially if the objective is to simplify the forecasting model. The list of suggested variables in this study produced by the application of the selection method is given in Chapter Three.

2.11 Summary

A number of ELD and MH-ELD forecasting approaches from previous studies are discussed in this chapter. However, due to some issues in MH-ELD forecasting as presented in this chapter i.e. high forecasting error, complex, nonlinear and uncertainty time series data pattern, and limited recent historical data, the FTS approach is believed to be one alternative approach to overcome the forecasting problem.

Moreover, it has been observed that various studies have been proposed to perform effective weighted schemes in FTS algorithms and these have resulted in significant achievements as well. However, no one has explored the use of the weighted subsethood algorithm to aggregate FTS observations into a meaningful FTS model. As a result, an enhanced FTS algorithm is to be developed to capitalise on the potency of WSBA in segmented FTS -based forecasting model to accomplish higher forecasting accuracy in MH-ELD forecasting problem.

Fuzzy relationship weights are determined either based on knowledge which could be elicited from domain experts or their chronological order. Since each fuzzy relationship will reoccur, from the researcher's perspective, classifying them into different trends and converting the counts of trends to incremental weights is reasonable for making more accurate predictions. Hence, most of the previous studies used various FLR trend-weighted schemes in their proposed FTS algorithms.

Universiti Utara Malaysia

However, it has become apparent that the major limitation of the FTS algorithms presented in this chapter is lower interpretability of the fuzzy relationship strength in FLRG in terms of describing the degree of the strength relationship between the dependent variable linguistic term and every independent linguistic term. Also, the limitation of previous studies shows the lack of consideration of a meaningful FTS final model interpretation by describing the degree of relative importance of the independent linguistic term to dependent linguistic term. Moreover, no complete FTS forecasting process algorithm in detail using phase by phase and step by step by considering two type of FTS models; one factor and M-factor FTS. All these matters will cause less information about the relationship that naturally represents how humans make judgments and decisions and less guide to conduct complete FTS forecasting process.

Therefore, to reconcile these issues of MH-ELD and FTS algorithms, a new FTS forecasting methodology is hereby proposed. Additionally, since the current defuzzification methods as described in this chapter do not consider the numeric value from the condition of weighted subsethood fuzzy reasoning rules, a new of defuzzification method is also proposed. The methodology of the proposed FTS algorithm is explained in Chapter Three and the implementation of the enhanced FTS algorithm in the MH-ELD problem is presented in Chapter Four.

Universiti Utara Malaysia

CHAPTER THREE
METHODOLOGY

3.1 Introduction

As discussed in the previous chapter, enhancing FTS forecasting algorithms can be classified into five categories. As for this present study, the focus is on two of the five categories; enhancing certain steps of conventional FTS algorithms, and implementing the enhanced FTS algorithm to suit a specific application. In this case, the specific application is to solve the MH-ELD forecasting problem.

Having those said, this chapter describes the steps employed in this study to enhance the FTS forecasting algorithm from the models initiated by Chen (1996) and Cheng (2008), and later, proposes the enhancement of the conventional FTS algorithm based on Weighted Subsethood Based Algorithm. Since the data applied in this study refer to segmented FTS, the modified FTS algorithm is termed as Weighted Subsethood Segmented Fuzzy Time Series (WeSuSFTS) forecasting algorithm.

Universiti Utara Malaysia

In precise, this study developed a WeSuSFTS forecasting algorithm for execution in One-factor and M-factor FTS. Simultaneously, this study introduced a simple defuzzification method in the WeSuSFTS algorithm. In order to determine the efficiency of the proposed MH-ELD forecasting model, the validation process was carried out by comparing the forecasting errors of the proposed model with the conventional FTS models, Chen's model and Cheng's model. The next section provides the overview of the constructed WeSuSFTS forecasting algorithm, while Sections 3.3, 3.4, 3.5 and 3.6 provides the detailed discussions on phases 1, 2, 3 and 4 of the algorithm respectively, while Section 3.7 is the summary of the chapter.

3.2 Overview of Enhanced Algorithms

Figure 3.1 demonstrates the comparison between Chen, Cheng, and WeSuSFTS algorithms. The enhanced steps in Cheng and WeSuSFTS are shaded in gray and yellow, respectively.

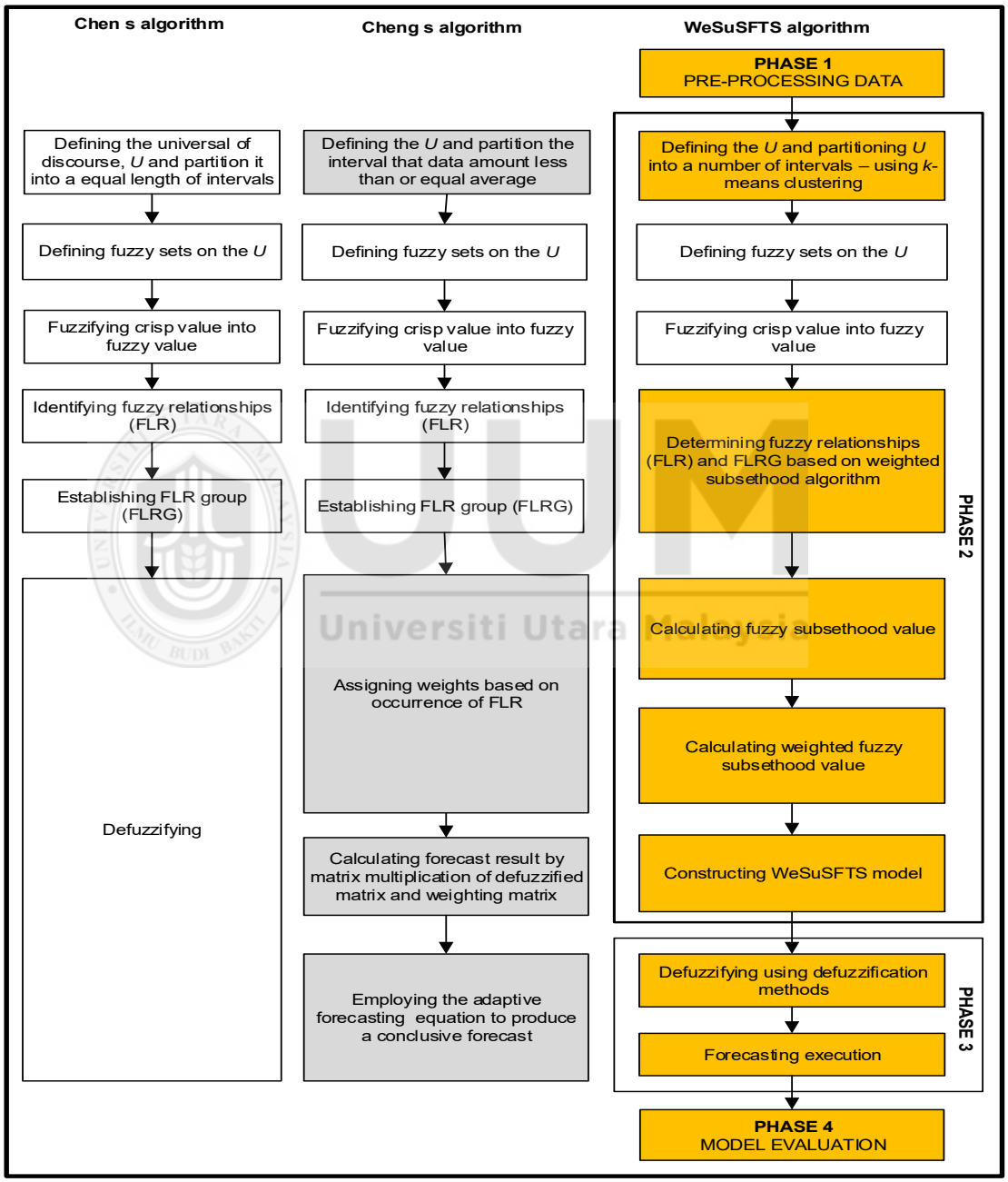


Figure 3.1. Comparison between Chen (1996), Cheng (2008), and WeSuSFTS algorithm

Universiti Utara Malaysia

Figure 3.1 presents the six steps embedded in Chen's algorithm, eight steps in Cheng's algorithm and eleven steps in WeSuSFTS algorithm where the WeSuSFTS steps in the figure are for comparison purpose. Step 1 in Chen's algorithm (Defining *U* and partition it into equal length of intervals) is similar to that of Cheng's. The difference is the way Cheng partitioned the *U*. Nonetheless, the Step 1 (Phase 1) of the proposed WeSuSFTS algorithm is pre-processing data. Subsequently, Step 2 (Defining the *U* and partitioning *U* into a number of intervals - using *k*-means clustering) did not differ much from both the conventional FTS algorithms due to its significance in any FTS algorithm. Detailed steps of the enhanced algorithm are elaborated in the next section. Based on Figure 3.1, following is the Chen's, Cheng's and WeSuSFTS algorithm.

- Chen's FTS algorithm (Chen, 1996)

  Step 1: Defining the universal of discourse, *U* and partition it into a equal length of intervals.

  Step 2: Defining fuzzy sets on the *U*.

  Step 3: Fuzzifying crisp value into fuzzy value.

  Step 4: Identifying fuzzy relationships (FLR).

  Step 5: Establishing FLR group (FLRG).

  Step 6: Defuzzifying

- Cheng's FTS algorithm(Cheng et al., 2008)

  Step 1: Defining the *U* and partition the interval that data amount less than or equal average.

  Step 2: Defining fuzzy sets on the *U*.

  Step 3: Fuzzifying crisp value into fuzzy value.

  Step 4: Identifying fuzzy relationships (FLR).

Universiti Utara Malaysia

Step 5: Establishing FLR group (FLRG).

Step 6: Assigning weights based on occurrence of FLR.

Step 7: Calculating forecast result by matrix multiplication of defuzzified matrix and weighting matrix.

Step 8: Employing the adaptive forecasting equation to produce a conclusive forecast.

- WeSuSFTS algorithm

  The WeSuSFTS algorithm is composed of four phases: Phase 1: Pre-processing data, Phase 2: Modelling of WeSuSFTS, Phase 3: Model implementation and Phase 4: Model evaluation. The following steps is for comparison purpose with Chen's and Cheng's algorithms as stated in Figure 3.1.

  Step1: Phase 1

  Step2: Defining the *U* and partitioning *U* into a number of intervals – using *k*-means clustering.

  Step 3: Defining fuzzy sets on the *U*.

  Step 4: Fuzzifying crisp value into fuzzy value.

  Step 5: Determining fuzzy relationships (FLR) and FLRG based on weighted subsethood algorithm.

  Step 6: Calculating fuzzy subsethood value.

  Step 7: Calculate weighted fuzzy subsethood value.

  Step 8: Constructing WeSuSFTS model.

  Step 9: Defuzzifying using defuzzification methods.

  Step 10: Forecasting execution.

  Step 11: Phase 4

Universiti Utara Malaysia

In Chen's and Cheng's algorithms, Step 2 (Defining fuzzy sets on the *U*) and Step 3 (Fuzzifying crisp value into fuzzy value), which denote Step 3 and 4 in WeSuSFTS algorithm. Step 4 (Identifying FLR), and Step 5 (Establishing FLRG) in Chen's algorithm is similar to Step 4 and 5 in Cheng's algorithm, but differs from WeSuSFTS algorithm as the steps in the latter algorithm are combined into a single step, Step 5 (Determining FLR and FLRG based on weighted subsethood algorithm). All FTS algorithms discussed in this chapter apply the same FLR mechanism. The FLRG in Chen's and Cheng's algorithms applies definition (Section 2.2.6) in the previous chapter, while the FLRG in WeSusFTS algorithm was constructed based on Step 1 of the subsethood algorithm (see subsection 2.3, Chapter Two).

Step 6 (Defuzzifying) is the final step in Chen's algorithm, while Cheng's algorithm enhances Chen's by incorporating three additional steps. The steps are Step 6 (Assigning weights based on occurrence of FLR), Step 7 (Calculating forecast result by matrix multiplication of defuzzified matrix and weighting matrix) and Step 8 (Employing the adaptive forecasting equation to produce a conclusive forecast), as presented in Figure 3.1. In Cheng's algorithm, FLR weights are considered in Step 6 (Assigning weights based on occurrence of FLR). The Cheng's weights are determined based on either knowledge that may be elicited from domain experts or weight chronological order (Cheng et al., 2008). One can also categorise Cheng's algorithm as FTS algorithm based on the trend-weighted method. In comparison to WeSuSFTS algorithm, the weights are calculated based on weighted subsethood algorithm as stated in Step 6 (Calculating fuzzy subsethood value) and Step 7 (Calculating weighted fuzzy subsethood value).

Universiti Utara Malaysia

Step 7 in Cheng's algorithm (calculating the forecast result by matrix multiplication of defuzzified matrix and weighting matrix) is to employ the forecast result into a conclusive forecast value in the final step (Step 8). As for the WeSuSFTS algorithm, the forecasting model is constructed first (Step 8) prior to defuzzifying (Step 9) and forecasting steps (Step 10). The modified defuzzification methods are introduced in this step 9 (Defuzzifying using defuzzification methods). One crucial step in FTS algorithm is to validate the FTS model. Due to absence of the best forecasting model for each type of dataset, the WeSuSFTS model was validated through model evaluation process in Phase 4.

Since this study propose two types of WeSuSFTS models, Figure 3.2 portrays Phase 1 of One-factor and M-factor in WeSuSFTS algorithms. Each algorithm in Phase 1 is composed of four steps. The difference is in the last step, where the independent variables are identified using certain mechanism, is elaborated in the next section.

Universiti Utara Malaysia

In precise, the methodology of this study is comprised of four phases; data pre-processing, model development, model implementation, and model evaluation. Although the main part of WeSuSFTS modelling lies in the second phase, the FTS forecasting process becomes incomplete without the other three phases. The details of WeSuSFTS algorithm is presented in Figure 3.3. The next section provides step-by-step algorithm for each phase. The following chapter describes the application of the proposed WeSuSFTS in forecasting MH-ELD.

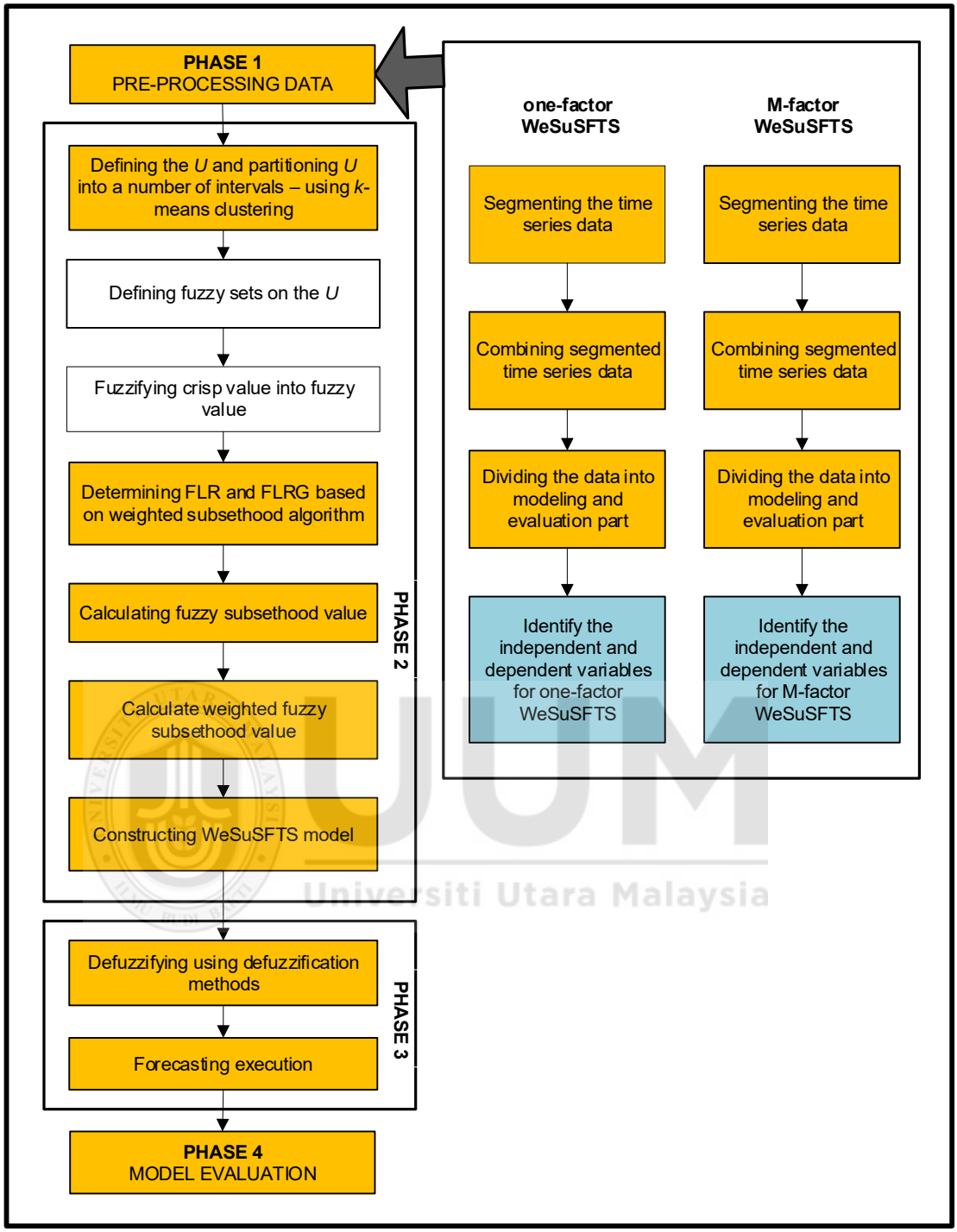


Figure 3.2. The difference in steps between One-factor and M-factor for WeSuSFTS algorithm

Universiti Utara Malaysia

PHASE 1: Pre-processing data

Step 1: Segmenting the time series data.

Step 2: Combining segmented time series.

Step 3: Dividing the data into modelling and evaluation parts.

Step 4: Identifying the independent and dependent variables(s).

PHASE 2: Modelling of WeSuSFTS

Step 1: Defining the universal of discourse, *U* and partitioning *U* into a number of intervals.

Step 2: Defining fuzzy sets on the *U*.

Step 3: Fuzzifying crisp value into fuzzy value.

Step 4: Determining FLR and FLRG.

Step 5: Calculating fuzzy subsethood (Su) value.

Step 6: Calculating weighted fuzzy subsethood (WeSu) value.

Step 7: Constructing WeSuSFTS model.

Universiti Utara Malaysia

PHASE 3: Model Implementation.

Step 1: Defuzzifying fuzzy value into crisp value.

Step 2: Forecasting execution.

PHASE 4: Model evaluation.

Step 1: Defining and calculating forecasting error measurement.

Step 2: Comparing forecasting error measurement among different defuzzification methods.

Figure 3.3. WeSuSFTS forecasting algorithm

3.3 Phase 1: Pre-processing Data

Phase 1 is the fundamental phase and refers to the preparation phase prior to Phase 2. Pre-processing data involves processing of historical data first, before moving on to further calculation steps. This phase hinders mistake from occurring while conducting this study, such as addressing the incorrectly structured data in modelling and the validation part. The four steps in this phase are:

Step (1): Segmenting time series data.

Step (2): Combining segment time series.

Step (3): Dividing data into modelling and evaluation parts.

Step (4): Identifying independent and dependent variables.

The following explains the steps embedded in this phase.

Universiti Utara Malaysia

3.3.1 Step (1): Segmenting Time Series

Segmentation in this study denotes separating load time series into new week of the year series, thus causing breaks in two big events named as moving holiday of big event 1 (MH1) and big event 2 (MH2) trend vectors. Historical data were segmented into two; MH event week and complement of MH event week. The definition of complement of a MH event week are the days not in the MH event week. The first day of MH falls in the middle of the MH event week (the fourth day in the week). The week does not have to start with Sunday or end with Saturday. In other words, this study chooses MH weeks only in modelling WeSuSFTS forecasting algorithm. Figure 3.4 shows the example selection of MH week in calendar form.

Day	Date	Event	Week
.	.		Complement of MH event week
.	.		
Tuesday	24 January 2017		
Wednesday	25 January 2017		MH1 event's week
Thursday	26 January 2017		
Friday	27 January 2017		
Saturday	28 January 2017	MH1	
Sunday	29 January 2017		
Monday	30 January 2017		
Tuesday	31 January 2017		
Wednesday	1 February 2017		Complement of MH event week
.	.		
.			
.	.		
Wednesday	21 June 2017		
Thursday	22 June 2017		MH2 event's week
Friday	23 June 2017		
Saturday	24 June 2017		
Sunday	25 June 2017	MH2	
Monday	26 June 2017		
Tuesday	27 June 2017		
Wednesday	28 June 2017		
Thursday	29 June 2017		Complement of MH event week
.	.		
.	.		
.	.		

Figure 3.4. Example of MH week in year 2017

3.3.2 Step (2): Combining Segmented Time Series

Based on Section 3.3.1, as in Bessec et al. (2016), this study proposes an alternative data set by combining two-year data into MH data merely to forecast the last observations. This adjustment assumed that the data were spread evenly over the combined periods. This study proposes the combination of the segmented time series data, F_m, as follows:

$$F_m = F_{1,1}, F_{1,2}, F_{1,3}, \dots, F_{1,j}, \dots, F_{i,1}, F_{i,2}, F_{i,3}, \dots, F_{i,j}. \quad (3.1)$$

Where,

F_m is MH-ELD segmented time series data,

$F_{1,1}, F_{1,2}, F_{1,3}, \ldots, F_{1,j}$ are MH-ELD time series data of the first MH big event segment (MH1) that have *j* data points,

$F_{i,1}, F_{i,2}, F_{i,3}, \ldots, F_{i,j}$ are MH-ELD time series data of i_{th} MH big event segment (MHi) that have *j* data points,

i signifies the number of MH segments, while *j* indicates the amount of data in segmented time series.

Figure 3.5 displays a graphical example on the combination process of segmented time series data using two MH segments (i = 2) weekly (j = 7 days), also called as 'known segmentation break'.

Universiti Utara Malaysia

Based on Figure 3.5, the combination of segmented time series data is presented in the following:

Let MH1 week in a certain year is $F_{1,1}, F_{1,2}, F_{1,3}, \ldots, F_{1,7}$, whereas MH2 week in a certain year is $F_{2,1}, F_{2,2}, F_{2,3}, \ldots, F_{2,7}$. Next, based on Equation (3.1), the MH segmented time series data are:

$$F_m = F_{1,1}, F_{1,2}, F_{1,3}, \ldots, F_{1,7}, F_{2,1}, F_{2,2}, F_{2,3}, \ldots, F_{2,7}.$$

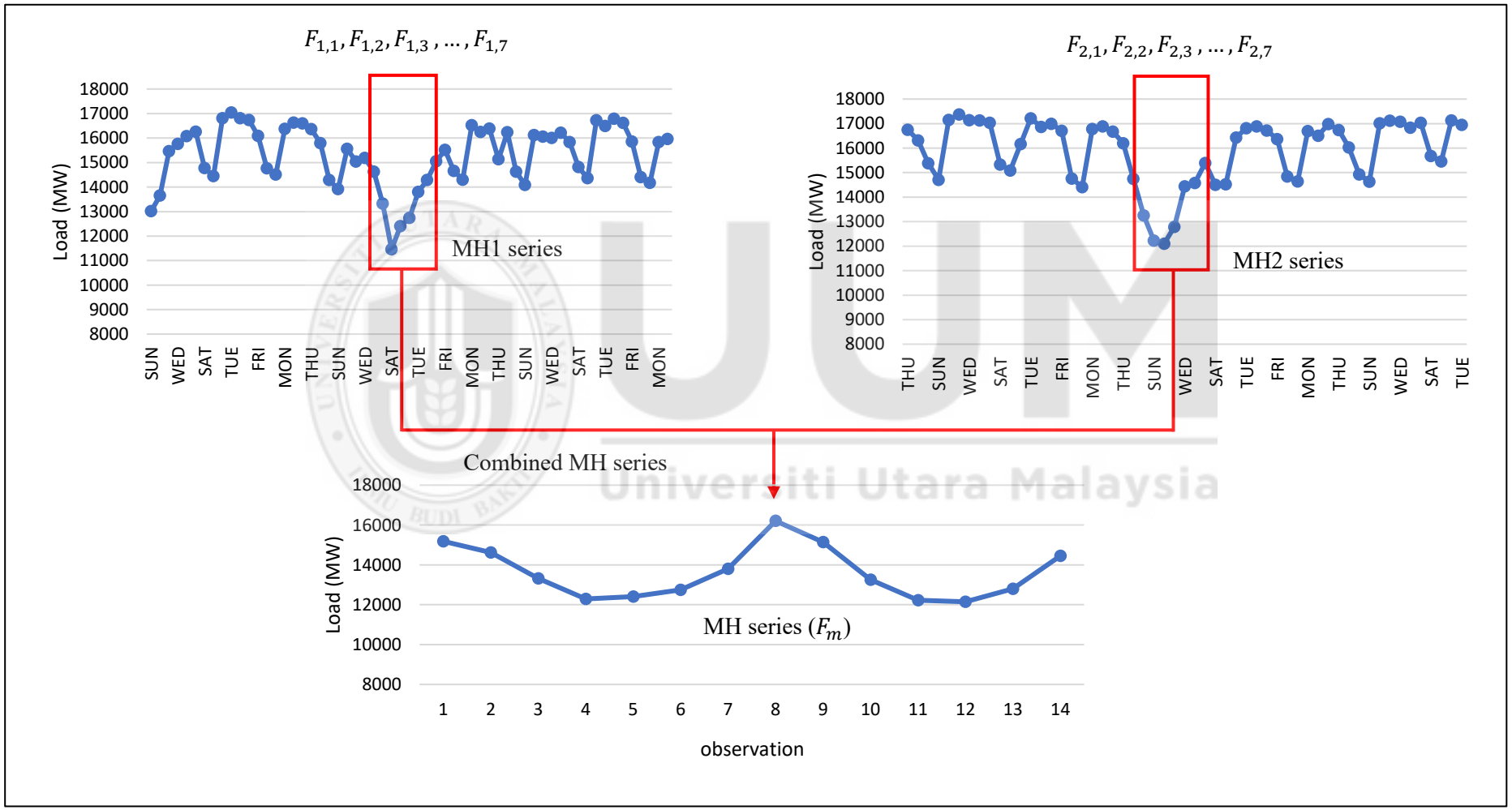


Figure 3.5. Known segmentation break

Universiti Utara Malaysia

3.3.3 Step (3): Dividing the Data into Modelling and Evaluation Parts

The purpose of this step is to prepare the time series data for validating the forecasting model. This study used out-of-sample validation method by single modeling-evaluation split approach (as discussed in Section 2.7 in Chapter Two) due to the limited number of data set and this approach also mimic the real forecasting scenario. Figure 3.6 illustrates the process of data partitioning in this study based on Besses et al., (2016).

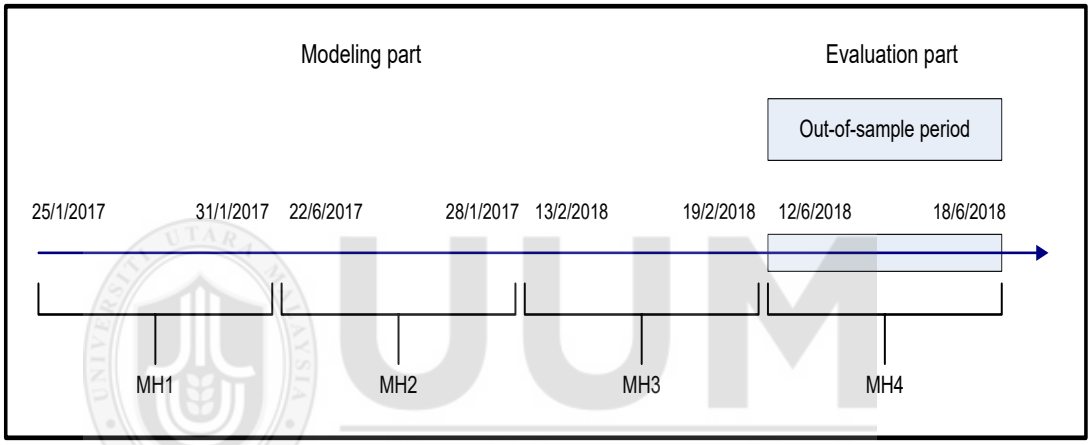


Figure 3.6. Data partition

As in Figure 3.6, the modelling part of the data consisted of seven days each for MH1, MH2, and MH3. As for the evaluation part, the data consisted of seven days for MH4. This study had divided the segmented time series into three MH weeks for modelling part and one MH week for evaluation part.

The data for the modelling part were used to construct the WeSuSFTS model proposed in this study. Next, the WeSuSFTS model would be used to forecast percent changes of MH-ELD. Finally, forecasting error was calculated using the actual data in evaluation part to measure the forecasting accuracy by using out-of-sample data (post-

Universiti Utara Malaysia

sample). Details of the evaluation process are depicted in Phase 4. It further proves that the forecasting process mimicked the real process of forecasting.

3.3.4 Step (4): Identifying Independent and Dependent Variables

The variables were determined in this step. This step is crucial because different pairs of independent and dependent variables resulted in different models with varied forecasting accuracies. By adopting Ebrahimi and Moshari's (2013) and Hidayah et al.'s (2017) works, instead of using the actual electricity load data for the universal of discourse, percentage change of load between forecasted load and the prototype week load were used in this study as the independent variables as stated in Equation 3.2. Prototype week reflects week without holiday or surrounded by holiday before MH. The percentage change formula in this study is given in Equation (3.2):

$$C_{t+1} = \frac{L_{t+1} - L_p}{L_p} \times 100\% \tag{3.2}$$

Universiti Utara Malaysia

Where,

$C_{t+1} =$ percent change load of the forecasted day

$L_{t+1} =$ load of the forecasted day

$L_p =$ load of the same day type of the prototype week

Typically, the prototype week is the nearest week. However, if the nearest week is interrupted with irregular events or the pattern deviates from the regular fluctuation, the week cannot be assigned as prototype week. Hence, the second nearest week would be selected as the prototype week and so on.

In this vein, Ebrahimi and Moshari (2013) suggested load average of the nearest weekend as input. As such, the new variable, which is percentage change of load from the same day of the prototype week, is proposed in this study. As given earlier, prototype week denotes week without holiday or surrounded by holiday before MH. This notion contradicts the suggestion put forward by Ebrahimi and Moshari (2013), whereby the nearest weekend is unsuitable to serve as benchmark in certain cases. For instance, referring to Figure 3.7, 16 Dec 2001 (Sunday) was MH1. Therefore, the whole week recorded an increase of load up to 2500 MW (maximum). On the contrary, upon selecting the nearest prototype week, the whole week would have decreased to 3200 MW.

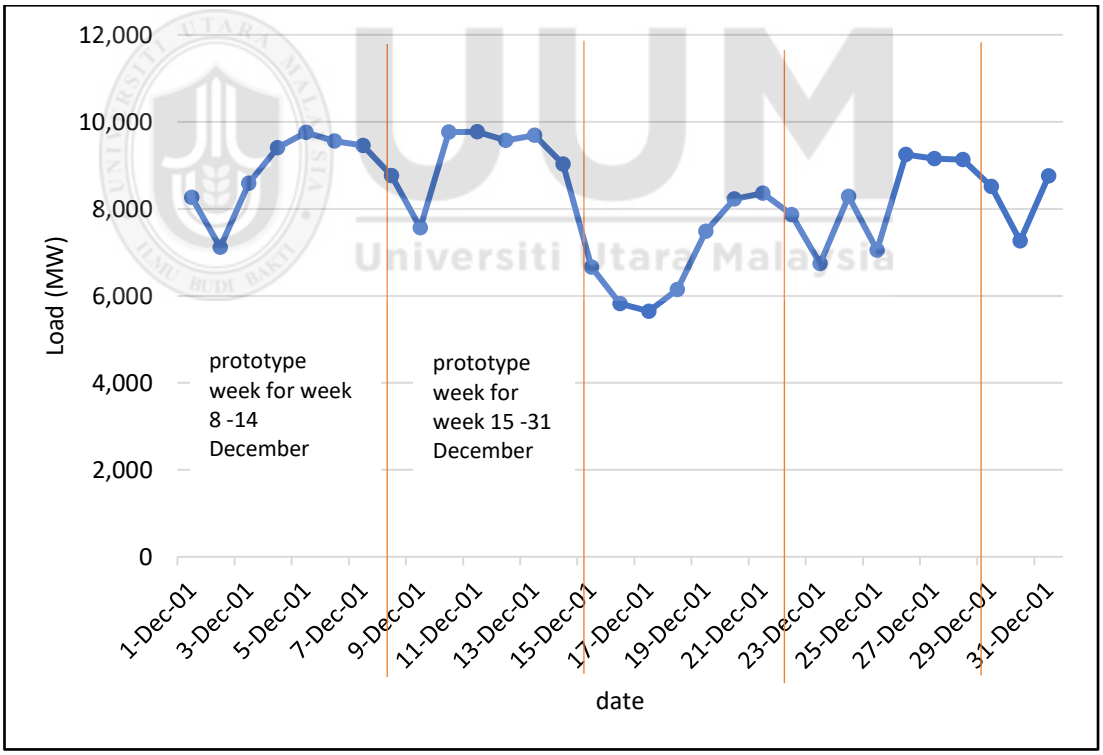


Figure 3.7. Illustration of prototype week

An example of percent changes calculation based on Figure 3.7:

$$L_{p(16\ Dec\ 2001)(Sunday)} = 5818MW$$

$$L_{t(23\ Dec\ 2001)(Sunday)} = 6737MW$$

$$C_{23\ Dec\ 2001} = \frac{6737 - 5818}{5818} \times 100\% = \ 15.8\%$$

Where t+1 = 23 Dec 2001. One can interpret that the load on the next day (L_{t+1}) could increase by 15% from the same day of the last week (L_p). Since the prototype week selected is a huge event (MH1), the $C_{23\ Dec}$ value cannot represent the actual percent changes from the normal day. Thus, the second or the third nearest week may be selected as the prototype week. Table 3.1 shows the value of C_{23Dec} is -10% based on the following calculation:

$$L_{p(9\ Dec\ 2001)(Sunday)} = 7564MW$$

$$L_{t(23\ Dec\ 2001)(Sunday)} = 6737MW$$

$$C_{23\ Dec\ 2001} = \frac{6737 - 7564}{7564} \times 100\% = -10.9\%$$

The retrieved value shows that the electricity load on 23 Dec 2001 $\left(L_{t(23\ Dec\ 2001)}\right)$ decreased by 10.9% from any normal day. This result is more appropriate to interpret, when compared to the previous one when dealing with MH. From these two numerical example of actual historical data, it implies that the day type of the MH affects the percentage change value, and in the end affects the accuracy of the ELD forecasting.

The measurement of percentage change between current load and prototype load in this study is in agreement with the percentage change reported by Ismail et al. (2016). In Ismail et al. (2016) study, the weekend percentage change was determined based on

Universiti Utara Malaysia

the difference between weekend load (Saturday or Sunday) and average weekday value for the same week. During public holiday, percent change was measured based on the difference between public holiday value and previous week value of the same day (Ismail et al. (2016). In this present study, the calculation from prototype week had considered the effect of coincidence of other holiday in the week. In this study, the calculations from the prototype week may have been influenced by day types.

By referring to Table 2.6 in Section 2.10, most of the previous studies included day types as the factors in their MH-ELD forecasting models because the day types can affect the forecasting accuracy. For example, a holiday occurs on Saturday or Sunday instead of the other weekdays brings bigger error to load forecasting (Song et al., 2005; Srinivasan et al., 1995). A MH also can occur on other holiday (Çevik & Çunkaş, 2016), or a holiday was declared before or after the MH (Çevik & Çunkaş, 2016; Srinivasan et al., 1995).

The day type refers to the holiday type (Çevik & Çunkaş, 2016; Yap & Yap, 2012), the day of the week (Ebrahimi & Moshari, 2013; Song et al., 2005; Srinivasan et al., 1995; Yap & Yap, 2012) or both as a coincidence day (Ebrahimi & Moshari, 2013) that is a day with more than one holiday. In other words, coincidence term signifies coincidence of forecasted day with another holiday or weekend (Sunday or Saturday) or with holiday replacement day.

Therefore, by considering the above matters, in order to capture the coincidence effect, the qualitative aspect of the coincidence variables was embedded into the model through the specification of three categorical variables that represents coincidence in the day, where the forecasted day coincides–before the holiday/weekend (BH_{t+1}), coincides after holiday/weekend (AH_{t+1}), or coincides with another holiday on the

same day (SH_{t+1}). The definition of coincident variables was adopted from Ebrahimi and Moshari (2012). From Ebrahimi and Moshari (2013), coincidence term in their study signifies coincidence of forecasted day with another holiday such as weekends (Sunday or Saturday).

Furthermore, in order to capture the holiday type as big event effect, this study proposes qualitative variable (E_{t+1}) to identify if the forecasted day is a big event or otherwise. From the scope of this study and the definition from TNB, big events in Malaysia are HRA and CNY, in which both events are MH. The definition is enhanced as the days are declared as Public Holiday. For example, Malaysia declares the first and second day of both HRA and CNY as Public Holiday. Therefore, both days are considered as big event. Table 3.1 summarises the independent and dependent variables employed in this study.

Universiti Utara Malaysia

Table 3.1

List of Variables

Variable name	**Symbol**	**Explanation**
Next day percentage changes	C_{t+1}	In the defuzzification process, variable C_{t+1} is a forecasted value for next day percent changes
Current percentage changes	C_t	
Current load	L_t	
Forecasted day coincide before the holiday/weekend	BH_{t+1}	$BH_{t+1} = \begin{cases} 1, & if\ before\ coincidence \\ 0, & Otherwise \end{cases}$
Forecasted day coincide after holiday/weekend	AH_{t+1}	$AH_{t+1} = \begin{cases} 1, & if\ after\ coincidence \\ 0, & Otherwise \end{cases}$
Forecasted day coincide with another holiday/weekend	SH_{t+1}	$SH_{t+1} = \begin{cases} 1, & coincidence \\ 0, & Otherwise \end{cases}$
Type of forecasted day	E_{t+1}	$E_{t+1} = \begin{cases} 1, & if\ big\ event \\ 0, & Otherwise \end{cases}$

Based on Table 3.1, only 'Next day percentage changes' is the dependent variable, while all others are independent variables.

Based on the objectives and the scope of this study, two FTS models were selected, namely One-factor segmented FTS (One-factor WeSuSFTS), and M-factor segmented FTS (M-factor WeSuSFTS).

- Model 1: One-factor WeSuSFTS

This study defines the One-factor WeSuSFTS mathematical model function as follows by adopting Equation 2.5 in Chapter 2:

$$C_{t+1} = C_t * R_{t+1,t} \tag{3.3}$$

Where, $C_{t+1}$and C_t are segmented FTS denoted percentage change in time *t*+1 and in previous time, *t* respectively. $R_{t+1,t}$ is a fuzzy relation, and $*$ denotes the max-min composition operator on fuzzy sets, while C_{t+1} is said to be caused by C_t. The function in Equation (3.3) shows that the dependent variable, percentage change in time *t*+1, C_{t+1}, is affected by a factor/independent variable, namely percentage of change in previous time *t*, C_t only. Next, FLRG in One-factor WeSuSFTS model is based on the right-hand side (RHS) by groping the RHS based on the left-hand side (LHS), as expressed in Equation (3.4):

$$C_t \rightarrow C_{t+1} \tag{3.4}$$

- Model 2: M-factor WeSuSFTS

The general M-factor FTS definition (Singh, 2016) is stated in Chapter 2. In this study, M-factor WeSuSFTS adheres to the following definition:

Universiti Utara Malaysia

$$C_{t+1} = (C_t, L_t, AH_{t+1}, BH_{t+1}, SH_{t+1}, E_{t+1}) * (R_{t+1,t}, R_{t+1,t+1}) \quad (3.5)$$

Where, C_{t+1} is segmented FTS, while $L_t, C_t, AH_{t+1}, BH_{t+1}, SH_{t+1}$, and E_{t+1} are the factors/ independent variables of the forecasting problems. R is a fuzzy relation and $*$ represents the max-min composition operator on fuzzy sets, while C_{t+1} is caused by $L_t, C_t, AH_{t+1}, BH_{t+1}, SH_{t+1}$, and E_{t+1}. The function in Equation (3.5) shows that C_{t+1} is affected by more than a factor, thus known as M-factor segmented FTS. The FLR in M-factor WeSuSFTS model is expressed in Equation (3.6).

$$C_t, L_t, AH_{t+1}, BH_{t+1}, SH_{t+1}, E_{t+1} \rightarrow C_{t+1} \quad (3.6)$$

In order to reduce the complexity of M-factor WeSuSFTS model, the independent variables were selected using Autoregressive Distributed Lag (ARDL) model (Mansor, et al., 2014) and correlation analysis (Buitrago & Asfour, 2017; Kown et al., 2014). Variable C_{t+1} was the only dependent variable, while the other variables were independent ones. Based on ARDL selection model, the final model is selected based on *p-value* less than 10% of significance level. Meanwhile, based on correlation, the independent variables were selected based on a threshold value or the cut of point of correlation value based on the decision made by the researcher, $0 < a < 1$. In this study, Pearson correlation was used as a tool to show the association between two variables. Equation (3.7) presents the Pearson correlation formula.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n(\sum x^2) - (\sum x)^2][n(\sum y^2 - (\sum y)^2)]}} \quad (3.7)$$

When $r > a$, the variable was selected as independent variables in this study.

Universiti Utara Malaysia

Where, n is the number of paired data, x is either $C_t, L_t, AH_{t+1}, BH_{t+1}, SH_{t+1}$ and E_{t+1} data, while y is C_{t+1}.

3.4 Phase 2: Model Development

The main enhancement of the primary FTS procedure was in this phase. The steps of implementation of the proposed algorithm is summarised in the following:

Step 1: Defining universal of discourse, *U*, and partitioning *U* into several intervals

Step 2: Defining fuzzy sets on *U*

Step 3: Fuzzifying crisp value into fuzzy value

Step 4: Determining FLR and FLRG

Step 5: Calculating fuzzy subsethood value (Su-value)

Step 6: Calculating weighted fuzzy subsethood value (WeSu-value)

Step 7: Constructing WeSuSFTS model

Universiti Utara Malaysia

The steps in this phase are presented in the following.

3.4.1 Step (1): Defining Universal of Discourse, *U*, and Partitioning *U* into Several Intervals

This step is adopted from Tinh et al. (2016) and; Tinh and Dieu (2017), by applying *k*-means clustering algorithm for generating *U* and partitioning *U* into several intervals of historical data. However, modification of the algorithm in this study was done by considering Elbow method in identifying the number of intervals. The formula of *U* in this study is expressed in Equation (3.8):

$$U = \left[LB_{Center_1}, UB_{Center_k}\right] \tag{3.8}$$

Where LB_{Center_1} is lower boundary of the first interval, while UB_{Center_k} is upper boundary of the last interval.

The *k*-means clustering technique was employed in this study to classify the historical MH data into clusters and to adjust the clusters into fuzzy intervals to generate intervals from the numerical data. In this present study, the *k*-means clustering algorithm was used to avoid zero value of denominator in fuzzy subsethood calculation in the next step, whereby the calculation cannot proceed and the process would have come to a halt. Next, the intervals must be revised (Mansor et al., 2018). The well-known *k*-means clustering algorithm has been described in Chapter Two.

The crucial step in *k* means clustering is specifying the number of clusters (*k*). In this study, the Elbow method was implemented to identify "good" "*k*" for *k* means clustering in WeSuSFTS procedure. By using the Elbow method, *k* was selected at which the Sum of Square Error (SSE) decreased sharply in the SSE plot graph. The following steps display the construction of interval based on *k*-means clustering results and *U* identification.

Step 1: Apply *k*-means clustering for some values of *k*, for example, *k* = 2, 3, 4,

Step 2: Calculate SSE for all *k* in Step 1. The SSE is defined as the sum of the squared distance between each member of the cluster and its centroid (within group sum of square). The following denotes SSE:

Universiti Utara Malaysia

$$SSE = \sum_{i=1}^{k} \sum_{x \epsilon c_i} d(x, c_i)^2 \quad (3.9)$$

In this study, distances were computed by using simple Euclidean distance (*d*):

$$d(x, c_i) = \sqrt{\sum_{i=1}^{k} (x - c_i)^2} \quad (3.10)$$

Step 3: Plot the graph number of cluster (*k*) versus within group of SSE.

Step 4: Choose "good" *k* from the "Elbow point" in the graph. The Elbow method identifies "good" *k* for *k* means clustering in the WeSuSFTS procedure. The Elbow method selects *k* at which the SSE decreased sharply in the SSE plot graph.

Step 5: Apply the *k*-means clustering algorithm based on "good" *k* in Step 4 to partition the historical time series data into *k* clusters and to sort the cluster center in ascending order.

Adjust the *k*-means clustering yields into intervals based on the following rules. Assume that $Center_i, i = 1,2,3, \dots, k$ are adjacent cluster centers, while *k* is the number of cluster. The upper bound first cluster ($UB_{Center1}$) and the lower bound adjacent cluster ($LB_{Center2}$) can be calculated using Equation (3.11).

$$UB_{Center_i} = \frac{Center_i + Center_j}{2} \quad (3.11)$$

Where

Universiti Utara Malaysia

$LB_{Center_j} = UB_{Center_i}$

UB_{Center_i} is the upper bound cluster $i, i = 1,2, \dots, k$.

k is the total number of clusters.

Center$_i$ and *Center*$_j$ are the cluster center value, $i, i = 1,2, \dots, k$, and $j, j = 2,3, \dots, k-1$.

Therefore,

$$UB_{Center_1} = \frac{Center_1 + Center_2}{2}$$

Then $LB_{Center2} = UB_{Center1}$.

Due to absence of cluster prior to the first cluster and no next cluster after the last cluster, both lower bound first cluster and upper bound last cluster were calculated using Equations (3.12) and (3.13):

Universiti Utara Malaysia

$$UB_{Center_k} = Center_k + \left(Center_k - LB_{Center_k}\right) \quad (3.12)$$

$$LB_{Center_1} = Center_1 - \left(UB_{Center_1} - Center_1\right) \quad (3.13)$$

Step 6: Lower bound of cluster 1 and upper bound of cluster k were used to generate the universal of discourse using the following equation:

$$U = \left[LB_{Center_1}, UB_{Center_k}\right]$$

3.4.2 Step (2): Defining Fuzzy Sets

A membership function is a function from a universal set *U* to the interval [0,1]. A fuzzy set *A* is defined by its membership function μ_A over *U*. Mandal et al., (2009) asserted that the triangular membership function (TMF) offers minimum error in most cases of fuzzy problems. As such, the TMF was employed in this study to present the fuzzy set values.

Let *U* be the universal of discourse. A fuzzy set of linguistic variable *A* on the universal of discourse *U* can be defined as follows:

$$A = \{(x, \mu_A(x)) | x \in U\} \tag{3.14}$$

Where μ_A is the membership function of *A*, $x: U \rightarrow [0,1]$, and $\mu_A(x)$ is the degree of membership of the element x in the fuzzy set A. By referring to Equation (3.14), for a linguistic variable *A*, A_i is the linguistic terms, and u_i is the interval of *U* for A_i, while a fuzzy set of linguictic terms on the u_i can be defined as in Equation (3.15) as follows:

$$A_i = \{(x, \mu_{A_i}(x)) | x \in u_i\} \tag{3.15}$$

Where μ_{A_i} is the membership function of A_i, $x: u_i \rightarrow [0,1]$, $\mu_{A_i}(x)$ is the degree of membership of the element x in the fuzzy set A_i, and u_i is the interval of *U* for A_i based on *k*-means clustering procedure as in Phase 2 Step (1).

Universiti Utara Malaysia

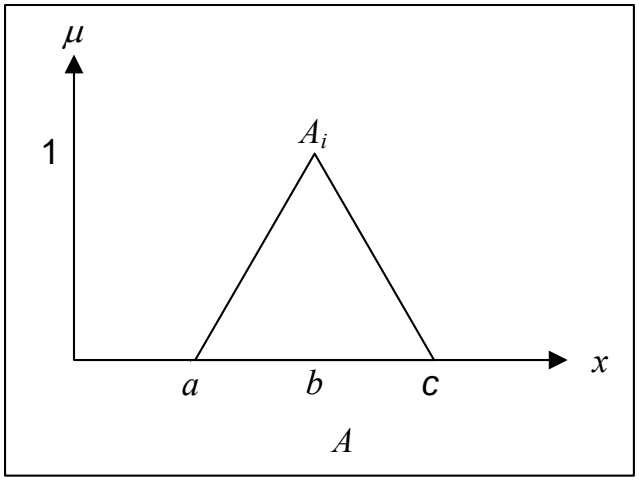


Figure 3.8. General graphical triangular membership function fuzzy set linguistic term A_i

Figure 3.8 displays the general graphical TMF fuzzy set linguistic term for A_i. The TMF of fuzzy sets is expressed in Equation (3.16):

$$\mu_{A_i}(x) = \begin{cases} 0, & x \leq a \\ \dfrac{(x-a)}{(b-a)}, & a < x \leq b \\ \dfrac{(c-x)}{(c-b)}, & b < x \leq c \\ 0, & x > c \end{cases} \tag{3.16}$$

Universiti Utara Malaysia

where *a*, *b*, and *c* refer to the final cluster centroid value from *k*-means clustering algorithm in Phase 2 Step (1). This function can be represented as Equation (3.17).

$$\mu_{A_i}(x) = max\left\{0, min\left[\frac{(x-a)}{(b-a)}, \frac{(c-x)}{(c-b)}\right]\right\} \tag{3.17}$$

Suppose the number of intervals of the linguistic variable, *A*, in Phase 2 Step (1) is three with *LB, UB*, and $U = [-30.33, -12.23]$, $u_1 = [-30.33, -25.39]$, $u_2 = [-25.39, -19.35]$, and $u_3 = [-19.35, -12.23]$. The linguistic variable, *A*, have a fuzzy linguistic term $A_i, i = 1,2,\text{and } 3$. Then, Figures 3.9 and 3.10 illustrate the

graphical membership function of A and graphical membership function of A with values from k-means clustering respectively.

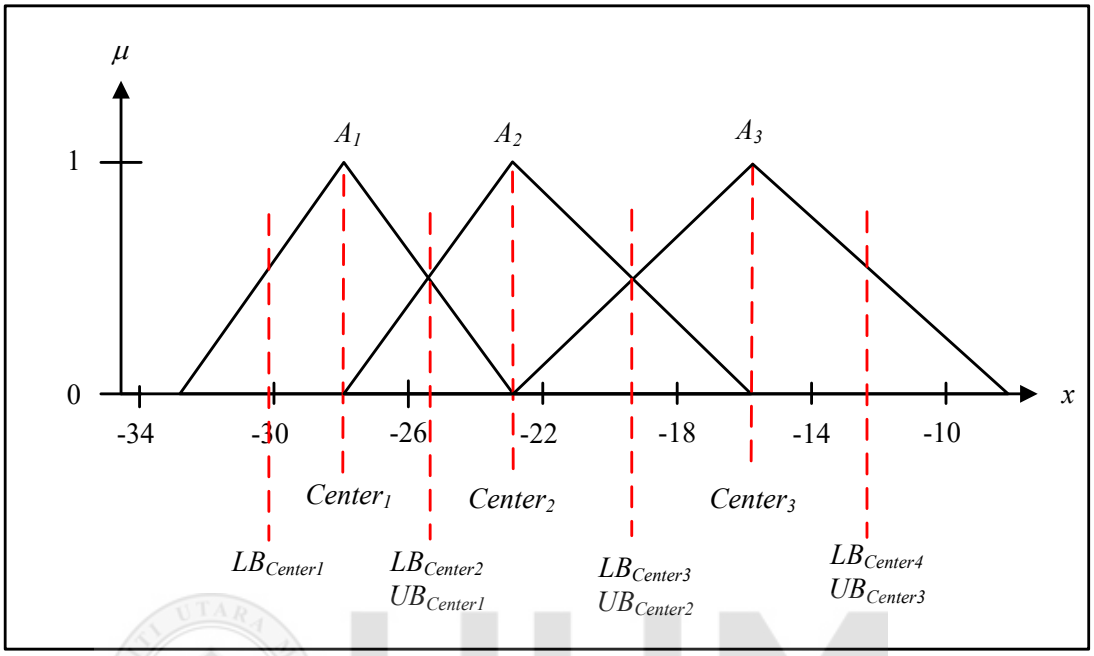


Figure 3.9. Graphical membership function of A

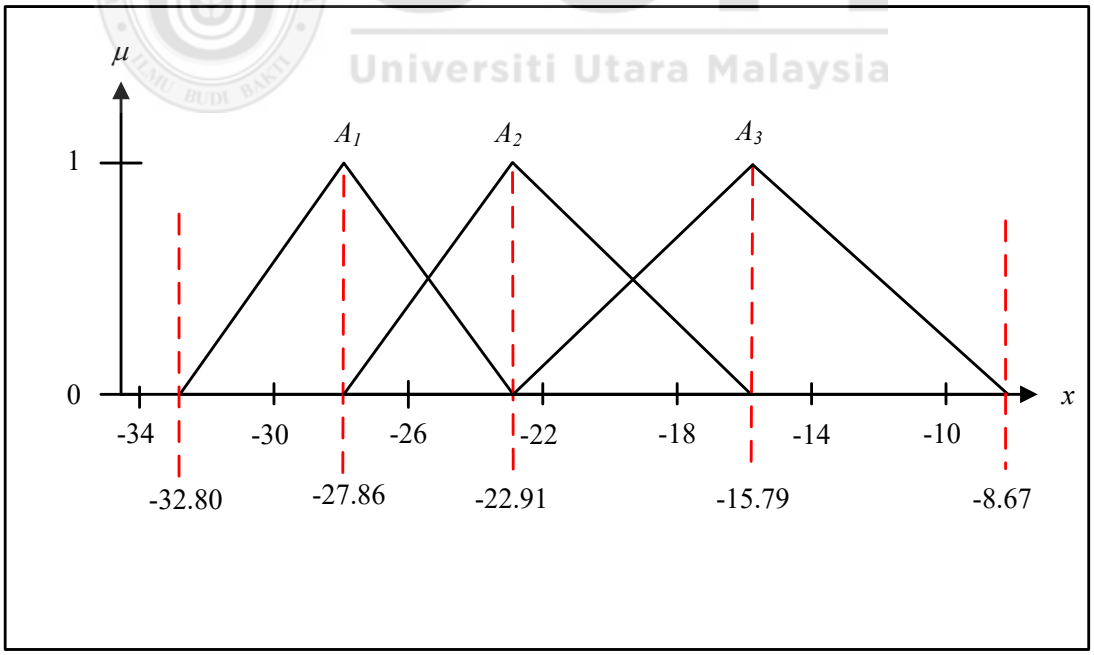


Figure 3.10. Graphical membership function of A with values from k-means clustering

For example, based on Figure 3.9, the membership functions of A_1, A_2, and A_3 are depicted in Equations (3.18) to (3.20).

$$\mu_{A_1}(x) = max\left\{0, min\left[\frac{\left(x-(-32.81)\right)}{4.95}, \frac{(-22.91-x)}{4.95}\right]\right\} \quad (3.18)$$

$$\mu_{A_2}(x) = max\left\{0, min\left[\frac{\left(x-(-27.86)\right)}{4.95}, \frac{(-15.79-x)}{14.15}\right]\right\} \quad (3.19)$$

$$\mu_{A_3}(x) = max\left\{0, min\left[\frac{(x-(-22.91)}{7.12}, \frac{(-8.67-x)}{7.12}\right]\right\} \quad (3.20)$$

Where this study assumes the first and the last fuzzy triangles are symmetric.

3.4.3 Step (3): Fuzzifying Crisp Value into Fuzzy Value

The TMF, as stipulated in Phase 2 Step (2), was employed in this study to fuzzify the independent and dependent variables into fuzzy linguistic term. Each crisp value was fuzzified based on the highest degree of membership function by adhering to Equation (3.16). Table 3.2 presents the example of fuzzy linguistic values in relevance to *A* crisp values.

Universiti Utara Malaysia

For instance, upon fuzzifying *A,* the crisp value $x = -24.227$. Let a_1, a_2 and a_3 the fuzzy values of A_1, A_2 and A_3, respectively. Based on the membership function in Equations (3.18), (3.19), and (3.20) in previous step (Phase 2 Step (2)), where fuzzy linguistic terms were A_1, A_2, and A_3, the results obtained are tabulated in Table 3.2, where $a_1 = 0.2661$, $a_2 = 0.7339$, and $a_3 = 0$.

As the membership function value of A_2 emerged as the highest degree of membership function (a_2 = 0.7339), the fuzzy linguistic term *A* for $x = -24.227$ was A_2.

Table 3.2

Degree of Membership Function Value

Fuzzy Linguistic term	A_1	A_2	A_3
$\mu_A(x)$	0.2661	0.7339	0

3.4.4 Step (4): Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG)

In the subsethood-based algorithm (SBA), this step is equivalent to defining the data set into subgroups, as elaborated in Section 2.3 of Chapter Two. Establishing the FLR in this step had been based on the fuzzified data in Phase 2 Step (3). The FLR was first constructed based on the definition of FLR given in Chapter Two (see section 2.2.4). Next, observations for similar linguistic term dependent variable were grouped together. The fixed number of subgroups was based on the fixed number of fuzzy set for the dependent linguistic variable. The FLRG was built by grouping observations with similar fuzzy set in dependent fuzzy linguistic term.

Let FTS be $F(t)$ and $F(t-1)$. FTS relationships assume that $F(t)$ is caused by $F(t-1)$. Let $F(t-1) = B_j$ and $F(t) = A_i$. The FLR between $F(t-1)$ and $F(t)$ can be denoted as $B_j \rightarrow A_i$ where B_j (current state) refers to the left-hand side (LHS) and A_i (next state) refers to the right-hand side (RHS) of the FLR.

Relationships with the same fuzzy set on the RHS can be further placed into a relationship group. These relationship groups are also referred to as FLRG. Suppose there are relationships such that

$$B_{j1} \rightarrow A_i$$
$$B_{j2} \rightarrow A_i$$
.
.
.
$$B_{jk} \rightarrow A_i$$

Then they can be grouped into a relationship group as follows:

$$B_{j1}B_{j2}, \ldots, B_{jk} \rightarrow A_i$$

The same fuzzy set can appear more than once on the LHS of the relationship group. If the RHS have *s* fuzzy sets in the FLRG, hence *s* also refers to a number of subgroup based on SBA.

Universiti Utara Malaysia

Table 3.3

Example of FLR

Observation	*B*	*A*	FLR
	LHS	RHS	
1	B_4	A_3	$B_4 \rightarrow A_3$
2	B_3	A_2	$B_3 \rightarrow A_2$
3	B_2	A_3	$B_2 \rightarrow A_3$
4	B_3	A_2	$B_3 \rightarrow A_2$
5	B_2	A_3	$B_2 \rightarrow A_3$
6	B_4	A_3	$B_4 \rightarrow A_3$
7	B_3	A_1	$B_3 \rightarrow A_1$
8	B_1	A_2	$B_1 \rightarrow A_2$
9	B_4	A_3	$B_4 \rightarrow A_3$

For example, suppose columns 1, 2, and 3 in Table 3.3 are the results retrieved from Phase 2 Step (3) for dependent linguistic variable, A, and independent linguistic variable, B. These independent and dependent linguistic variables were termed as LHS and RHS of this FLR, respectively. The FLR column in Table 3.3 reflects the FLR

between LHS and RHS (FLR is defined in Chapter Two - Section 2.2.4). Next, FLRG in Table 3.4 was constructed based on observations with similar dependent fuzzy linguistic term. In this case, as there are three fuzzy linguistic terms in RHS ($A_i, i = 1,2,3$) , the number of subgroups is also three.

Table 3.4

Example of FLRG

Observation	FLRG	Subgroup
7	$B_3 \rightarrow A_1$	Subgroup 1
2, 4, 8	$B_3, B_3, B_1 \rightarrow A_2$	Subgroup 2
1, 3, 5, 6, 9	$B_4, B_2, B_2, B_4, B_4 \rightarrow A_3$	Subgroup 3

3.4.5 Step (5): Calculating Fuzzy Subsethood Value

This step is adopted from Rasmani and Shen (2003, 2005) in calculating the fuzzy subsethood value (Su-value). This step refers to pre-calculation before calculating the weighted fuzzy subsethood value. Table 3.5 presents the Su-values.

Universiti Utara Malaysia

Table 3.5

Fuzzy Subsethood Values

		$\boldsymbol{B}$			
		$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	...	$\boldsymbol{B_k}$
$\boldsymbol{A}$	$\boldsymbol{A_1}$	$S(A_1, B_1)$	$S(A_1, B_2)$	...	$S(A_1, B_k)$
	$\boldsymbol{A_2}$	$S(A_2, B_1)$	$S(A_2, B_2)$	...	$S(A_2, B_k)$
	⋮	⋮	⋮	⋱	⋮
	$\boldsymbol{A_s}$	$S(A_s, B_1)$	$S(A_s, B_2)$	...	$S(A_s, B_k)$

Elements $A_1, A_2, \ldots, A_s$ denote linguistic fuzzy terms in A. Meanwhile, $B_1, B_2, \ldots, B_k$ signify linguistic fuzzy terms in B. The relationship between dependent linguistic variable and fuzzy linguistic is as follows:

$$Dependent\ fuzzy\ linguistic\ variable = \{fuzzy\ term_1, \dots, fuzzy\ term_s\}$$

or simplify to $A = \{A_1, A_2, \dots, A_s\}$. Where s is the number of linguistic fuzzy terms used in A.

A similar general notation for independent fuzzy linguistic variable is as given below:

$$Independent\ fuzzy\ linguistic\ variable = \{fuzzy\ term_1, \dots, fuzzy\ term_k\}$$

or simplify to $B = \{B_1, B_2, \dots, B_k\}$. Where k is the number of fuzzy terms used in B.

Where element $S(A_i, B_j)$ in Table 3.5 refers to fuzzy subsethood value and the value indicating the degree of fuzzy set B_j is a subset of fuzzy set A_i that also describes the degree of relationship between dependent variable linguistic term (A_i) and every independent linguistic term (B_j), as expressed in Equation (3.21).

$$S(A_i, B_j) = \frac{\sum_{x \in U} min\left\{\mu_{A_i}(x), \mu_{B_j}(x)\right\}}{\sum_{x \in U} \mu_{A_i}(x)} \tag{3.21}$$

Can be simplified to value:

$$S(A_i, B_j) = \frac{\sum_{observation} min\left\{\mu_{A_i}(x), \mu_{B_j}(x)\right\}}{\sum_{observation} \mu_{A_i}(x)} \tag{3.22}$$

Where $S(A_i, B_j) \in [0,1],\ i = 1,2, \dots, s$. And $j = 1,2, \dots, k$.

For example, in calculating $S(A_2, B_1)$ based on Table 3.4 for Subgroup 2, three observations were gained; observation numbers 2, 4, and 8. The crisp elements are $x_{t=2}, x_{t=4}$ and $x_{t=8}$. The crisp element, x, at time 2, $t = 2$ in variable A is denoted as

$A(x_{t=2})$. Thus, $A(x_{t=2}) = -22.3622$, $A(x_{t=4}) = -22.1537$, and $A(x_{t=8}) = -22.2272$. Meanwhile, $B(x_{t=2}) = -17.1537$, $B(x_{t=4}) = -14.5249$ and $B(x_{t=8}) = -27.8572$.

Upon applying the fuzzifying step in Phase 2 Step (3),

$$\mu_{A_2}(x_{t=2}) = \mu_{A_2}(-22.3622) = 0.92306$$

$$\mu_{A_2}(x_{t=4}) = \mu_{A_2}(-22.1537) = 0.89378$$

$$\mu_{A_2}(x_{t=8}) = \mu_{A_2}(-24.2272) = 0.7339$$

and

$$\mu_{B_1}(x_{t=2}) = \mu_{B_1}(-17.1537) = 0$$

$$\mu_{B_1}(x_{t=4}) = \mu_{B_1}(-14.5249) = 0$$

$$\mu_{B_1}(x_{t=8}) = \mu_{B_1}(-27.8572) = 0.9995$$

The value of $\mu_{A_2}(x_{t=2})$ shows the membership degree of element $x_{t=2}$ to fuzzy set A_2. The same definition was used for similar notations of $\mu_{A_2}(x_{t=4})$, $\mu_{A_2}(x_{t=8})$, $\mu_{B_1}(x_{t=2})$, $\mu_{B_1}(x_{t=4})$, and $\mu_{B_1}(x_{t=8})$. The fuzzy subsethood value of B_1 to A_2, denoted as $S(A_2, B_1)$, is expressed in Equation (3.23).

$$S(A_2, B_1) = \frac{\sum_{observation\ 2,4,8} min\left[\mu_{A_2}(x), \mu_{B_1}(x)\right]}{\sum_{observation\ 2,4,8} \mu_{A_2}(x)} \tag{3.23}$$

$$= \frac{min\left[\mu_{A_2}(x_{t=2}), \mu_{B_1}(x_{t=2})\right] + min\left[\mu_{A_2}(x_{t=4}), \mu_{B_1}(x_{t=4})\right] + min\left[\mu_{A_2}(x_{t=8}), \mu_{B_1}(x_{t=8})\right]}{\mu_{A_2}(x_{t=2}) + \mu_{A_2}(x_{t=4}) + \mu_{A_2}(x_{t=8})}$$

Universiti Utara Malaysia

$$= \frac{\min(0.92306,0) + \min(0.89378,0) + \min(0.7339,0.9995)}{0.92306 + 0.89378 + 0.7339}$$

$$= \frac{0.7339}{2.55074} = 0.2877$$

The Su-values tabulated in Table 3.6 had been derived from Su-value calculations using Equation (3.22) for $i = 1,2,3$ and $j = 1,2,3,4$. If more than one independent variable, the Su-value is calculated and presented for each independent variable.

Table 3.6

Example of Fuzzy Subsethood Values

		$\boldsymbol{B}$			
		$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	$\boldsymbol{B_3}$	$\boldsymbol{B_4}$
$\boldsymbol{A}$	$\boldsymbol{A_1}$	0.0000	0.0000	0.9144	0.0861
	$\boldsymbol{A_2}$	0.2877	0.0881	0.6119	0.0843
	$\boldsymbol{A_3}$	0.0218	0.3798	0.1334	0.5778

Universiti Utara Malaysia

3.4.6 Step (6): Calculating Weighted Fuzzy Subsethood Value

Calculating the weighted fuzzy subsethood value (WeSu-value) is a calculation of relative weight based on Su-value. The weight mechanism was based on Rasmani and Chen (2004). Table 3.7 shows the diagram of WeSu-value.

Table 3.7

Weighted Fuzzy Subsethood Values

		$\boldsymbol{B}$			
		$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	...	$\boldsymbol{B_k}$
$\boldsymbol{A}$	$\boldsymbol{A_1}$	$W(A_1, B_1)$	$W(A_1, B_2)$	...	$W(A_1, B_k)$
	$\boldsymbol{A_2}$	$W(A_2, B_1)$	$W(A_2, B_2)$	...	$W(A_2, B_k)$
	⋮	⋮	⋮	⋱	⋮
	$\boldsymbol{A_s}$	$W(A_s, B_1)$	$W(A_s, B_2)$	...	$W(A_s, B_k)$

The elements of the weighted fuzzy subsethood, $W(A_i, B_j)$, in Table 3.7 are related to the values that describe the degree of relative important independent linguistic fuzzy term to dependent linguistic fuzzy term. Next, the calculated Su-value was used to determine WeSu-value using Equation (3.24):

$$W(A_i, B_j) = \left(\frac{S(A_i, B_j)}{\max\limits_{j=1,2,\dots,k} S(A_i, B_j)} \right) \tag{3.24}$$

where A_i is a respective subgroup.

For instance, by referring to Su-value in Table 3.6 in Phase 2 Step (5), $S(A_2, B_1) = 0.2877$, $S(A_2, B_2) = 0.0881$, $S(A_2, B_3) = 0.6119$, and $S(A_2, B_4) = 0.0843$. Thus, the weighted fuzzy subsethood of B_1 to A_2 denoted as $W(A_2, B_1)$ is defined in the following:

Universiti Utara Malaysia

$$W(A_2, B_1) = \left(\frac{S(A_2, B_1)}{\max\limits_{j=1,2,3,4} S(A_2, B_j)} \right) \tag{3.25}$$

Hence,

$$W(A_2, B_1) = \left(\frac{S(A_2, B_1)}{\max[S(A_2, B_1), S(A_2, B_2), S(A_2, B_3), S(A_2, B_4)]} \right)$$

$$= \left(\frac{0.2877}{\max[0.2877, 0.0881, 0.6119, 0.0843]} \right)$$

$$= \frac{0.2877}{0.6119}$$

$$= 0.4702$$

The results of WeSu-value in Table 3.8 were calculated based on WSBA calculation using Equation (3.24) for $i = 1,2,3$ and $j = 1,2,3,4$.

When there is more than one independent variable, the WeSu-value is calculated and constructed for each independent variable. Intuitively, linguistic term with the highest subsethood value emerged as the most important and that with the lowest as the least important independent variable.

Table 3.8

Example of Weighted Fuzzy Subsethood Values

		$\boldsymbol{B}$			
		$\boldsymbol{B_1}$	$\boldsymbol{B_2}$	$\boldsymbol{B_3}$	$\boldsymbol{B_4}$
	$\boldsymbol{A_1}$	0.0000	0.0000	1.0000	0.0941
$\boldsymbol{A}$	$\boldsymbol{A_2}$	0.4702	0.1440	1.0000	0.1377
	$\boldsymbol{A_3}$	0.0377	0.6573	0.2309	1.0000

Universiti Utara Malaysia

3.4.7 Step (7): Constructing WeSuSFTS Model

The IF-THEN rule statement is proposed to formulate the WeSuSFTS model in this step. This process is known as WeSuSFTS Inference Engine. The WeSuSFTS model is composed of a set of fuzzy rules in the following form:

IF (condition) **THEN** (conclusion)

With operator **OR** use max operations and **AND** use min operations.

Based on Rasmani and Shen (2003), the number of rules is based on the number of linguistic variable fuzzy terms in RHS base on FLRG and it is equivalent to the number of Subgroups in FLRG. The condition part involves the WeSu-value from Phase 2 Step (6) that serves as a multiplicative factor for the respective independent linguistic

variable fuzzy term. The rule set is simplified as any linguistic fuzzy term, wherein multiplicative factor equals to 0 is automatically discarded from the model. Figure 3.11 displays the general WeSuSFTS model.

$Rule\ 1$: IF $B\ is\ W(A_1, B_1)B_1$ OR $W(A_1, B_2)B_2$ OR ... OR $W(A_1, B_k)B_k$

THEN $A\ is\ A_1$.

$Rule\ 2$: IF $B\ \ is\ W(A_2, B_1)B_1$ OR $W(A_2, B_2)B_2$ OR ... OR $W(A_2, B_k)B_k$

THEN $A\ is\ A_2$.

.
.
.

$Rule\ s$: IF $B\ is\ W(A_s, B_1)B_1$ OR $W(A_s, B_2)B_2$ OR ... OR $W(A_s, B_k)B_k$

THEN $A\ is\ A_s$.

Figure 3.11. General WeSuSFTS model with an independent linguistic variable (One-factor WeSuSFTS)

Universiti Utara Malaysia

If more than an independent linguistic term is used in a study, the model will consist of rules with two operators; OR and AND. Here, operators OR and AND apply max and min operators. For a general example with multiple independent linguistic variables, let *m* be the number of independent variables/factors. Figure 3.12 displays the general WeSuSFTS model for multiple independent linguistic variables or known as M-factor WeSuSFTS model.

Where

V denotes independent variables, therefore, $V_1, V_2, \ldots V_m$ are *m* independent variables.

V_1 consists of *k* fuzzy linguistic terms, $V_1 = \{B_1, B_2, \ldots, B_k\}$.

V_2 consists of *l* fuzzy linguistic terms, $V_2 = \{C_1, C_2, \ldots, C_l\}$.

V_m consists of *p* fuzzy linguistic terms, $V_m = \{Z_1, Z_2, \ldots, Z_p\}$.

A consists of s fuzzy linguistic terms, $A = \{A_1, A_2, \dots, A_s\}$.

$Rule\ 1$: IF $V_1\ is\ [W(A_1, B_1)B_1$ OR $W(A_1, B_2)B_2$ OR ... OR $W(A_1, B_k)B_k]$

AND $V_2\ is[W(A_1, C_1)C_1$ OR $W(A_1, C_2)C_2$ OR ... OR $W(A_1, C_l)C_l]$

AND ... AND $V_m\ is\ [W(A_1, Z_1)Z_1\ OR \dots OR\ W(A_1, Z_p)Z_p]$

THEN $A\ is\ A_1$.

$Rule\ 2$: IF $V_1\ is\ [W(A_2, B_1)B_1$ OR $W(A_2, B_2)B_2$ OR ... OR $W(A_2, B_k)B_k]$

AND $V_2\ is[W(A_2, C_1)C_1$ OR $W(A_2, C_2)C_2$ OR ... OR $W(A_2, C_l)C_l]$

AND ... AND $V_m\ is\ [W(A_2, Z_1)Z_1\ OR \dots OR\ W(A_2, Z_p)Z_p]$

THEN $A\ is\ A_2$.

.
.
.

$Rule\ s$: IF $V_1\ is\ [W(A_s, B_1)B_1$ OR $W(A_s, B_2)B_2$ OR ... OR $W(A_s, B_k)B_k]$

AND $V_2\ is[W(A_s, C_1)C_1$ OR $W(A_s, C_2)C_2$ OR ... OR $W(A_s, C_l)C_l]$

AND ... AND $V_m\ is\ [W(A_s, Z_1)Z_1\ OR \dots OR\ W(A_s, Z_p)Z_p]$

THEN $A\ is\ A_s$.

Figure 3.12. General WeSuSFTS model for multiple independent linguistic variables (M-factor WeSuSFTS)

Based on WeSu-value in Table 3.8 for Phase 2 Step (6), the WuSuSFTS model is presented in Figure 3.13. The full model reflects a model that has considered all WeSu-values.

Universiti Utara Malaysia

$Rule\ 1$: IF $B\ is\ 0B_1$ OR $0B_2$ OR $1B_3$ OR $0.0941B_4$

THEN $A\ is\ A_1$.

$Rule\ 2$: IF $B\ is\ 0.4702B_1$ OR $0.1440B_2$ OR $1B_3$ OR $0.13771B_4$

THEN $A\ is\ A_2$.

$Rule\ 3$: IF $B\ is\ 0.0377B_1$ OR $0.6573B_2$ OR $0.2309B_3$ OR $1B_4$

THEN $A\ is\ A_3$.

Figure 3.13. An example of the WeSuSFTS full model

The model is capable to be simplified as any linguistic fuzzy term with weight equals to 0 is automatically removed from the model. The simplified model is as displayed in the following:

$Rule\ 1$: IF $B\ is\ B_3$ OR $0.0941B_4$

THEN $A\ is\ A_1$.

$Rule\ 2$: IF $B\ is\ 0.4702B_1$ OR $0.1440B_2$ OR B_3 OR $0.1377B_4$

THEN $A\ is\ A_2$.

$Rule\ 3$: IF $B\ is\ 0.0377B_1$ OR $0.6573B_2$ OR $0.2309B_3$ OR B_4

THEN $A\ is\ A_3$.

Figure 3.14. An example of the WeSuSFTS simplified model

3.5 Phase 3: Model Implementation

After building the WeSuSFTS model in Phase 2, the implementation of the model was continued by using data from the evaluation part in Phase 3, which is composed of two steps, as follows:

Universiti Utara Malaysia

Step (1): Defuzzifying fuzzy value into crisp value

Step (2): Forecasting execution

These steps are elaborated as follows:

3.5.1 Step (1): Defuzzifying Fuzzy Value into Crisp Value

The goal of this step is to introduce a defuzzification method that is able to defuzzify fuzzy output from WeSuSFTS inference engine with small forecasting error. The defuzzified values are the forecasted values of percent change of MH-ELD by using WeSuSFTS forecasting models. From the idea of general and specific distribution defuzzification methods as stated in Chapter Two, this study introduced a new defuzzification by modifying Center of Gravity (COG) and Fuzzy Mean (FM) (Leekwijck & Kerre, 1999) where these formula are stated in Equation (3.26) and (3.27).

Universiti Utara Malaysia

$$COG(A) = \frac{\sum_{x_{min}}^{x_{max}} x.A(x)}{\sum_{x_{min}}^{x_{max}} A(x)} \tag{3.26}$$

$$FM(A) = \frac{\sum_{i=1}^{N_A} \alpha_i a_i}{\sum_{i=1}^{N_A} \alpha_i} \tag{3.27}$$

where N_A represents the number of fuzzy output sets, α_i is the degree of each output set (as a result of the inference), and a_i is the numerical value of output set i. The formulae show that COG calculates the forecasted value when A is considered to be a probability distribution. The new defuzzification in this study, named as Average Rule defuzzification method (AR), is based on average and numeric value of WSBA rules.

Since COG and FM are also the average defuzzification method, this study adopts the formulae to AR formula.

However, compared to AR defuzzification method, the numerical value is not from output as FM, but referred to the calculation result in *condition* part of WeSuSFTS reasoning rules. Since the parameter of independent variable in form of TMF (*a,b,c*) in this study is obtained from *k*-means clustering method, parameter *b* (peak point of membership function) is used as one of the AR defuzzification parameters besides the numeric value of condition part of fuzzy rule (*R*). This is because *b* value in *k*-means clustering method is the center of the cluster.

Since this study uses *k*-means clustering to identify the centre of each cluster, the use of the centre value as a peak value in the membership function is preferred. This is because in the *k*-means clustering algorithm, the data in a particular interval are closest to the cluster centre's particular interval. Therefore, this study modifies the defuzzification process where the TMF used is a non-symmetrical triangle for defuzzification calculation.

Universiti Utara Malaysia

The AR numerator is the summation of the product of numerical values from WSBA rules and their respective peak-point of dependent fuzzy membership function. Therefore, this study introduced four different denominators to represent four new AR defuzzification methods. The selection of the best AR method is based on smallest forecasting error. The robustness of selected AR method is examined also since COG and FM are robust defuzzification (Leekwijck & Kerre, 1999).

The four of AR defuzzification formula are:

i. Average rule using sum of peak points as denominator presented as

$$F_{AR_1} = \frac{\sum_{i=1}^{s} R_i M_i}{\sum_{i=1}^{s} M_i} \tag{3.28}$$

ii. Average rule using sum of numeric value from *condition* part of rules as denominator presented as

$$F_{AR_2} = \frac{\sum_{i=1}^{s} R_i M_i}{\sum_{i=1}^{s} R_i} \tag{3.29}$$

iii. Average rule using number of intervals U_i as denominator presented as

$$F_{AR_3} = \frac{\sum_{i=1}^{s} R_i M_i}{N(u)} \tag{3.30}$$

iv. Average rule using number of active intervals U_i as denominator presented as

$$F_{AR_4} = \frac{\sum_{i=1}^{s} R_i M_i}{n(u)} \tag{3.31}$$

$F_{AR_1}, F_{AR_2}, F_{AR_3}$ and F_{AR_4} are the defuzzified outputs which are the forecasted values (percent changes of MH-ELD) by using each of the respective defuzzification methods. R_i is the calculation value of fuzzy rule condition part from rule *i* and *s* is the total number of rules. M_i denotes the peak-point value for *i* triangular membership function conclusion part. *N(u)* refers to the number of interval of *U,* while *n(u)* indicates the number of active interval(s) of *U*. Active intervals of *U* signify the number of intervals, where the numeric value from calculation in rule (*R*) is not equal to zero.

Universiti Utara Malaysia

Two properties of validity test were used in this study on the selected best AR method; smallest forecasting error (Tinh & Dieu, 2017) and robustness (Leekwijck & Kerre, 1999). The AR defuzzification method is selected as the best if and only if the AR method has smallest forecasting error and robust. Therefore, the forecasting errror was calculated first, then followed by checking the robustness criteria.

The following are the steps in development of AR defuzzification methods.

Step1: Find the similar previous defuzzification that also consider the weight, average and the numeric value from a certain mechanism calculation.

Step 2: List the suggested AR formula.

Step 3: Calculate the forecasting error.

Step 4: Decide the best AR method.

Universiti Utara Malaysia

Step 5: Check the robustness of selected AR defuzzification method based on Leekwijck and Kerre, (1999).

The AR defuzzification method is considered as robust if a small variation in any of the degrees of membership should not result in a big change in the defuzzified value (Leekwijck & Kerre, 1999). This means that a small variation of any of the input parameter in defuzzification formula should only result in small changes of the output. In this study, the variation is based on Mean Squared Error (MSE) value of output. The procedure of checking robustnest numerically as follows:

Step 1: Construct seven data sets (A, B, ..., G) of peak-point in TMF of dependent variable. Each data set also have seven data, where data set A has changes on

first data only, data set B has changes on second data only, and so on until data set G has changes on seventh data only, while other data are unchanged. The changes are 0.5 increment, 0.5 decrement, 1.0 increment and 1.0 decrement. Therefore, total of data sets according to type of changes are:

$$7\ data\ sets\ (A, B, \dots, G)$$
$$\times 4\ types\ of\ data\ changes\ (+0.5, -0.5, +1.0, -1.0)$$
$$= 28\ data\ sets.$$

Step 2: Execute selected AR defuzzification method (AR with smallest forecasting error) to 28 data sets in Step (1).

Step 3: Calculate MSE for each data set.

Step 4: Make a conclusion.

Universiti Utara Malaysia

For instance to demonstrate the AR calculation, this study explains the calculation based on the WeSuSFTS model illustrated in previous Figure 3.14 as shown in Figure 3.15. Where the arrow $(---\rightarrow)$ to R_1, R_2 and R_3 to show that R_i is the numeric value from calculation in conditional part of WeSuSFTS reasoning rules.

$Rule\ 1$: [IF $B\ is\ B_3$ OR $0.0941B_4$] $---------------\rightarrow R_1$
THEN $A\ is\ A_1$.
$Rule\ 2$: [IF $B\ is\ 0.4702B_1$ OR $0.144B_2$ OR B_3 OR $0.1377B_4$] $---\rightarrow R_2$
THEN $A\ is\ A_2$.
$Rule\ 3$: [IF $B\ is\ 0.0377B_1$ OR $0.6573B_2$ OR $0.2309B_3$ OR B_4] $---\rightarrow R_3$
THEN $A\ is\ A_3$.

Figure 3.15. Example of R_i

The following instances demonstrate how AR_1, AR_2, AR_3 and AR_4 are calculated based on information in Figure 3.15. Suppose the crisp value for *B* is -17.1136. By using certain triangular membership function of *B* based on fuzzy set as stated in Table 4.12 and Figure 4.6, then $\mu_{B_1} = 0,\ \mu_{B_2} = 0.2188,\ \mu_{B_3} = 0.7812$, and $\mu_{B_4} = 0$.

In this example, the total number of rules, *s* = 3, $R_{i,}\ i = 1,2$ and 3. The number of independent variable is one only, that is *B*. Hence, the calculation for numeric value in conditional part of WeSuSFTS reasoning rules, for each R_i, with operator **OR** use max operation are as follows.

$$R_1 = \max[\mu_{B_3}, (0.0941)\mu_{B_4}] = \max[0.7812, (0.0941)(0)]$$
$$= 0.7812$$

$$R_2 = \max[(0.4722)\mu_{B_1}, (0.144)\mu_{B_2}, \mu_{B_3}, (0.1377)\mu_{B_4}]$$
$$= \max[(0.4722)(0), (0.144)(0.2188), 0.7812, (0.1377)(0)]$$
$$= 0.7812$$

$$R_3 = \max[(0.0377)\mu_{B_1}, (0.6573)\mu_{B_2}, (0.2309)\mu_{B_3}, \mu_{B_4}]$$
$$= \max[(0.0377)(0), (0.6573)(0.2188), (0.2309)(0.7812), 0]$$
$$= 0.1804$$

Based on the membership function stated in Figure 3.8 in Phase 2 Step (2), the center value of each TMF is the peak-point (M) of TMF fuzzy set *A*. Therefore, $M_1 = -27.88, M_2 = -22.91$, and $M_3 = -15.79$. Thus, by referring to Equation (3.28), forecast value of percent changes of ELD based on AR_1 defuzzification is:

Universiti Utara Malaysia

$$F_{AR_1} = \frac{\sum_{i=1}^{3} R_i M_i}{\sum_{i=1}^{3} M_i}$$

$$= \frac{(0.7812)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{-27.88 + (-22.91) + (-15.79)}$$

$$= 0.6387$$

Based on Equation (3.29), forecast value percent changes of ELD based on AR_2 defuzzification is:

$$F_{AR_2} = \frac{\sum_{i=1}^{3} R_i M_i}{\sum_{i=1}^{3} R_i}$$

$$= \frac{(0.7812)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{0.7812 + 0.7812 + 0.1804}$$

$$= -24.4008$$

By referring to Equation (3.30), forecast value percent changes of ELD based on AR_3 defuzzification is:

$$F_{AR_3} = \frac{\sum_{i=1}^{3} R_i M_i}{N(u)}$$

$$= \frac{(0.7812)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{3}$$

$$= -14.1752$$

By referring to Equation (3.31), forecast value percent changes of ELD based on AR_4 defuzzification is:

$$F_{AR_4} = \frac{\sum_{i=1}^{3} R_i M_i}{n(u)}$$

$$= \frac{(0.7812)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{3}$$

Universiti Utara Malaysia

$$= -14.1752$$

For the previous examples, both AR_3 and AR_4 have the same denominator value, mainly because all numeric value from calculation of the *condition* in rules are not equal to zero. The following example is to differentiate the calculation of AR_3 and AR_4: let's say that the calculation for one numeric value in conditional part of R_1 condition is zero. Hence, $N(u) = 3$ and $n(u) = 2$. Then,

$$F_{AR_3} = \frac{\sum_{i=1}^{3} R_i M_i}{N(u)}$$

$$= \frac{(0)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{3}$$

$$= -6.9153$$

$$F_{AR_3} = \frac{\sum_{i=1}^{3} R_i M_i}{N(u)}$$

$$= \frac{(0)(-27.88) + (0.7812)(-22.91) + (0.1804)(-15.79)}{2}$$

$$= -10.3729$$

3.5.2 Step (2): Forecasting Execution

This study employed the WeSuSFTS to forecast percent changes in MH-ELD. After the forecasted percent changes value is obtained from previous step, the value would be used to calculate the forecasting value of MH-ELD by using Equation (3.32) (Hidayah et al., 2017).

$$\hat{y}_{t+1} = y_t + \left(\frac{F}{100} \times y_t\right) \tag{3.32}$$

Where y_{t+1} represents the MH-ELD forecasted value, y_t is the actual MH-ELD previous value, and F denotes the forecasted percent changes value obtained from the WeSuSFTS model in Phase 3 Step (1).

3.6 Phase 4: Model Evaluation

The main purpose of this phase is to validate by evaluating the performance of WeSuSFTS methods. This is performed by comparing the forecasting error measurement from WeSuSFTS model with different defuzzification methods. This phase is composed of two steps, as follows:

Step (1) : Define error measurement

Step (2): Compare forecasting error measurement among different defuzification methods

The detailed explanation of this phase is given as follows:

Universiti Utara Malaysia

3.6.1 Step (1): Defining Error Measurement

Typically, the performance of forecasting technique is measured with forecasting error. Despite the availability of several error measures, only four error measures were considered in this study as they are amongst the most popular methods among researchers and practitioners (Lazim, 2013). The four forecasting error measures are listed below:

i. Absolute Percentage Forecasting Error (APE)

$$APE = \left|\left(\frac{e_t}{y_t}\right) * 100\right| \tag{3.33}$$

ii. Mean Absolute Percentage Forecasting Error (MAPE)

$$MAPE = \sum_{t=1}^{n} \frac{\left|\left(\frac{e_t}{y_t}\right) * 100\right|}{n} \tag{3.34}$$

iii. Root Mean Squared Forecasting Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \tag{3.35}$$

iv. Mean Squared Forecasting Error (MSE)

$$MSE = \frac{\sum_{t=1}^{n} e_t^2}{n} \tag{3.36}$$

where $e_t = y_t - \hat{y}_t$; y_t is actual observation of MH-ELD at point t and $\hat{y}_t$ is the forecasted value of y_t.

Universiti Utara Malaysia

3.6.2 Step (2): Comparing Forecasting Error Measurement among Different Defuzzification Methods

Since there are four defuzzification methods introduced to defuzzify outputs from WeSuSFTS forecasting model, the next task is to choose the defuzzification method with the lowest value of forecasting error. This chosen defuzzification method would be considered for WeSuSFTS model to forecast MH-ELD. Besides, the accuracy of the WeSuSFTS model with the chosen defuzzication method would be compared with two conventional FTS models; Chen and Cheng's models.

3.7 Summary

The development of WeSuSFTS forecasting algorithm is elaborated in this chapter with a range of defuzzification methods to be used to defuzzify WeSuSFTS fuzzy output. The two types of WeSuSFTS algorithm-based models presented in this chapter are One-factor and M-factor WeSuSFTS, along with several process and calculation instances. Each step in the algorithm is described with example. The One-factor WeSuSFTS can be implemented to first-order WeSuSFTS, if the independent variable is the first lag of the dependent variable. Similarly, M-factor WeSuSFTS can be implemented to high-order WeSuSFTS, mainly because the independent variables are the lags of the dependent variable.

In summary, the WeSuSFTS forecasting algorithm is proposed to overcome the MH-ELD forecasting problems stated in Chapter One by using fuzzy reasoning and weighted subsethood based algorithm. Besides that, the proposed WeSuSFTS forecasting algorithm has some advantages compared to other algorithm where this algorithm lists the complete forecasting process starting from preprocessing phase and ending with the model evaluation phase. The complete forecasting procedure can guide forecasters in forecasting problems with time series data.

Besides, the segmentation process in Phase 1 Step (1) and Step (2), gives an alternative segmentation process to Similar day method in FTS forecasting. The MH segmentation process is also adaptable to other type of unique time series data. Besides, the modified defuzzification methods in Phase 3 Step (1) give alternative defuzzification methods to suit the nature of WeSuSFTS model.

Furthermore, the other advantage of WeSuSFTS forecasting algorithm is that it can reveal FLR strength in FLRG in Phase 2 Step (4). Therefore, it does not only show the relationship between LHS to RHS, but also the strength of the relationship using Su-value interpretation. Moreover, the proposed WeSuSFTS model gives a meaningful FTS model interpretation using fuzzy reasoning rule model stated in Phase 2 Step (7). In a nutshell, the proposed WeSuSFTS forecasting algorithm able to give more information about the relationship that naturally represents how human make judgments and decision, and give more guidance in conducting a complete forecasting problem.

As a summary of this chapter, Figure 3.16 displays the flowchart of WeSuSFTS algorithm for forecasting problem. The next chapter presents the results and the analysis of the WeSuSFTS algorithm implementation in MH-ELD forecasting problem.

Universiti Utara Malaysia

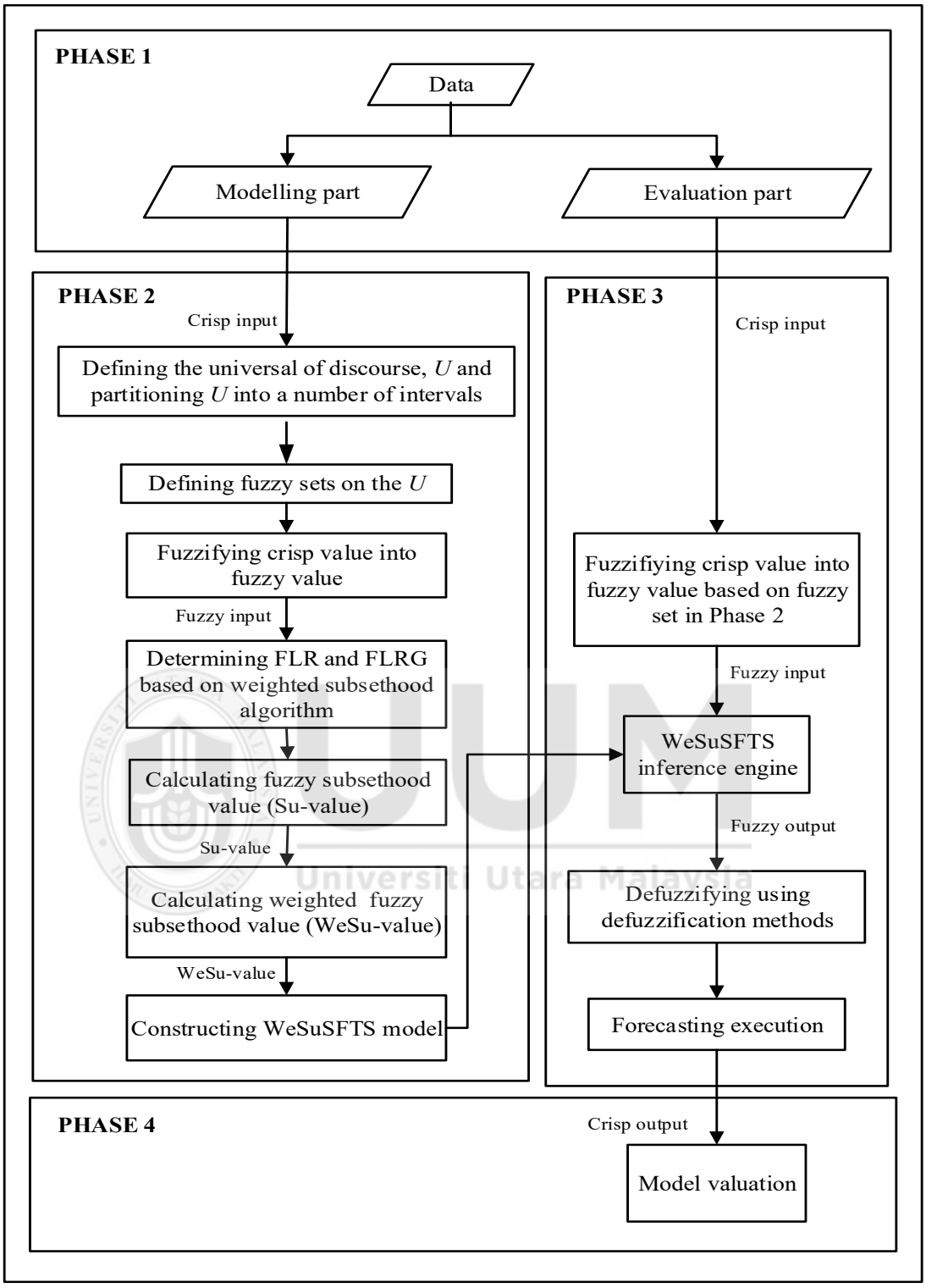


Figure 3.16. Flowchart of WeSuSFTS algorithm for forecasting problem

Universiti Utara Malaysia

CHAPTER FOUR
RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the results of applying the proposed enhanced fuzzy time series (FTS) procedure, the weighted subsethood segmented method (WeSuSFTS), in order to forecast moving holiday-electricity load demand (MH-ELD) in Malaysia. The descriptive analysis of MH-ELD pattern in Malaysia for years 2017 and 2018 is presented in Section 4.2. The results and discussion pertaining to WeSuSFTS algorithm are provided step-by-step in Sections 4.3 to 4.6. This chapter ends with Section 4.7 as a summary section.

4.2 Overview of Moving Holiday Electricity Load Demand Pattern

This section provides some overview of MH-ELD data pattern before discussing the results from the application of proposed WeSuSFTS forecasting algorithm in next sections. The Malaysia MH-ELD data used in this study were collected from Grid System Operator for Peninsular Malaysia (https://www.gso.org.my/). Two special events in MH were analysed in this study; Hari Raya Aidilfitri (HRA) and Chinese New Year (CNY). Figures 4.1 to 4.3 illustrate the impact of HRA and CNY celebration on ELD pattern for years 2017 and 2018 (Refer Appendix A-C for the ELD data). Figure 4.1 displays the effect of HRA MH for ELD, which resulted in a significant decrease of ELD pattern, whereas a decrease of ELD pattern is illustrated in Figures 4.2 and 4.3 in both years of 2017 and 2018 respectively due to CNY MH.

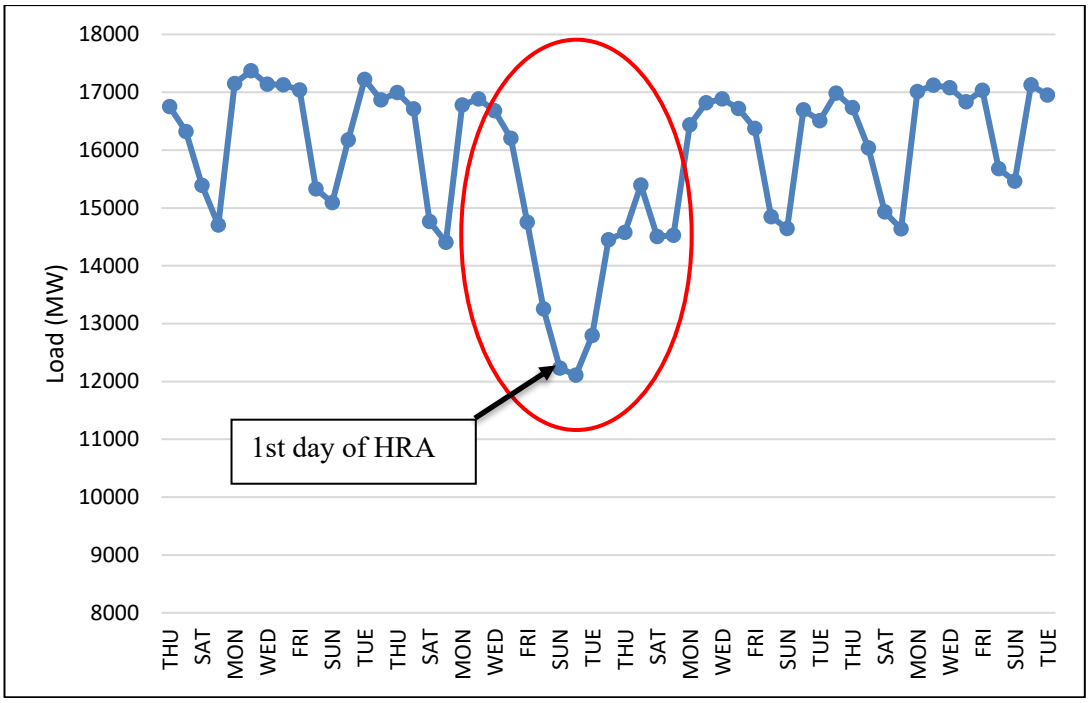


Figure 4.1. Electricity load demand from 1/6/2017 to 25/7/2017

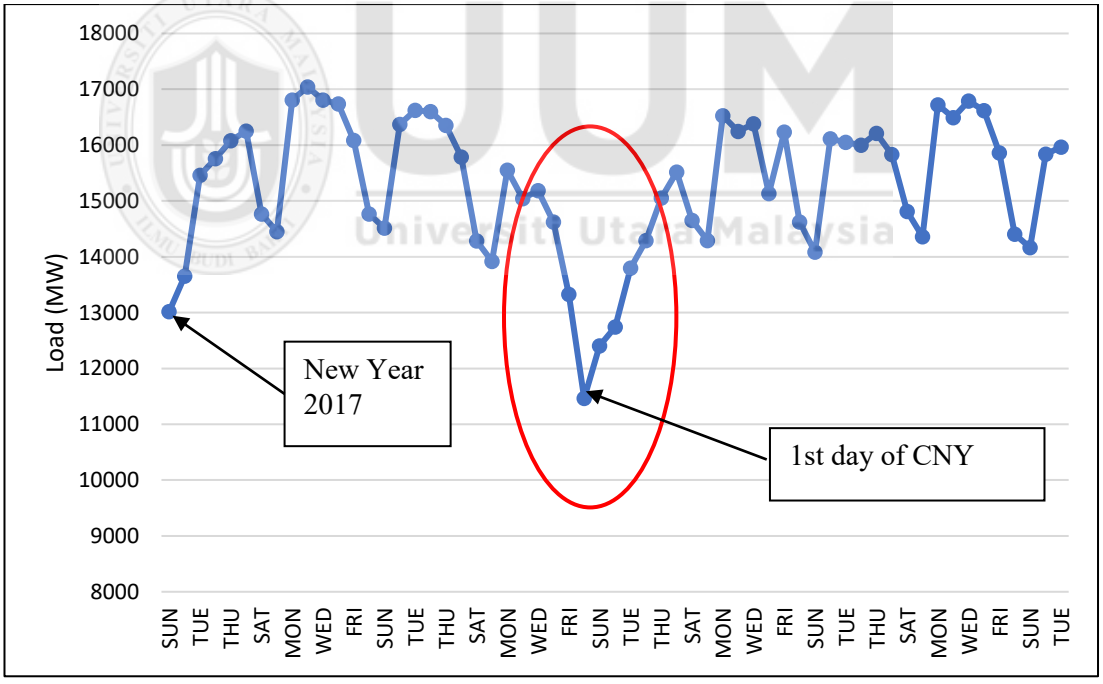


Figure 4.2. Electricity load demand from 1/1/2017 to 28/2/2017

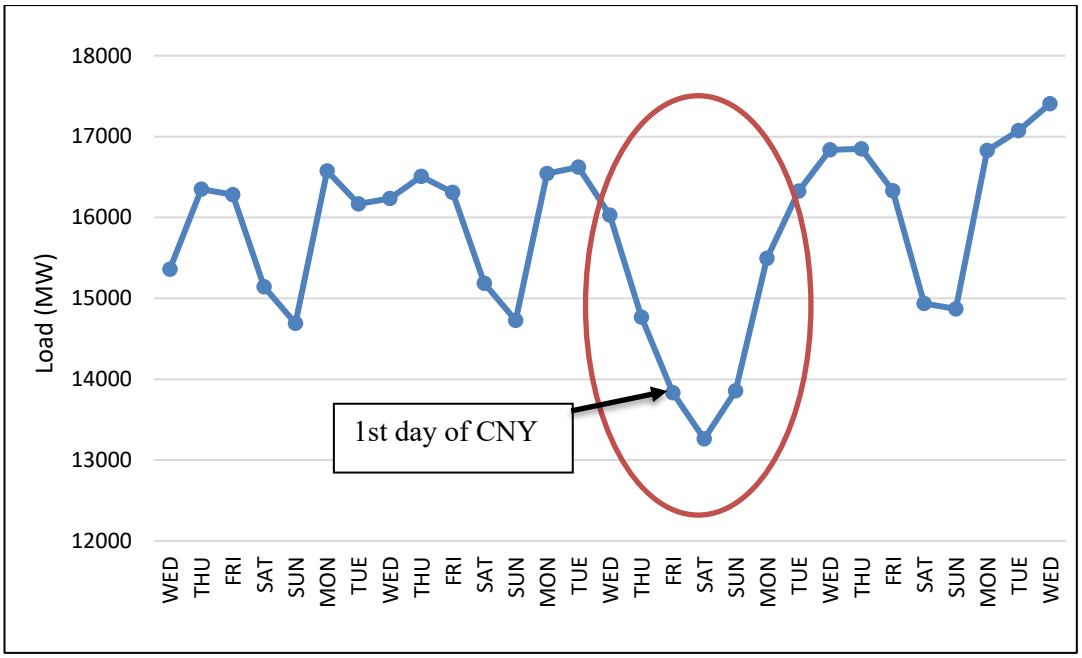


Figure 4.3. Electricity load demand from 31/1/2018 to 28/2/2018

The MH impact appeared to be greater when compared to other holiday (New Year celebration), as portrayed in Figure 4.2. Besides, days (Sunday, Monday, Saturday) also did exert an impact of MH. This present study reveals that the demand for electricity load did not only affect MH, but also around the MH. This, therefore, is one of the many reasons and one of the steps embedded in the WeSuSFTS forecasting algorithm, as depicted in the previous chapter that proposes the segmentation of time series data by considering the MH week.

Based on the impact of MH in a week, Table 4.1 presents the electricity percentage change load between current load and prototype load for three weeks of MH in 2017 and 2018. The example calculation of percentage change in Table 4.1 is presented in Section 3.3.4 and Section 4.3.4. The red arrows in Figure 4.4, denote the first day of MH. It shows a non-linear and irregular pattern in ELD of MH series. The process of

Universiti Utara Malaysia

Table 4.1

Percentage Change for Combined Segment Time Series

Observation(t)	Day	Event	Percentage change
1	Wednesday		-9.644
2	Thursday		-12.631
3	Friday		-17.154
4	Saturday	1st day CNY	-22.362
5	Sunday	2nd day CNY	-14.525
6	Monday	3rd day CNY	-22.154
7	Tuesday		-16.982
8	Thursday		-4.665
9	Friday		-11.717
10	Saturday		-10.235
11	Sunday	1st day HRA	-15.104
12	Monday	2nd day HRA	-27.857
13	Tuesday	3rd day HRA	-24.227
14	Wednesday		-13.376
15	Tuesday		2.808
16	Wednesday		-1.269
17	Thursday		-10.553
18	Friday	1st day CNY	-15.192
19	Saturday	2nd day CNY	-12.682
20	Sunday		-5.914
21	Monday		-6.341

Universiti Utara Malaysia

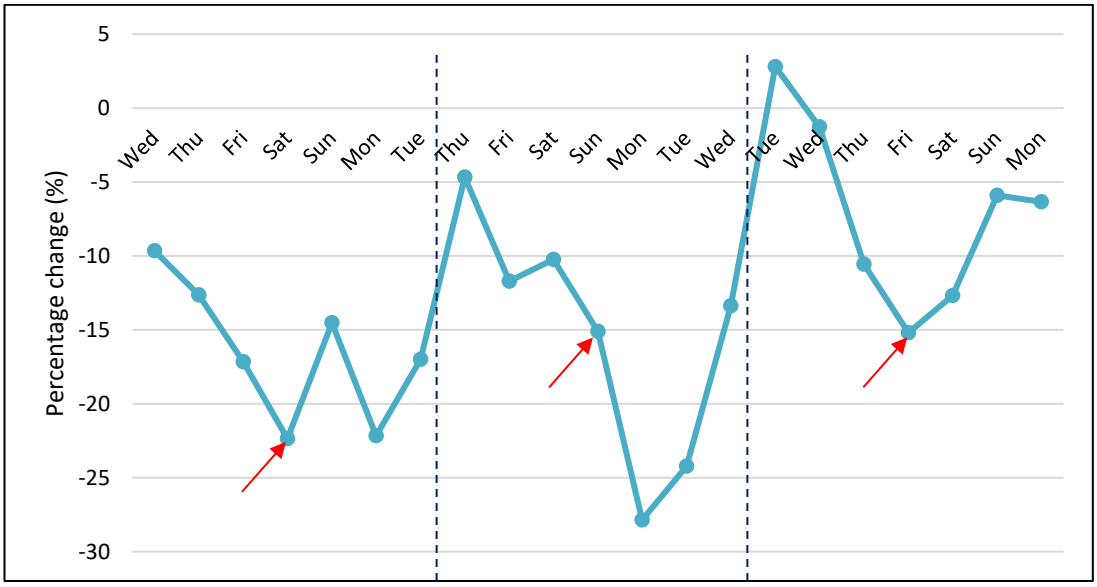


Figure 4.4. Percentage of change in MH series

constructing the MH series as in Figure 4.4, is shown in Sections 3.3.1 and 3.3.2. The highest decrease in electricity percentage changes load was -27.9%, which fell on Monday - the third day of MH. That day was also a replacement holiday due to the second day of MH which fell on a Sunday.

If the ELD data is not analyzed, wrong assumption about the data could be made, for example, the load demand percent changes could always drop sharply at the first day or two days of MH in the week. However, from the overview of percent changes in Table 4.1 and the time series pattern in Figure 4.4, the ELD percent changes does not always be the lowest at the first day of MH. For example, the percent changes dropped 27.86% from previous week at observation 12. Moreover, ELD percent changes did not show a high change for two consecutive MH days. For example, observations 4 (first day of MH event), 5 (second day of MH event) and 6 (third day of MH event). The first day of load demand showed a sharp drop at observations 4 and 6 but not at observation 5. These indicate the existence of uncertainty in MH-ELD data series.

The next sections present the outcomes of the application of WeSuSFTS algorithm for each step of the four phases.

4.3 Results of Phase 1: Pre-processing data

As mentioned in Chapter Three, Phase 1 consists of four main steps

Step (1): Segmenting the time series data.

Step (2): Combining segmented time series data.

Step (3): Dividing the data into modelling and evaluation parts.

Step (4): Identifying the independent and dependent variables(s).

4.3.1 Results of Step (1): Segmenting Time Series Data

As outlined in Chapter One, the data used for WeSuSFTS algorithm in this study were obtained from the Grid System Operator website (Operator, 2020) for years 2017 and 2018. The Grid System Operator website is responsible for the day-to-day real-time operation, the management of the electricity peninsular grid system, as well as the short- and medium-term planning of the transmission network and generation facilities. This study segmented the historical data into MH week and complement of MH week. Here, MH week refers to the first day of MH event that falls in the middle of the week (e.g., the fourth day in the week). Thus, based on Bessec et al. (2016) and explanation in Sections 3.3.1 to 3.3.3, four MH weeks were identified from the segmentation process for both 2017 and 2018, as exhibited in Table 4.2.

Table 4.2

Moving Holiday Week Segmentation

Day	**Date**			
	Moving holiday week 1 (F_1)	Moving holiday week 2 (F_2)	Moving holiday week 3 (F_3)	Moving holiday week 4 (F_4)
1	25-Jan-17	22-Jun-17	12-Feb-18	12-Jun-18
2	26-Jan-17	23-Jun-17	13-Feb-18	13-Jun-18
3	27-Jan-17	24-Jun-17	14-Feb-18	14-Jun-18
4	28-Jan-17	25-Jun-17	15-Feb-18	15-Jun-18
5	29-Jan-17	26-Jun-17	16-Feb-18	16-Jun-18
6	30-Jan-17	27-Jun-17	17-Feb-18	17-Jun-18
7	31-Jan-17	28-Jun-17	18-Feb-18	18-Jun-18

From Table 4.2, there are four MH segmented time series data with different date as on Table 4.1. Let MH week 1, week 2, week 3 and week 4 are denoted as F_1, F_2, F_3 and F_4 respectively by referring to definition of time series segmentation in Section 3.3.2. Seven days were chosen for each MH week. Day 4 for each MH week is the first

day of MH event. Therefore, day 1, 2 and 3 are three days before MH event and; day 5, 6 and 7 are three days after MH event. Thus, based on explanation in Section 3.3.1, MH1, MH2, MH3 and MH4 fall on 28 January 2017, 25 Jun 2017, 15 February 2018 and 15 June 2018 respectively.

4.3.2 Results of Step (2): Combining Segmented Time Series Data

After collecting all the segmented time series data, they were combined into a set of time series data based on Equation (3.1). The ELD data were termed as MH-ELD segmented time series data (see Table 4.3). Therefore, by referring to Equation (3.1) and Table 4.3, there were 28 data point starting from Day 1 with data value 15187.00 ($F_{1,1}$) and end at Day 28 with data value 14607.00 ($F_{4,7}$). Then, MH-ELD segmented time series data are denoted as $F_m = F_{1,1}, F_{1,2}, F_{1,3}, \dots, F_{1,7}, \dots, F_{4,1}, F_{i,2}, F_{i,3}, \dots, F_{4,7}$.

4.3.3 Results of Step (3): Dividing the Data into Modelling and Evaluation Parts

As depicted in Chapter Three Section 3.3.3, the data in this study (see Table 4.3) were segregated into two parts. The data from $F_{1,1}$ to $F_{3,7}$ were dedicated to the modelling part, while the remaining last data for the evaluation part. $F_{1,1}$ corresponds to moving holiday week 1 day 1 and $F_{3,7}$ corresponds to moving holiday week 3 day 7. Thus, data from days 1-21 were used in Phases 1 and 2, whereas data from days 22-28 were applied for model implementation and evaluation in Phases 3 and 4.

Universiti Utara Malaysia

Table 4.3

Segmented Electricity Load Demand Time Series Data

Day	ELD	Notation	Day	ELD	Notation
1	15187.00	$F_{1,1}$	15	16623.00	$F_{3,1}$
2	14623.00	$F_{1,2}$	16	16027.00	$F_{3,2}$
3	13325.00	$F_{1,3}$	17	14765.00	$F_{3,3}$
4	12295.82	$F_{1,4}$	18	13833.00	$F_{3,4}$
5	12405.00	$F_{1,5}$	19	13261.00	$F_{3,5}$
6	12745.00	$F_{1,6}$	20	13856.00	$F_{3,6}$
7	13800.00	$F_{1,7}$	21	15495.00	$F_{3,7}$
8	16205.00	$F_{2,1}$	22	17896.00	$F_{4,1}$
9	15147.38	$F_{2,2}$	23	16668.00	$F_{4,2}$
10	13252.00	$F_{2,3}$	24	14869.00	$F_{4,3}$
11	12231.00	$F_{2,4}$	25	13656.00	$F_{4,4}$
12	12147.47	$F_{2,5}$	26	13122.00	$F_{4,5}$
13	12795.00	$F_{2,6}$	27	13039.00	$F_{4,6}$
14	14448.00	$F_{2,7}$	28	14607.00	$F_{4,7}$

4.3.4 Results of Step (4): Identifying Independent and Dependent Variables

This study focuses on two types of models from the proposed FTS algorithm, as elaborated in Chapter Three. The models are One-factor WeSuSFTS and M-factor WeSuSFTS.

The One-factor WeSuSFTS model was constructed based on an independent and a dependent variable, in which the independent variable data refers to lag one of the dependent variable data. Instead of using the actual electricity load data for universal of discourse, this study employed percentage change load between forecasted load and prototype week load. The definition of prototype week is explained in Section 3.3.4 in Chapter Three. The data used to construct One-factor WeSuSFTS model are tabulated in Table 4.4. From Table 4.4, since the focus of this study is to forecast next day MH-ELD, hence *current percent changes* (C_t) served as the independent variable, while *next day percent changes* (C_{t+1}) functioned as the dependent variable for One-factor

WeSuSFTS model. After the C_{t+1} and C_t values were calculated by using Equation (3.2), for the time series stated in Table 4.4, observation 1 corresponds to day 1 in Table 4.3, observation 2 corresponds to day 2, and so on.

Table 4.4

Data for One-factor WeSuSFTS Modelling Part

Observation	ELD_{t+1}	C_{t+1}	C_t
1	15187.00	-9.6442	-9.5049
2	14623.00	-12.6307	-9.6442
3	13325.00	-17.1537	-12.6307
4	12295.82	-22.3622	-17.1537
5	12405.00	-14.5249	-22.3622
6	12745.00	-22.1537	-14.5249
7	13800.00	-16.9825	-22.1537
8	16205.00	-4.6653	-1.1146
9	15147.38	-11.7168	-4.6653
10	13252.00	-10.2350	-11.7168
11	12231.00	-15.1038	-10.2350
12	12147.47	-27.8572	-15.1038
13	12795.00	-24.2272	-27.8572
14	14448.00	-13.3761	-24.2272
15	16623.00	2.8078	-0.1870
16	16027.00	-1.2690	2.8078
17	14765.00	-10.5531	-1.2690
18	13833.00	-15.1922	-10.5531
19	13261.00	-12.6819	-15.1922
20	13856.00	-5.9143	-12.6819
21	15495.00	-6.3407	-5.9143

For example, by using Equation (3.2), C_{t+1}value at observation 10 (24 June 2017) is:

$$C_{t+1} = \frac{L_{t+1} - L_p}{L_p} \times 100\%$$

$$C_{24June2017} = \frac{ELD_{24June2017} - ELD_{17June2017}}{ELD_{17June2017}} \times 100\%$$

$$= \frac{13252 - 14763}{14763} \times 100\% = -10.2350\%$$

Where $C_{24June2017}$ is the forecasted percent changes on 24 June 2017 (C_{t+1}), $ELD_{24June2017}$ is the forecasted load on 24 June 2017 (L_{t+1}) and $ELD_{17June2017}$ is the load of the same day type of the prototype week (L_p). In this case, the prototype week is the previous week. Meanwhile, C_t value is at observation 10 and C_{t+1} value is at observation 9. The value of -10.2350% means that the forecasted load on that specific date decreases 10.235% from previous week due to MH effect.

As mentioned in Section 3.3.4 in Chapter Three, the C_t, L_t, the type of coincidence day and the type of holiday are considered as potential independent variables in this study based on some literature review. Table 4.5 shows the example of data and the corresponding explanation about the type of coincidence day and the type of holiday. The coincidence day type refers to the forecasted day that coincides with the day-before the holiday/weekend (BH_{t+1}), coincides with the day-after holiday/weekend (AH_{t+1}), or coincides with another holiday such as weekends on the same day (SH_{t+1}). Meanwhile, the holiday type for the forecasted day is called as either a big event day or not a big event day (E_{t+1}), that is whether the forecasted day is also the CNY (or HRA) days or not.

Based on Table 4.5, (27/1/2017) is the forecasted day with $BH_{t+1} = 1, AH_{t+1} = 0, SH_{t+1} = 0$ and $E_{t+1} = 0$. It means that the day was before day one of CNY (CNY1), not after CNY, not coincide with other holiday and not CNY (that is not big event) respectively. Mean while, for (28/1/2017), $BH_{t+1} = 1, AH_{t+1} = 0, SH_{t+1} = 1$ and $E_{t+1} = 1$ since this day was after CNY1, but not after CNY, a coincidence day with Saturday and was CNY1 (the big event day) respectively. However for (29/1/2017), $BH_{t+1} = 1, AH_{t+1} = 1, SH_{t+1} = 1$ and $E_{t+1} = 1$ since this day was before

Universiti Utara Malaysia

replacement CNY2, after CNY1, on Sunday (coincidence with week end) and a big event day respectively.

Table 4.5

Example of the Coincidence Day (BH_{t+1}, AH_{t+1} *and* SH_{t+1}) *and Holiday Type* (E_{t+1}) *data, and the Explanations*

Date(t+1)	Day-type	Explanation of the day	*BH*	*AH*	*SH*	*E*
25/1/2017	WED		0	0	0	0
26/1/2017	THU		0	0	0	0
27/1/2017	FRI	The day was before CNY, therefore, $BH = 1$	1	0	0	0
28/1/2017	SAT	The day was before CNY2, weekend, big event (CNY1), therefore $BH = 1, SH = 1$ and $E = 1$.	1	0	1	1
29/1/2017	SUN	The day was before replacement CNY2, after CNY1, weekend, big event (CNY2), therefore $BH = 1, AH = 1, SH = 1$ and $E = 1$.	1	1	1	1
30/1/2017	MON	The day was after CNY2, big event (replacement CNY2), therefore $AH = 1$ and $E = 1$.	0	1	0	1
31/1/2017	TUE	The day was after replacement CNY, therefore $AH = 1$.	0	1	0	0

Table 4.6

Correlation Analysis Results between Dependent Variable C_{t+1} *and Six Independent Variables*

Variables	C_t	L_t	BH_{t+1}	AH_{t+1}	SH_{t+1}	E_{t+1}
r	0.708	0.735	-0.383	-0.31	-0.212	-0.673

Table 4.7

Data for M-factor (M=2) WeSuSFTS Model

Observation	ELD_{t+1}	C_{t+1}	C_t	L_t
1	15187.00	-9.6442	-9.5049	15043.00
2	14623.00	-12.6307	-9.6442	15187.00
3	13325.00	-17.1537	-12.6307	14623.00
4	12295.82	-22.3622	-17.1537	13325.00
5	12405.00	-14.5249	-22.3622	12295.82
6	12745.00	-22.1537	-14.5249	12405.00
7	13800.00	-16.9825	-22.1537	12745.00
8	16205.00	-4.6653	-1.1146	16679.00
9	15147.38	-11.7168	-4.6653	16205.00
10	13252.00	-10.2350	-11.7168	15147.38
11	12231.00	-15.1038	-10.2350	13252.00
12	12147.47	-27.8572	-15.1038	12231.00
13	12795.00	-24.2272	-27.8572	12147.47
14	14448.00	-13.3761	-24.2272	12795.00
15	16623.00	2.8078	-0.1870	16544.00
16	16027.00	-1.2690	2.8078	16623.00
17	14765.00	-10.5531	-1.2690	16027.00
18	13833.00	-15.1922	-10.5531	14765.00
19	13261.00	-12.6819	-15.1922	13833.00
20	13856.00	-5.9143	-12.6819	13261.00
21	15495.00	-6.3407	-5.9143	13856.00

Universiti Utara Malaysia

As for M-factor WeSuSFTS model, Table 4.6 tabulates the correlation (r) values between C_{t+1} and each independent variable ($C_t, L_t, BH_{t+1}, AH_{t+1}, SH_{t+1}$ and E_{t+1}). From Table 4.6, the results show BH_{t+1}, AH_{t+1}, SH_{t+1} and E_{t+1} produced negative relationship to C_{t+1}. Meanwhile, both C_t and L_t have positive relationship with C_{t+1}. It means that when C_t and L_t increase, C_{t+1} also increases, however when BH_{t+1}, AH_{t+1}, SH_{t+1} and E_{t+1} increase, C_{t+1} will decrease.

This study applies the cut of correlation value, a = 0.70 in independent variables' correlation analysis, mainly because r > 0.70 indicates relatively strong correlation between the dependent and each independent variable. Table 4.6 shows that the r values, that is correlation values between *next day percent changes in* MH-ELD (C_{t+1}) and *current percent changes in* MH-ELD (C_t) and *current load* (L_t) exceeded 0.70; hence these two variables were selected as factors in M-factor WeSuSFTS. Therefore, for M-factor WeSuSFTS model, C_t and L_t serve as independent variables, while C_{t+1} is the dependent variable. Hence, the value of M in this case is 2. Since M value is 2, the WeSuSFTS model can be called also as Two-factor WeSuSFTS or M-factor (M=2) WeSuSFTS model. Table 4.7 displays the complete data for M-factor (M=2) WeSuSFTS modelling part.

Universiti Utara Malaysia

4.4 Results of Phase 2: Model Development

Phase 2 consists of seven steps mainly:

Step 1: Defining the universal of discourse, *U* and partitioning *U* into some length intervals.

Step 2: Defining fuzzy sets.

Step 3: Fuzzifying crisp value into fuzzy value.

Step 4: Determining FLR and FLRG.

Step 5: Calculating fuzzy subsethood value (SBA).

Step 6: Calculating weighted fuzzy subsethood value (WSBA).

Step 7: Constructing WeSuSFTS model.

The explanation steps and the results in this phase for One-factor and M-factor (M=2) WeSuSFTS models are presented as follows.

4.4.1 Results of Step (1): Defining Universal of Discourse, *U*, and Partitioning *U* into Several Length Intervals Length

The *k*-means clustering was carried out with different *k*; where *k* refers to the number of clusters. This study ran from $k = 2$ to $k = 10$ or 11. In order to choose the most suitable *k* value, the Elbow method was adopted to identify the number of intervals, as discussed in Chapter Three. Table 4.8 presents the results retrieved from the Elbow method for variables C_t, L_t and C_{t+1} by construction of interval based on *k*-means clustering-method which has been explained in Chapter Three at Section 3.4.1.

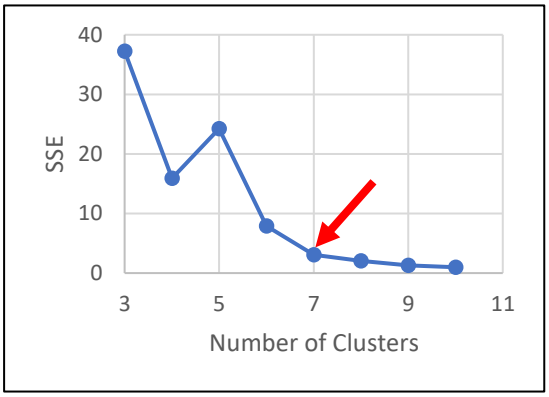
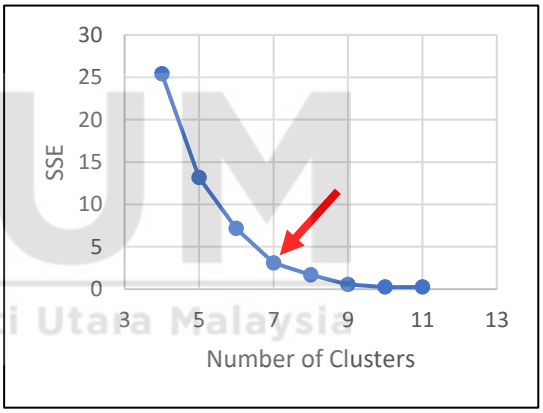
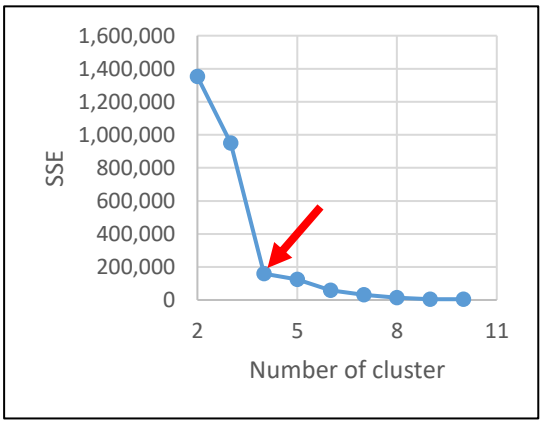
From Table 4.8, different number of clusters (*k*) produce different within groups sum square error (SSE). However, by increasing the number of clusters does not guarantee the value of SSE will decrease. For example, for C_{t+1} data, SSE value at $k = 4$ is 15.932 then increases to 24.243 at $k = 5$ but then decreases to 7.929 at $k = 6$. Hence, there is a need to add more *k* to assist in identifying the best number of clusters that also serves as the number of intervals of the universal discourse in this study.

Universiti Utara Malaysia

Despite no guarantee in providing the best outcome, the Elbow method offers the essential guideline to identify the number of intervals for this step by identifying the best number of clusters that can give drastic decrease of SSE. From Table 4.8, SSE value at seven intervals decreases sharply and close to 0 as portrayed in the SSE graph. When the number of clusters is more than seven, the SSE values are quite uniform. Hence seven intervals appeared to be the best number of intervals for variables C_{t+1} and C_t. Meanwhile, SSE value at four intervals decreases sharply and closer to 0, but becomes uniform after four intervals. Hence four intervals appeared to be the best number of intervals for variables L_t.

Table 4.8

Elbow Method Results

Variable	Within Group SSE	Elbow method
C_{t+1}	**k** / **SSE**: 3 / 37.25; 4 / 15.932; 5 / 24.243; 6 / 7.929; 7 / 3.08; 8 / 2.043; 9 / 1.291; 10 / 0.982	
C_t	**k** / **SSE**: 4 / 25.41; 5 / 13.163; 6 / 7.18; 7 / 3.093; 8 / 1.704; 9 / 0.555; 10 / 0.246; 11 / 0.246	
L_t	**k** / **SSE**: 2 / 1351855.4; 3 / 949338.7; 4 / 159614.2; 5 / 125019.6; 6 / 58834.7; 7 / 30663.4; 8 / 14180.6; 9 / 4731.4; 10 / 4731.4	

Universiti Utara Malaysia

Based on the Elbow method results, this study proceeded to divide U into several interval lengths. Tables 4.9 and 4.10 present the outcomes from *k*-means clustering for the final cluster identified from the Elbow method. The final cluster centers are the point of peak value (*b* value) in the membership function, as explained in Section 4.4.2.

Table 4.9

Interval Length

u	Variable		
	C_{t+1}	C_t	L_t
u_1	[-30.33, -25.39]	[-30.33, -25.39]	[11902.12, 12970.97]
u_2	[-25.39, -19.35]	[-25.39, -19.20]	[12970.97. 14229.25]
u_3	[-19.35, -13.67]	[-19.20, -13.24]	[14229.24, 15684.34]
u_4	[-13.67, -8.59]	[-13.24, -8.14]	[15684.34, 17146.86]
u_5	[-8.59, -3.45]	[-8.14, -3.07]	
u_6	[-3.45, 0.77]	[-3.07, 0.98]	
u_7	[0.77, 4.85]	[0.98, 4.64]	

Universiti Utara Malaysia

Table 4.10

k-means Final Cluster Center based on Elbow Method Results

Variable	Cluster						
	1	2	3	4	5	6	7
C_{t+1}	-27.86	-22.91	-15.79	-11.55	-5.64	-1.27	2.81
C_t	-27.86	-22.91	-15.49	-11.00	-5.29	-0.86	2.81
L_t	12436.60	13505.40	14953.10	16415.60			

Referring to Tables 4.9 and 4.10, as well as Equations (3.8) and (3.11) to (3.13) from Chapter Three, universal of discourse, was constructed for each variable, as shown in the following:

$$U_{C_{t+1}} = [-30.33, 4.85],\ U_{C_t} = [-30.33, 4.64],\ U_{L_t} = [11902.70, 17146.86\ ]$$

After that, *U* was divided into several interval lengths based on the equations presented in Chapter Three (Equations (3.8) – (3.13)). Table 4.9 presents the intervals. Refer u_2 for C_{t+1}, $u_2(C_{t+1})$ in Table 4.9 as an example. Based on Section 3.4.1 in Chapter Three, interval length of second interval C_{t+1},

$$u_2(C_{t+1}) = [LB_{center2}, UB_{center2}]$$

Where,

$$LB_{center2} = UB_{center1} = \frac{Center_1 + Center_2}{2} = \frac{-27.86 + (-22.91)}{2} = -25.39$$

$$UB_{Center_2} = \frac{Center_2 + Center_3}{2} = \frac{-27.86 + (-15.79)}{2} = -19.35$$

Hence,

$$u_2(C_{t+1}) = [LB_{center2}, UB_{center2}] = [-25.39, -19.35]$$

Universiti Utara Malaysia

$Center_1$ and $Center_2$ are the final cluster center for cluster 1 and 2 respectively which are based on *k*-means clustering results. Meanwhile, $UB_{center1}$, $UB_{center2}$ and $LB_{center2}$ are upper boundary of first and second interval for C_{t+1} and lower boundary for second interval of C_{t+1} correspondingly.

From Table 4.9, for each of the seven intervals of universal discourse, *U*, variable C_{t+1}has different size of interval lengths for its corresponding C_t and L_t. This means that the partitioning of *U* procedure in this step is a success since the process produced not equal length of intervals. As a result, the values of the final cluster centers as shown in Table 4.9 are also not the same for each cluster, even though C_{t+1} and C_t have the same centers for Clusters 1 and 2.

4.4.2 Results of Step (2): Defining Fuzzy Sets

The triangular membership function (TMF) was employed for fuzzy sets of linguistic fuzzy variables C_t, L_t and C_{t+1} by adhering to the intervals tabulated in Table 4.9. Figure 4.5 illustrates the general graphical TMF for all fuzzy sets. Referring to Figure 4.5, the fuzzy set was developed using *a*, *b*, and *c* values where the values were from the final cluster center as stated in Table 4.10. All the TMF parameters for C_{t+1}, $L_{t,}$ and C_t are listed in Table 4.11 to 4.13 respectively. The values stated in Table 4.11 to 4.13 are the final cluster values from Table 4.10 where first TMF and the last TMF constructed by symmetry TMF. Figures can be used to illustrate TMF for each variable based on its corresponding values in Tables 4.11 to 4.13. Figure 4.6 for instance, shows the membership function for variable C_{t+1}. As given in Chapter Three, the fuzzy set may be defined by using Equation (3.14).

$$\mu_{fuzzy\ set}(x) = \begin{cases} 0, & x \le a \\ \dfrac{(x-a)}{(b-a)}, & a < x \le b \\ \dfrac{(c-x)}{(c-b)}, & b < x \le c \\ 0, & x > c \end{cases}$$

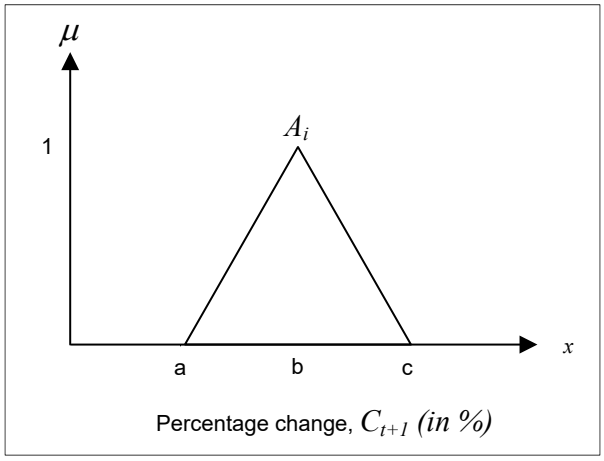


Figure 4.5. General triangular membership function

Table 4.11

Triangular Membership Function Parameters for C_{t+1}

Fuzzy set	***a***	***b***	***c***
A_1, *Very large decrease*	-32.8	-27.86	-22.91
A_2, *Large decrease*	-27.86	-22.91	-15.79
A_3, *Medium decrease*	-22.91	-15.79	-11.55
A_4, *Small decrease*	-15.79	-11.55	-5.64
A_5, *Very small decrease*	-11.55	-5.64	-1.27
A_6, *No change*	-5.64	-1.27	2.81
A_7, *Very small increase*	-1.27	2.81	6.88

Table 4.12

Triangular Membership Function Parameters for L_t

Fuzzy set	***a***	***b***	***c***
C_1, *Very low*	11367.70	12436.55	13505.40
C_2, *Low*	123436.55	13505.40	14953.08
C_3, *Medium*	13505.40	14953.08	16415.60
C_4, *High*	14953.08	16415.60	17878.12

Universiti Utara Malaysia

Table 4.13

Triangular Membership Function parameters for C_t

Fuzzy set	***a***	***b***	***c***
B_1, *Very large decrease*	-32.8	-27.86	-22.91
B_2, *Large decrease*	-27.86	-22.91	-15.49
B_3, *Medium decrease*	-22.91	-15.49	-11.00
B_4, *Small decrease*	-15.49	-11.00	-5.29
B_5, *Very small decrease*	-11.00	-5.29	-0.86
B_6, *No change*	-5.29	-0.86	2.81
B_7, *Very small increase*	-0.86	2.81	6.47

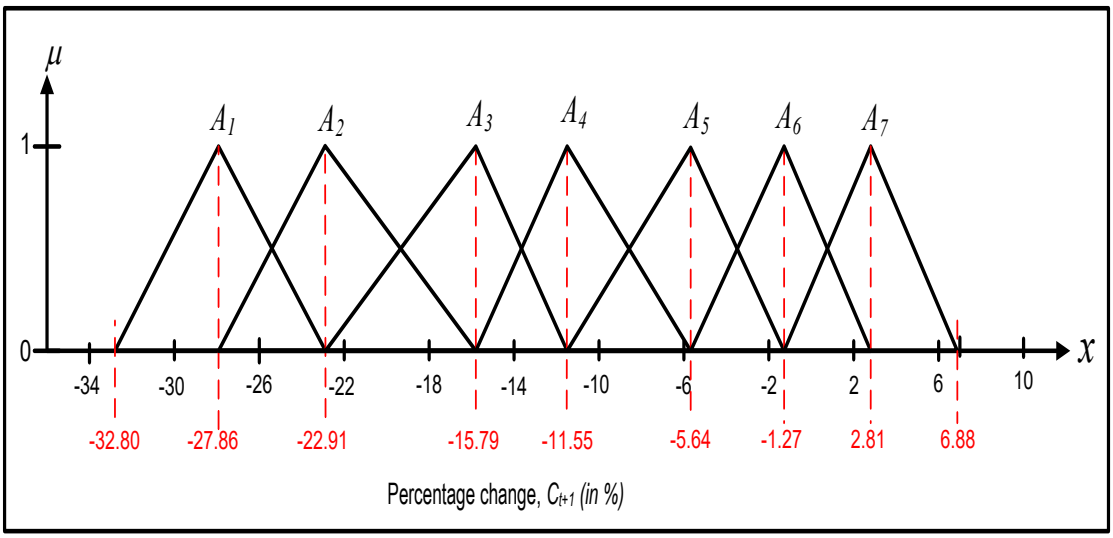
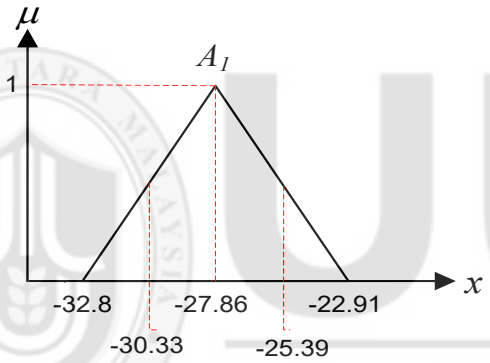
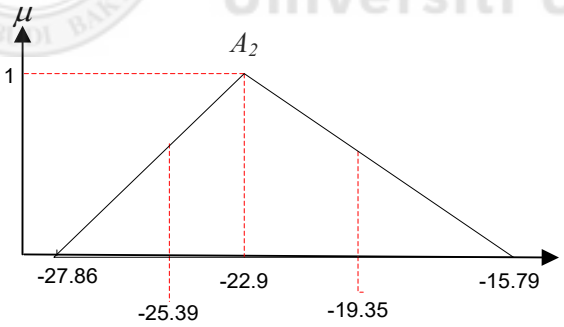


Figure 4.6. Triangular membership function for C_{t+1}

Universiti Utara Malaysia

Table 4.14

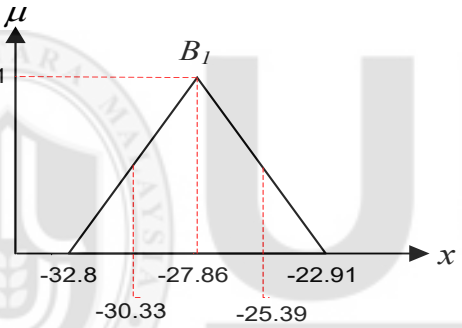
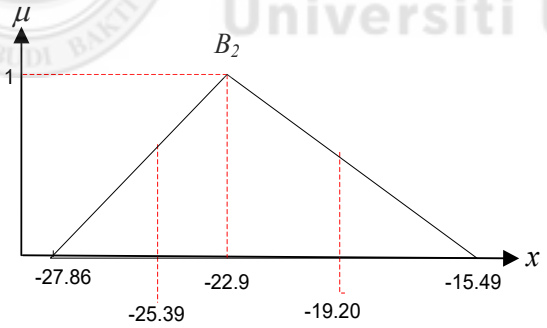
Membership Function of Fuzzy Sets A_1 and A_2

Interval	Linguistic term	Fuzzy set	Membership function, $\mu_A(x)$
$u_{A1} = [-30.33, -25.39)$	A_1		$\mu_{A_1}(x) = max\left\{0, min\left[\frac{(x+32.80)}{(-27.86+32.80)}, \frac{(-22.91-x)}{(-22.91+27.86)}\right]\right\}$
$u_{A2} = [-25.39, -19.35)$	A_2		$\mu_{A_2}(x) = max\left\{0, min\left[\frac{(x+27.86)}{(-22.91+27.86)}, \frac{(-15.79-x)}{(-15.79+22.91)}\right]\right\}$

Universiti Utara Malaysia

Table 4.15

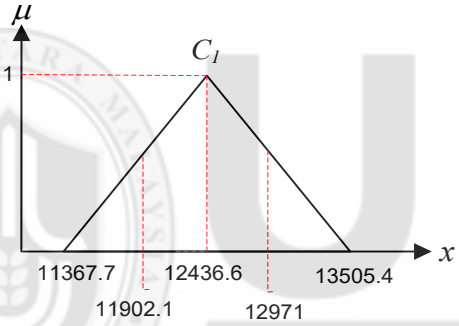
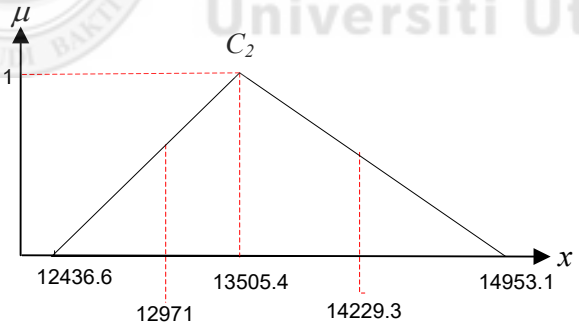
Membership Function of Fuzzy Sets B_1 and B_2

Interval	**Linguistic term**	**Fuzzy set**	**Membership function, $\mu_B(x)$**
$u_{B_1} = [-30.33, -25.39)$	B_1		$\mu_{B_1}(x) = max\left\{0, min\left[\frac{(x+32.80)}{(-27.86+32.80)}, \frac{(-22.91-x)}{(-22.91+27.86)}\right]\right\}$
$u_{B_2} = [-25.39, -19.20)$	B_2		$\mu_{B_2}(x) = max\left\{0, min\left[\frac{(x+27.86)}{(-22.91+27.86)}, \frac{(-15.49-x)}{(-15.49+22.91)}\right]\right\}$

Universiti Utara Malaysia

Table 4.16

Membership Function for of Fuzzy Sets C_1 and C_2

Interval	**Linguistic term**	**Fuzzy set**	**Membership function, $\mu_C(x)$**
u_{C_1} $= [11902.12, 12970.97)$	C_1		$\mu_{C_1}(x)$ $= max\left\{0, min\left[\frac{(x+11367.7)}{(12436.6-11367.7)}, \frac{(13505.4-x)}{(13505.4-12436.6)}\right]\right\}$
u_{C_2} $= [12970.97, 14229.25)$	C_2		$\mu_{C_2}(x)$ $= max\left\{0, min\left[\frac{(x+12436.6)}{(13505.4-12436.6)}, \frac{(14953.1-x)}{(14953.1-13505.4)}\right]\right\}$

Universiti Utara Malaysia

Tables 4.14 to 4.16 show values of A_1 and A_2 $B_1$and B_2, and C_1 and C_2 respectively as examples of relation among intervals' length, graph of fuzzy membership function, and equation of fuzzy membership function.

4.4.3 Results of Step (3): Fuzzifying Crisp Values into Fuzzy Values

This step focuses on the fuzzification of crisp values of C_{t+1}, C_t, and L_t to their corresponding fuzzy linguistic terms based on their highest degree of membership functions. Table 4.17, 4.18 and 4.19 tabulate the results respectively, where the

Table 4.17

Fuzzifying Result of C_{t+1}

Observation	Crips value	Fuzzy Linguistic term
1	-9.644	A_4
2	-12.631	A_4
3	-17.154	A_3
4	-22.362	A_2
5	-14.525	A_3
6	-22.154	A_2
7	-16.982	A_3
8	-4.665	A_5
9	-11.717	A_4
10	-10.235	A_4
11	-15.104	A_3
12	-27.857	A_1
13	-24.227	A_2
14	-13.376	A_4
15	2.808	A_7
16	-1.269	A_6
17	-10.553	A_4
18	-15.192	A_3
19	-12.682	A_4
20	-5.914	A_5
21	-6.341	A_5

Universiti Utara Malaysia

notation for C_{t+1}, *Next day percentage changes* $= \{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$ = {*Very large decrease, Large decrease, Medium decrease, Small decrease, Very small decrease, No change, Very small increase*}. Meanwhile, the notation for C_t, *Current percentage changes* $= \{B_1, B_2, B_3, B_4, B_5, B_6, B_7\}$ = {*Very large decrease, Large decrease, Medium decrease, Small decrease, Very small decrease, No change, Very small increase*}, and the notation for L_t, *Current load*$= \{C_1, C_2, C_3, C_4\}$ = {*Very low, Low, Medium, High*}.

Table 4.18

Fuzzifying Result for C_t

Observation	Crips value	Fuzzy linguistic term
1	-9.505	B_4
2	-9.644	B_4
3	-12.631	B_4
4	-17.154	B_3
5	-22.362	B_2
6	-14.525	B_3
7	-22.154	B_2
8	-1.115	B_6
9	-4.665	B_5
10	-11.717	B_4
11	-10.235	B_4
12	-15.104	B_3
13	-27.857	B_1
14	-24.227	B_2
15	-0.187	B_6
16	2.808	B_7
17	-1.269	B_6
18	-10.553	B_4
19	-15.192	B_3
20	-12.682	B_4
21	-5.914	B_5

Universiti Utara Malaysia

Table 4.19

Fuzzifying Result for L_t

Observation	Crips value	Fuzzy linguistic term
1	15043	C_3
2	15187	C_3
3	14623	C_3
4	13325	C_2
5	12296	C_1
6	12405	C_1
7	12745	C_1
8	16679	C_4
9	16205	C_4
10	15147	C_3
11	13252	C_2
12	12231	C_1
13	12147	C_1
14	12795	C_1
15	16544	C_4
16	16623	C_4
17	16027	C_4
18	14765	C_3
19	13833	C_2
20	13261	C_2
21	13856	C_2

Universiti Utara Malaysia

4.4.4 Results of Step (4): Determining Fuzzy Logical Relationship (FLR) and Fuzzy Logical Relationship Group (FLRG)

Referring to the fuzzification results retrieved in Phase 2 Step (3), both FLR and FLRG were constructed by grouping the observations with similar dependent fuzzy linguistic term. FLR in Table 4.20 corresponds to the FLR between C_t and C_{t+1}. In other words, Table 4.20 presents the FLR based on the fluctuation of fuzzy data from fuzzy

linguistic term in independent variables (LHS) to fuzzy linguistic term dependent variable (RHS). Next, the FLR was grouped into the same RHS. As a result, seven groups were formed as the number of fuzzy dependent linguistic term in this study was seven. Tables 4.20 to 4.23 display the FLR and FLRG for One-factor WeSuSFTS and M-factor (M=2) WeSuSFTS model, respectively.

Table 4.20

Fuzzy Logical Relationship for One-factor WeSuSFTS

Observation	C_t	C_{t+1}	**FLR**
	LHS	**RHS**	
1	B_4	A_4	$B_4 \rightarrow A_4$
2	B_4	A_4	$B_4 \rightarrow A_4$
3	B_4	A_3	$B_4 \rightarrow A_3$
4	B_3	A_2	$B_3 \rightarrow A_2$
5	B_2	A_3	$B_2 \rightarrow A_3$
6	B_3	A_2	$B_3 \rightarrow A_2$
7	B_2	A_3	$B_2 \rightarrow A_3$
8	B_6	A_5	$B_6 \rightarrow A_5$
9	B_5	A_4	$B_5 \rightarrow A_4$
10	B_4	A_4	$B_4 \rightarrow A_4$
11	B_4	A_3	$B_4 \rightarrow A_3$
12	B_3	A_1	$B_3 \rightarrow A_1$
13	B_1	A_2	$B_1 \rightarrow A_2$
14	B_2	A_4	$B_2 \rightarrow A_4$
15	B_6	A_7	$B_6 \rightarrow A_7$
16	B_7	A_6	$B_7 \rightarrow A_6$
17	B_6	A_4	$B_6 \rightarrow A_4$
18	B_4	A_3	$B_4 \rightarrow A_3$
19	B_3	A_4	$B_3 \rightarrow A_4$
20	B_4	A_5	$B_4 \rightarrow A_5$
21	B_5	A_5	$B_5 \rightarrow A_5$

Universiti Utara Malaysia

Table 4.21

Fuzzy Logical Relationship Group for One-factor WeSuSFTS

Observation	FLRG	Subgroup
12	$B_3 \rightarrow A_1$	Subgroup 1
4,6,13	$B_3,B_3,B_1 \rightarrow A_2$	Subgroup 2
3,5,7,11,18	$B_4,B_2,B_2,B_4,B_4 \rightarrow A_3$	Subgroup 3
1,2,9,10,14,17,19	$B_4,B_4,B_5,B_4,B_2,B_6,B_3 \rightarrow A_4$	Subgroup 4
8,20,21	$B_6,B_4,B_5 \rightarrow A_5$	Subgroup 5
16	$B_7 \rightarrow A_6$	Subgroup 6
15	$B_6 \rightarrow A_7$	Subgroup 7

Table 4.22

Fuzzy Logical Relationship for M-factor (M=2) WeSuSFTS

Observation	C_t	L_t	C_{t+1}	FLR
	LHS_1	LHS_2	RHS	
1	B_4	C_3	A_4	$B_4, C_3 \rightarrow A_4$
2	B_4	C_3	A_4	$B_4, C_3 \rightarrow A_4$
3	B_4	C_3	A_3	$B_4, C_3 \rightarrow A_3$
4	B_3	C_2	A_2	$B_3, C_2 \rightarrow A_2$
5	B_2	C_1	A_3	$B_2, C_1 \rightarrow A_3$
6	B_3	C_1	A_2	$B_3, C_1 \rightarrow A_2$
7	B_2	C_1	A_3	$B_2, C_1 \rightarrow A_3$
8	B_6	C_4	A_5	$B_6, C_4 \rightarrow A_5$
9	B_5	C_4	A_4	$B_5, C_4 \rightarrow A_4$
10	B_4	C_3	A_4	$B_4, C_3 \rightarrow A_4$
11	B_4	C_2	A_3	$B_4, C_2 \rightarrow A_3$
12	B_3	C_1	A_1	$B_3, C_1 \rightarrow A_1$
13	B_1	C_1	A_2	$B_1, C_1 \rightarrow A_2$
14	B_2	C_1	A_4	$B_2, C_1 \rightarrow A_4$
15	B_6	C_4	A_7	$B_6, C_4 \rightarrow A_7$
16	B_7	C_4	A_6	$B_7, C_4 \rightarrow A_6$
17	B_6	C_4	A_4	$B_6, C_4 \rightarrow A_4$
18	B_4	C_2	A_3	$B_4, C_2 \rightarrow A_3$
19	B_3	C_2	A_4	$B_3, C_2 \rightarrow A_4$
20	B_4	C_2	A_5	$B_4, C_2 \rightarrow A_5$
21	B_5	C_2	A_5	$B_5, C_2 \rightarrow A_5$

Universiti Utara Malaysia

Table 4.22 show the FLR for M-factor (M=2) WesuSFTS model. Since there were two LHS (LHS_1 and LHS_2) of two independent variables, hence the FLR in Table 4.22 is for M-factor (M=2) WeSuSFTS model. It shows the contribution of fuzzy relationship of LHS to RHS of the model. For example, observation 1, B_4 and C_3 contribute to A_4; which interprets that—*small decrease* of current percent changes (B_4) and *medium* of current ELD (C_3) contribute to *small decrease* of forecasted MH-ELD percent changes (A_4). Meanwhile, Table 4.23 summarizes the contribution relationship of LHS to RHS by FLRG. The fuzzy relationship was grouped into similar RHS. Since there were seven fuzzy set in RHS, then seven subgroups were constructed in the FLRG. Table 4.23 shows which observations that contribute the FLRG and the corresponding subgroups. For example, from observation 4,6 and 13, two B_3, one B_1, one C_2 and two C_1 contribute to A_2 and denoted as $B_3, B_3, B_1, C_2, C_1, C_1 \rightarrow A_2$.

Table 4.23

Fuzzy Logical Relationship Group for M-factor (M=2) WeSuSFTS

Observation	FLRG	Subgroup
12	$B_3, C_1 \rightarrow A_1$	Subgroup 1
4,6,13	$B_3, B_3, B_1, C_2, C_1, C_1 \rightarrow A_2$	Subgroup 2
3,5,7,11,18	$B_4, B_2, B_2, B_4, B_4, C_3, C_1, C_1, C_2, C_3 \rightarrow A_3$	Subgroup 3
1,2,9,10,14,17,19	$B_4, B_4, B_5, B_4, B_2, B_6, B_3, C_3, C_3, C_4, C_3, C_1, C_4, C_2 \rightarrow A_4$	Subgroup 4
8,20,21	$B_6, B_4, B_5, C_4, C_2, C_2 \rightarrow A_5$	Subgroup 5
16	$B_7, C_4 \rightarrow A_6$	Subgroup 6
15	$B_6, C_4 \rightarrow A_7$	Subgroup 7

4.4.5 Results of Step (5): Calculating Fuzzy Subsethood Values

After developing the FLRG, the fuzzy subsethood value (Su-value) was calculated in this step for each subgroup in FLRG. The Su-value for One-factor WeSuSFTS model can be calculated by using Equation (4.1), while Equations (4.1) and (4.2) to determine the Su-value for M-factor (M=2) WeSuSFTS model.

$$S(A_i, B_j) = \frac{\sum_{x \in U} min\left\{\mu_{A_i}(x), \mu_{B_j}(x)\right\}}{\sum_{x \in U} \mu_{A_i}(x)} \tag{4.1}$$

$$S(A_i, C_j) = \frac{\sum_{x \in U} min\left\{\mu_{A_i}(x), \mu_{C_j}(x)\right\}}{\sum_{x \in U} \mu_{A_i}(x)} \tag{4.2}$$

For example, $S(A_2, B_1)$, from Table 4.23, data from observation 4, 6 and 13 contribute to Subgroup 2. Let

$$\mu_{A_2}(x_{t=4}) = \mu_{A_2}(-22.3622) = 0.92306$$

$$\mu_{A_2}(x_{t=6}) = \mu_{A_2}(-22.1537) = 0.89378$$

$$\mu_{A_2}(x_{t=13}) = \mu_{A_2}(-24.2272) = 0.7339$$

and

$$\mu_{B_1}(x_{t=4}) = \mu_{B_1}(-17.1537) = 0$$

$$\mu_{B_1}(x_{t=6}) = \mu_{B_1}(-14.5249) = 0$$

$$\mu_{B_1}(x_{t=13}) = \mu_{B_1}(-27.8572) = 0.9995$$

Universiti Utara Malaysia

The value of $\mu_{A_2}(x_{t=4})$ shows the membership degree of element $x_{t=4}$ to fuzzy set A_2. The same definition was used for similar notations of $\mu_{A_2}(x_{t=6})$, $\mu_{A_2}(x_{t=13})$, $\mu_{B_1}(x_{t=4})$, $\mu_{B_1}(x_{t=6})$, and $\mu_{B_1}(x_{t=13})$. The fuzzy subsethood value of B_1 to A_2, denoted as $S(A_2, B_1)$, is expressed in Equation (3.21) as given in Chapter Three.

$$S(A_2, B_1) = \frac{\sum_{observation\ 4,6,13} min\left[\mu_{A_2}(x), \mu_{B_1}(x)\right]}{\sum_{observation\ 4,6,13} \mu_{A_2}(x)} \tag{3.21}$$

$$= \frac{min\left[\mu_{A_2}(x_{t=4}), \mu_{B_1}(x_{t=4})\right] + min\left[\mu_{A_2}(x_{t=6}), \mu_{B_1}(x_{t=6})\right] + min\left[\mu_{A_2}(x_{t=13}), \mu_{B_1}(x_{t=13})\right]}{\mu_{A_2}(x_{t=4}) + \mu_{A_2}(x_{t=6}) + \mu_{A_2}(x_{t=13})}$$

$$= \frac{\min(0.92306,0) + \min(0.89378,0) + \min(0.7339,0.9995)}{0.92306 + 0.89378 + 0.7339}$$

$$= \frac{0.7339}{2.55074} = 0.2877$$

Tables 4.24 and 4.25 display the Su-values for One-factor and M-factor (M=2) WeSuSFTS, respectively. Su-values which stated in Table 4.24 presents the degree to which C_t is a subset of C_{t+1} in One-factor WeSuSFT model. For example, from the first-row value in Table 4.24, $S(A_1, B_3)$ is equal to 0.9144, $S(A_1, B_4)$ is equal to 0.0861 and $S(A_1, B_j), j = 1,2,5,6 \text{ and } 7$ are equal to zero. The Su-value from this example shows *medium decrease* of C_t (B_3) has high relationship to *very large decrease* of C_{t+1} (A_1) compared to *small decrease* of C_t (B_4). Meanwhile, *very large decrease* (B_1), *large decrease* (B_2), *very small decrease* (B_5), *no change* (B_6) and *very small increase* (B_7) of C_t not contributed any relationship to *very large decrease* of C_{t+1} (A_1).

Table 4.24

Fuzzy Subsethood Value for One-factor WeSuSFTS

		C_t						
		B_1	B_2	B_3	B_4	B_5	B_6	B_7
C_{t+1}	A_1	0	0	0.9144	0.0861	0	0	0
	A_2	0.2877	0.0881	0.6119	0.0843	0	0	0
	A_3	0.0218	0.3798	0.1334	0.5778	0.0525	0	0
	A_4	0.0718	0.1075	0.1686	0.4281	0.2740	0.1837	0
	A_5	0	0	0.1434	0.2813	0.3595	0.2975	0
	A_6	0	0	0	0	0	0.0006	0.9996
	A_7	0	0	0	0	0	0.8171	0.1835

Meanwhile, Table 4.25 provides the degree to which C_t and L_t is a subset of C_{t+1} for M-factor (M=2) WeSuSFTS model. The values also represent the degree of relationship between these variables. Higher Su-value, stronger the relationship. Su-values in Table 4.25 present the degree to which C_t and L_t are subset of C_{t+1}. The values also represent the degree of relationship between C_t and L_t to C_{t+1}. For example, from the first-row of Table 4.25, $S(A_1, B_3)$ is equal to 0.9144, $S(A_1, B_4)$ is equal to 0.0861 and $S(A_1, B_j), j = 1,2,5,6$ and 7 are equal to zero. Meanwhile $S(A_1, C_1)$ is equal to 0.8081 and $S(A_1, C_j), j = 2,3$ and 4 is equal to zero. The Su-value from this example shows *medium decrease* of C_t (B_3) has highest relationship to *very large decrease* of C_{t+1} (A_1) compared to *small decrease* of C_t (B_4) and *very low* of L_t (C_1). Meanwhile, *very large decrease* (B_1), *large decrease* (B_2), *very small decrease* (B_5), *no change* (B_6) and *very small increase* (B_7) of C_t and; *low* (C_2) *medium* (C_3) and *high* (C_4) of L_t do not contributed any relationship to *very large decrease* of C_{t+1} (A_1).

Universiti Utara Malaysia

Table 4.25

Fuzzy Subsethood Value for M-factor (M=2) WeSuSFTS

		C_t							L_t			
		B_1	B_2	B_3	B_4	B_5	B_6	B_7	C_1	C_2	C_3	C_4
C_{t+1}	A_1	0	0	0.9144	0.0861	0	0	0	0.8081	0	0	0
	A_2	0.2877	0.0881	0.6119	0.0843	0	0	0	0.7026	0.3259	0	0
	A_3	0.0218	0.3798	0.1334	0.5778	0.0525	0	0	0.4085	0.3489	0.4037	0
	A_4	0.0718	0.1075	0.1686	0.4281	0.2740	0.1837	0	0.1075	0.2018	0.5357	0.3673
	A_5	0	0	0.1434	0.2813	0.3595	0.2975	0	0.0875	0.8829	0.3902	0.2975
	A_6	0	0	0	0	0	0.0006	0.9996	0	0	0	0.8584
	A_7	0	0	0	0	0	0.8171	0.1835	0	0	0	0.9127

Universiti Utara Malaysia

4.4.6 Results of Step (6): Calculating Weighted Fuzzy Subsethood Values

Based on the Su-value for One-factor WeSuSFTS model, the weighted fuzzy subsethood value (WeSu-value) can be calculated by using Equation (4.3). On the other hand, WeSu-value for M-factor (M=2) WeSuSFTS model can be calculated by using Equations (4.3) and (4.4).

$$W(A_i, B_j) = \left(\frac{S(A_i, B_j)}{\max\limits_{j=1,2,\dots,7} S(A_i, B_j)} \right) \tag{4.3}$$

$$W(A_i, C_j) = \left(\frac{S(A_i, C_j)}{\max\limits_{j=1,2,\dots,4} S(A_i, C_j)} \right) \tag{4.4}$$

Tables 4.26 and 4.27 show the WeSu-value for One-factor and M-factor (M=2) WeSuSFTS, respectively. These values were applied to build the models in the next section.

Universiti Utara Malaysia

Table 4.26

Weighted Fuzzy Subsethood Value for One-factor WeSuSFTS

		C_t						
		B_1	B_2	B_3	B_4	B_5	B_6	B_7
C_{t+1}	A_1	0	0	1	0.0941	0	0	0
	A_2	0.4702	0.1440	1	0.1377	0	0	0
	A_3	0.0377	0.6573	0.2309	1	0.0909	0	0
	A_4	0.1677	0.2512	0.3939	1	0.6400	0.4290	0
	A_5	0	0	0.3990	0.7826	1	0.8275	0
	A_6	0	0	0	0	0	0.0006	1
	A_7	0	0	0	0	0	1	0.2246

Table 4.27

Weighted Fuzzy Subsethood Value for M-factor (M=2) WeSuSFTS

		C_t							L_t			
		B_1	B_2	B_3	B_4	B_5	B_6	B_7	C_1	C_2	C_3	C_4
	A_1	0	0	1	0.0941	0	0	0	1	0	0	0
	A_2	0.4702	0.1440	1	0.1377	0	0	0	1	0.464	0	0
	A_3	0.0377	0.6573	0.2309	1	0.0909	0	0	1	0.854	0.988	0
C_{t+1}	A_4	0.1677	0.2512	0.3939	1	0.6400	0.4290	0	0.201	0.377	1	0.686
	A_5	0	0	0.3990	0.7826	1.0000	0.8275	0	0.099	1	0.442	0.337
	A_6	0	0	0	0	0	0.0006	1	0	0	0	1
	A_7	0	0	0	0	0	1	0.2246	0	0	0	1

Universiti Utara Malaysia

From Table 4.26, the WeSu-values describe the degree of relative importance of C_t to C_{t+1} for One-factor WeSuSFTS model. WeSu-value equals to 1 represents that the linguistic term of C_t is the most important linguistic term that contributes to corresponding linguistic term of C_{t+1}. Lower WeSu-value means less importance the linguistic term of C_t to C_{t+1}. Meanwhile, any WeSu-value equal to zero means that the linguistic term of C_t is not important to corresponding linguistic terms of C_{t+1}.

For example, by referring to the second row of Table 4.26, $W(A_2, B_1)$ is equal to 0.4702, $W(A_2, B_2)$ is equal to 0.1440, $W(A_2, B_3)$ is equal to 1, $W(A_2, B_4)$ is equal to 0.1377, and $W(A_2, B_j)$ $j = 5,6$ and 7 is equal to zero respectively. The WeSu-value from this example shows *medium decrease* of C_t (B_3) is the most important linguistic term that contribute to *large decrease* of C_{t+1} (A_2) due to WeSu-value equal to 1. Besides, *very large decrease* (B_1) is the second most important linguistic term. Meanwhile, *large decrease* (B_2) and *small decrease* (B_4) of C_t show less important contribute to (A_2). However, *very small decrease* (B_5), *no change* (B_6) and *very small increase* (B_7) of C_t are not important to *large decrease* of C_{t+1} (A_2).

Similar to Table 4.26, WeSu-values in Table 4.27 present the degree of relative importance of C_t and L_t to C_{t+1}. For example, from the first-row in Table 4.27, $W(A_1, B_3)$ is equal to 1, $W(A_1, B_4)$ is equal to 0.0941 and $W(A_1, B_j), j = 1,2,5,6$ and 7 is equal to zero. Meanwhile $W(A_1, C_1)$ is equal to 1 and $W(A_1, C_j), j = 2,3$ and 4 are equal to zero. The WeSu-value from this example shows *medium decrease* of C_t (B_3) is the most important contribution to *very large decrease* of C_{t+1} (A_1) compared to *small decrease* of C_t (B_4) and *very low* of L_t (C_1). Meanwhile, *very large decrease* (B_1), *large decrease* (B_2), *very small decrease* (B_5), *no change* (B_6)

and *very small increase* (B_7) of C_t and; *low* (C_2) *medium* (C_3) and *high* (C_4) of L_t are not importance to *very large decrease* of C_{t+1} (A_1).

4.4.7 Results of Step (7): Constructing WeSuSFTS Model

After performing Step (6) in Phase 2, the WeSuSFTS model is ready for MH-ELD forecasting. This section presents the results of applying One-factor and M-factor (M=2) WeSuSFTS forecasting algorithms to forecast MH-ELD.

4.4.7.1 One-factor WeSuSFTS Model for Forecasting MH-ELD

Figure 4.7 portrays the One-factor WeSuSFTS model, which consists of seven fuzzy reasoning rules related to seven fuzzy sets in C_{t+1}. Each rule is comprised of WeSu-value, as well as linguistic terms of independent and dependent variables. The WeSu-value serves as a multiplicative factor for the independent linguistic term. The value of multiplicative factors represents the degree of 'importance' of the independent linguistic terms towards the dependent linguistic terms.

Universiti Utara Malaysia

For instance, ***Rule 1*** consists of fuzzy linguistic terms B_3 and B_4 that contribute to A_1. Apparently, only two out of seven independent linguistic terms were integral to A_1. Thus, the interpretation of ***Rule 1*** is as follows: if *current percent changes* display *medium decrease* or *small decrease*, hence the *next day percent changes* will be *very big decrease*.

Rule 1: **IF** C_t is B_3 **OR** $0.0941B_4$
THEN C_{t+1} is A_1

Rule 2: **IF** C_t is $0.4702B_1$ **OR** $0.144B_2$ **OR** B_3 **OR** $0.1377B_4$
THEN C_{t+1} is A_2

Rule 3: **IF** C_t is $0.0377B_1$ **OR** $0.6573B_2$ **OR** $0.2309B_3$ **OR** B_4 **OR** $0.2309B_5$
THEN C_{t+1} is A_3

Rule 4: **IF** C_t is $0.1677B_1$ **OR** $0.2512B_2$ **OR** $0.3939B_3$ **OR** B_4 **OR** $0.64B_5$ **OR** $0.429B_6$
THEN C_{t+1} is A_4

Rule 5: **IF** C_t is $0.3930B_3$ **OR** $0.7826B_4$ **OR** B_5 **OR** $0.8275B_6$
THEN C_{t+1} is A_5

Rule 6: **IF** C_t is $0.0006B_6$ **OR** B_7
THEN C_{t+1} is A_6

Rule 7: **IF** C_t is B_6 **OR** $0.2246B_7$
THEN C_{t+1} is A_7

Figure 4.7. One-factor WeSuSFTS forecasting model

Universiti Utara Malaysia

By referring to One-factor WeSuSFTS model exhibited in Figure 4.7, the model interpretation is:

i. B_3 and B_4 are important to A_1
ii. B_1, B_2, B_3, and B_4 are important to A_2
iii. B_1, B_2, B_3, B_4, and B_5 are important to A_3
iv. B_1, B_2, B_3, B_4, B_5, and B_6 are important to A_4
v. B_3, B_4, B_5, and B_6 are important to A_5
vi. B_6 and B_7 are important to A_6 and A_7

Interestingly, the WeSuSFTS model revealed additional meaningful information. In the model, independent linguistic term was significant to dependent linguistic term. Again, from ***Rule 1*** in Figure 4.7 as an example, the contribution of B_4 was very small

as the multiplicative factor value was below 0.1. Hence, the most important independent linguistic term that contributed to A_1 was B_3. The value of 0.0941 as multiplicative factor of B_4 was interpreted as the ratio of B_4 that contributed to A_1, when compared to B_3.

Figure 4.8 illustrates the analysis of WeSu-value. Based on ***Rules 1*** and ***2***, B_3 emerged as the most important that contributed to A_1 and A_2, while ***Rules 3*** and ***4*** preferred B_4 as the most important to A_3 and A_4. Next, B_5, B_7, and B_6 were the most important to A_5, A_6, and A_7, respectively in ***Rules 5***, ***6***, and ***7***, respectively. The bar chart in Figure 4.8 demonstrates a comparative analysis among the weights in different rules. Obviously, amongst most of the fuzzy terms, C_t contributed to A_4, as shown in bar line of ***Rule 4***. Nevertheless, only one fuzzy term C_t contributed to A_6, as presented in bar line of ***Rule 6***.

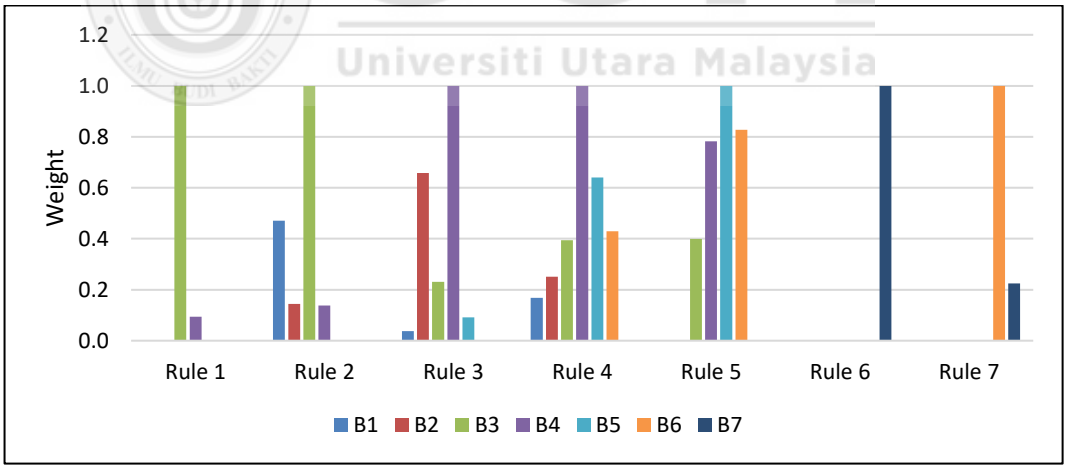


Figure 4.8. The fuzzy linguistic term weights in One-factor WeSuSFTS model

Consequently, the WeSuSFTS model was simplified by defining the 'cut value' first, and later constructing the simpler WeSuSFTS by removing the independent linguistic term with multiplicative factor value less than the 'cut value'. Hence, the WeSuSFTS model in Figure 4.7 was simplified to a new WeSuSFTS model, as displayed in Figure

4.9 with 0.1 ‘cut value’. However, this study focuses on WeSuSFTS without ‘cut value’.

Rule 1: **IF** C_t is B_3

THEN C_{t+1} is A_1

Rule 2: **IF** C_t is $0.4702B_1$ **OR** $0.144B_2$ **OR** B_3 **OR** $0.1377B_4$

THEN C_{t+1} is A_2

Rule 3: **IF** C_t is $0.6573B_2$ **OR** $0.2309B_3$ **OR** B_4 **OR** $0.0909B_5$

THEN C_{t+1} is A_3

Rule 4: **IF** C_t is $0.1677B_1$ **OR** $0.2512B_2$ **OR** $0.3939B_3$ **OR** B_4 **OR** $0.64B_5$ **OR** $0.429B_6$

THEN C_{t+1} is A_4

Rule 5: **IF** C_t is $0.3930B_3$ **OR** $0.7826B_4$ **OR** B_5 **OR** $0.8275B_6$

THEN C_{t+1} is A_5

Rule 6: **IF** C_t is B_7

THEN C_{t+1} is A_6

Rule 7: **IF** C_t is B_6 **OR** $0.2246B_7$

THEN C_{t+1} is A_7

Figure 4.9. Simpler WeSuSFTS model

Universiti Utara Malaysia

4.4.7.2 M-factor (M=2) WeSuSFTS Model for Forecasting MH-ELD

Figure 4.10 illustrates the M-factor (M=2) WeSuSFTS model, which consists of seven fuzzy reasoning rules related to four fuzzy sets in L_t, as well as seven fuzzy sets in C_t and C_{t+1}. Each rule comprises of weighted subsethood values and fuzzy linguistic terms of two independent and a dependent linguistic variable.

Rule 1: **IF** C_t is (B_3 **OR** 0.0941B_4)

AND L_t is C_1

THEN C_{t+1} is A_1

Rule 2: **IF** C_t is (0.4702B_1 **OR** 0.144B_2 **OR** B_3 **OR** 0.1377B_4)

AND L_t is (C_1 **OR** 0.4638C_2)

THEN C_{t+1} is A_2

Rule 3: **IF** C_t is (0.0377B_1 **OR** 0.6573B_2 **OR** 0.2309B_3 **OR** B_4 **OR** 0.0909B_5)

AND L_t is (C_1 **OR** 0.8541C_2 **OR** 0.9884C_3)

THEN C_{t+1} is A_3

Rule 4: **IF** C_t is (0.1677B_1 **OR** 0.2512B_2 **OR** 0.3939B_3 **OR** B_4 **OR** 0.64B_5 **OR** 0.429B_6)

AND L_t is (0.2007C_1 **OR** 0.3767C_2 **OR** C_3 **OR** 0.6856C_4)

THEN C_{t+1} is A_4

Rule 5: **IF** C_t is (0.3930B_3 **OR** 0.7826B_4 **OR** B_5 **OR** 0.8275B_6)

AND L_t is (0.0991C_1 **OR** C_2 **OR** 0.4419C_3 **OR** 0.3369C_4)

THEN C_{t+1} is A_5

Rule 6: **IF** C_t is (0.0006B_6 **OR** B_7)

AND L_t is C_4

THEN C_{t+1} is A_6

Rule 7: **IF** C_t is (B_6 **OR** 0.2246B_7)

AND L_t is C_4

THEN C_{t+1} is A_7

Figure 4.10. M-factor (M=2) WeSuSFTS forecasting model

Similar to the One-factor WeSuSFTS depicted in Section 4.4.7.1, the model in Figure 4.10 displays a similar way of interpretation. The variance lies in the additional element of the second factor incorporated into the model interpretation. For example, ***Rule 1*** is interpreted as follows: if *Current percent changes* have *medium decrease* or

Universiti Utara Malaysia

small decrease and if *Current load* is *very low*, hence the *next day percent changes* would have a *very big decrease*. By referring to the M-factor (M=2) WeSuSFTS forecasting model exemplified in Figure 4.10, the following outcomes may be interpreted:

i. B_3, B_4, and C_1 are important to A_1

ii. B_1, B_2, B_3, B_4, C_1, and C_2 are important to A_2

iii. B_1, B_2, B_3, B_4, B_5, C_1, C_2, and C_3 are important to A_3

iv. B_1, B_2, B_3, B_4, B_5, B_6, C_1, C_2, C_3, and C_4 are important to A_4

v. B_3, B_4, B_5, B_6, C_1, C_2, C_3, and C_4 are important to A_5

vi. B_6, B_7, and C_4 are important to A_6 and A_7

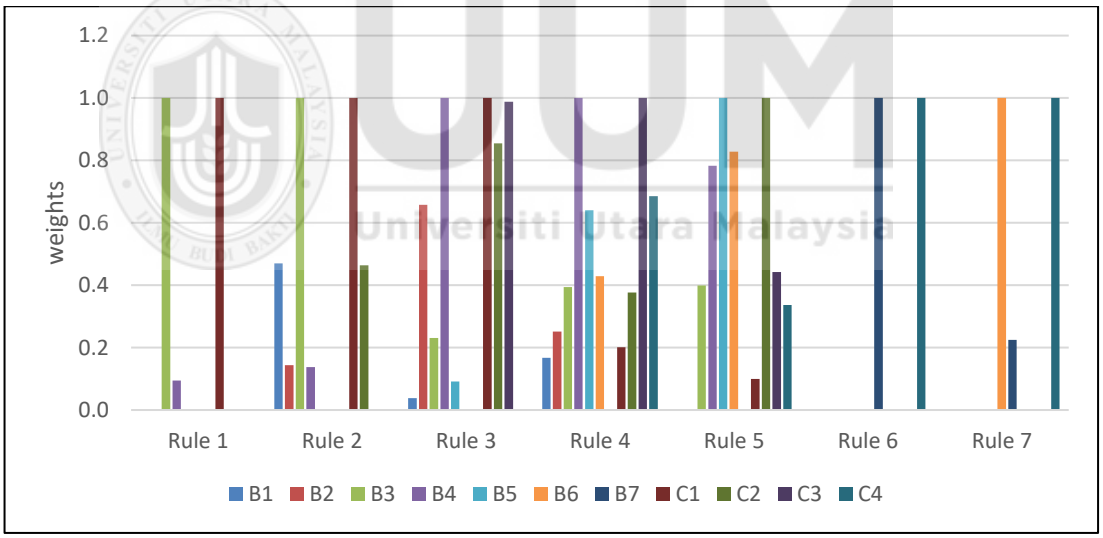


Figure 4.11. The fuzzy linguistic term weights in M-factor (M=2) WeSuSFTS model

Figure 4.11 illustrates the analysis of weights in M-factor (M=2) WeSuSFTS. The independent fuzzy linguistic term in each factor with the highest weighted subsethood value emerged as the most important fuzzy linguistic term that contributes to the dependent fuzzy linguistic term. Figure 4.11 shows that ***Rules 1*** and ***2*** evaluated B_3 and C_1 as the most important that contributed to A_1 and A_2, whereas ***Rule 3*** preferred

B_4 and C_1 as the most important to A_3. Next, B_4 and C_3 were the most important to A_4 in ***Rule 4***. In ***Rule 5***, B_5 and C_2 were the most important that contributed to A_5. Next, ***Rule 6*** outlined B_7 and C_4 as the most important for A_6 and B_6, while B_7 was the most important to A_7 in ***Rule 7***. The most important linguistic terms mentioned above were based on the highest weighted among fuzzy linguistic terms in C_t and L_t.

4.5 Results of Phase 3: Model Implementation

The implementation of the One-factor and M-factor (M=2) WeSuSFTS models were executed in this phase using the evaluation part of the data. Phase 3 consists of two steps which are:

Step (1): Defuzzifying fuzzy value into crisp value.

Step (2): Forecasting executing.

The following section presents the results.

Universiti Utara Malaysia

4.5.1 Results of Step (1): Defuzzifying Fuzzy Value into Crisp Value

The outputs of the WeSuSFTS models are of triangular fuzzy numbers. So, these fuzzy outputs should be defuzzified to become crisp values by using the defuzzifications method as explained in Chapter Three. The explanation and the examples of calculation of the defuzzification methods are shown in Section 3.5.1. This section divides the results of defuzzification into two; defuzzification results based on One-factor and M-factor (M=2) WeSuSFTS models.

4.5.1.1 One-factor WeSuSFTS Model

Different defuzzification methods generate different forecast values. Five defuzzification methods were applied in this study, including Center of Gravitity (COG), along with four new defuzzification methods, namely Average Rule defuzzification method 1 (AR_1), Average Rule defuzzification method 2 (AR_2), Average Rule defuzzification method 3 (AR_3), and Average Rule defuzzification method 4 (AR_4). The formulas of all the defuzzification methods derived from Equations (3.24) to (3.28), as depicted in Chapter Three. Basically, AR_1 to AR_4 were based on average value of peak point values at certain interval or rules. Table 4.28 and Figure 4.12 present the results of the actual and forecasted C_{t+1} values based on different defuzzification methods. Days 1-7 refer to MH week, wherein day 4 was HRA in year 2018.

As example of calculation AR_1, AR_2, AR_3 and AR_4 are available in Section 3.5.1 in Chapter Three. The following paragraph shows the calculation AR_1, AR_2, AR_3 and AR_4 WeSuSFTS models to forecast C_{t+1} at day 1 in evaluation part of data based on Figure 4.7.

Given that $C_t = 1.3449$, therefore, $\mu_{B_1} = 0$, $\mu_{B_2} = 0$, $\mu_{B_3} = 0$, $\mu_{B_4} = 0$, $\mu_{B_5} = 0$, $\mu_{B_6} = 0.3992$ and $\mu_{B_6} = 0.6008$. Based on Figure 4.6, the peak point of fuzzy set of C_{t+1} are $M_1 = -27.86$, $M_2 = -22.91$, $M_3 = -15.79$, $M_4 = -11.55$, $M_5 = -5.64$, $M_6 = -1.27$ and $M_7 = 2.81$. Therefore, based on Figure 4.7, the numeric value from rule calculation (R_i) are:

$$R_1 = \max[\mu_{B_3}, (0.0941)\mu_{B_4}] = \max[0, (0.0941)(0)]$$

$$= 0$$

$$R_2 = \max[\,(0.4702)\mu_{B_1}, (0.144)\mu_{B_2}, \mu_{B_3}, (0.1377)\mu_{B_4}]$$

$$= \max[(0.4702)(0), (0.144)(0), 0, (0.1377)(0)]$$

$$= 0$$

$$R_3 = \max[\,(0.0377)\mu_{B_1}, (0.6573)\mu_{B_2}, (0.2309)\mu_{B_3}, \mu_{B_4}, (0.0909)\mu_{B_5}]$$

$$= \max[(0.0377)(0), (0.6573)(0), (0.2309)(0), 0, (0.0909)(0)]$$

$$= 0$$

R_4

$$= \max[\,(0.1677)\mu_{B_1}, (0.2512)\mu_{B_2}, (0.3939)\mu_{B_3}, \mu_{B_4}, (0.6400)\mu_{B_5}, (0.4290)\mu_{B_6}]$$

$$= \max[(0.1677)(0), (0.2512)(0), (0.3939)(0), 0, (0.6400)(0), (0.4290)(0.3992)]$$

$$= 0.1713$$

$$R_5 = \max[\,(0.3930)\mu_{B_3}, (0.7826)\mu_{B_4}, \mu_{B_5}, (0.8275)\mu_{B_6}]$$

$$= \max[\,(0.3930)(0), (0.7826)(0), 0, (0.8275)(0.3992)]$$

$$= 0.3303$$

$$R_6 = \max[\,(0.0006)\mu_{B_6}, \mu_{B_7}] = \max[(0.0006)(0.3992), 0.6008]$$

$$= 0.6008$$

$$R_7 = \max[\,\mu_{B_6}, (0.2246)\mu_{B_7}] = \max[0.3992, (0.2246)(0.6008)]$$

$$= 0.3992.$$

The total number of rules is seven, while the values of R_1, R_2, and R_3 are equal to zero. therefore $n(u) = 4$ and $N(u) = 7$.

Hence,

Universiti Utara Malaysia

$$F_{AR_1}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{\sum_{i=1}^{7} M_i}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{(-27.86) + (-22.91) + (-15.79) + (-11.55) + (-5.64) + (-1.27) + 2.81}$$

$$= 0.042$$

$$F_{AR_2}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{\sum_{i=1}^{7} R_i}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{0 + 0 + 0 + 0.1713 + 0.3303 + 0.6008 + 0.3992}$$

$$= -2.319$$

$$F_{AR_3}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{N(u)}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{7}$$

$$= -0.498$$

$$F_{AR_4}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{n(u)}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{4}$$

$$= -0.871$$

Table 4.28 displays all the defuzzified values of percent changes of MH-ELD, C_{t+1} based on five defuzzification methods, COG, and four AR based methods, and the actual values of C_{t+1} for seven forecasted days. Figure 4.12 shows the corresponding graph to Table 4.28.

Universiti Utara Malaysia

Table 4.28

Comparison of C_{t+1} Actual and Forecasted Values from Five Defuzzification Methods

Day	Actual value C_{t+1}	Defuzzification methods				
		COG	**AR_1**	**AR_2**	**AR_3**	**AR_4**
1	-0.134	-2.841	0.042	-2.319	-0.498	-0.871
2	-7.738	-3.285	0.070	-2.840	-0.818	-1.431
3	-17.114	-11.920	0.212	-11.401	-2.489	-3.485
4	-20.968	-19.633	0.582	-20.251	-6.834	-9.568
5	-18.029	-17.885	0.288	-18.241	-3.384	-4.738
6	-17.318	-19.577	0.504	-20.094	-5.920	-8.288
7	-18.551	-19.633	0.561	-20.251	-6.593	-9.231

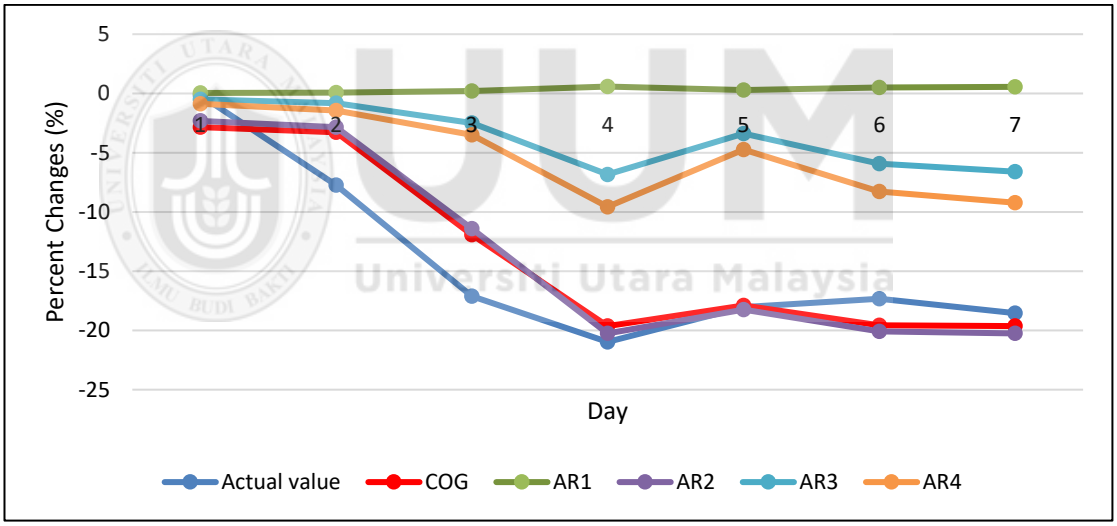


Figure 4.12. Actual and forecasted ELD percent changes values based on One-factor WeSuSFTS model.

Referring to Figure 4.12, the movement of the actual value for ELD *percent changes,* C_{t+1} in MH week decreased extremely from the first day to the fourth day, in which the fourth day was the MH. After that, the C_{t+1} movement increased gradually to the end of MH week or one can say that the movement was static at a range of -15% to -20%. Figure 4.12 graphically demonstrated that the COG defuzzification result was near similar to AR_2 defuzzification. This is because the center of the area value of

corresponding fuzzy sets in the COG defuzzification method is very close to the peak point value of corresponding fuzzy sets as used for the AR_2 defuzzification method. This happened due to the MH-ELD data used in this study produces a TMF that is almost symmetric based on Step (1) (Defining *U* and partitioning *U* into several intervals) and Step (2) (Defining fuzzy set) of Phase 2 in WeSuSFTS algorithms. Hence, these two defuzzification methods generated C_{t+1} forecasted values that were very close to the actual values. The outcomes from non-parametric Wilcoxson Signed Ranks statistical test showed that the difference between forecasted C_{t+1} value (based on AR_2 defuzzification method) and C_{t+1} actual value was insignificant at 0.05 significance level with *p*-value = 0.866.

Meanwhile, the forecasted C_{t+1} based on AR_1 defuzzification yielded the worst result. Although this study stated the AR defuzzification method as a distribution defuzzification group, but denominator of AR_1 is not a distribution form or not in interval form. While, the forecasted C_{t+1} values based on AR_3 and AR_4 defuzzification methods were near similar. This is because *N(u)* and *n(u)* value based on the rule's calculation were not of very large different.

4.5.1.2 M-factor (M=2) WeSuSFTS Model

The four defuzzification methods applied in this study were AR_1, AR_2, AR_3 and AR_4 based on Equations (3.24) to (3.27) respectively. The COG defuzzification method was omitted from this analysis due to the very close values displayed by COG and AR_2 which did not reveal any significant difference, as depicted in Section 4.5.1.1. Table 4.29 and Figure 4.13 present the actual and forecasted C_{t+1} values based on different defuzzification methods. Days 1-7 refer to MH week, while day 4 was HRA.

The following paragraph shows the calculation C_{t+1} forecasted value at day 1 in evaluation part by using the four defuzzification methods based on M-factor (M=2) WeSuSFTS model.

Given that $C_t = 1.3449$, therefore, $\mu_{B_1} = 0$, $\mu_{B_2} = 0$, $\mu_{B_3} = 0$, $\mu_{B_4} = 0$, $\mu_{B_5} = 0$, $\mu_{B_6} = 0.3992$ and $\mu_{B_6} = 0.6008$. Given $L_t = 17934$, then $\mu_{C_1} = 0$, $\mu_{C_2} = 0$, $\mu_{C_3} = 0$, $\mu_{C_4} = 1$. Based on Figure 4.6, the peak point of fuzzy set in C_{t+1} were $M_1 = -27.86$, $M_2 = -22.91$, $M_3 = -15.79$, $M_4 = -11.55$, $M_5 = -5.64$, $M_6 = -1.27$ and $M_7 = 2.81$. Therefore, based on Figure 4.10, the numeric value from rule calculation (R_i) are:

$$R_1 = \min\{\max[\mu_{B_3}, (0.0941)\mu_{B_4}], \max[\mu_{C_1}]\}$$
$$= \min\{\max[0, (0.0941)(0)], \max[(0)]\}$$
$$= 0$$

$$R_2$$
$$= \min\{\max[(0.4702)\mu_{B_1}, (0.144)\mu_{B_2}, \mu_{B_3}, (0.1377)\mu_{B_4}], \max[\mu_{C_1}, (0.4638)\mu_{C_2}]\}$$
$$= \min\{\max[(0.4702)(0), (0.144)(0), 0, (0.1377)(0)], \max[(0), (0.4638)(0)]\}$$
$$= 0$$

$$R_3 = \min\begin{Bmatrix}\max[(0.0377)\mu_{B_1}, (0.6573)\mu_{B_2}, (0.2309)\mu_{B_3}, \mu_{B_4}, (0.0909)\mu_{B_5}], \\ \max[\mu_{C_1}, (0.8541)\mu_{C_2}, (0.9884)\mu_{C_3}]\end{Bmatrix}$$

$$= \min\begin{Bmatrix}\max[(0.0377)(0), (0.6573)(0), (0.2309)(0), 0, (0.0909)(0)], \\ \max[0, (0.8541)(0), (0.9884)(0)]\end{Bmatrix}$$

$$= 0$$

Universiti Utara Malaysia

R_4

$$= \min\begin{Bmatrix}\max\left[(0.1677)\mu_{B_1}, (0.2512)\mu_{B_2}, (0.3939)\mu_{B_3}, \mu_{B_4}, (0.6400)\mu_{B_5}, (0.4290)\mu_{B_6}\right], \\ \max\left[(0.2007)\mu_{C_1}, (0.3767)\mu_{C_2}, \mu_{C_3}, (0.6856)\mu_{C_4}\right]\end{Bmatrix}$$

$$= \min\begin{Bmatrix}\max[(0.1677)(0), (0.2512)(0), (0.3939)(0), 0, (0.6400)(0), (0.4290)(0.3992)], \\ \max[(0.2007)(0), (0.3767)(0), 0, (0.6856)(1)]\end{Bmatrix}$$

$$= 0.1713$$

$$R_5 = \min\begin{Bmatrix}\max\left[(0.3930)\mu_{B_3}, (0.7826)\mu_{B_4}, \mu_{B_5}, (0.8275)\mu_{B_6}\right], \\ \max\left[(0.0991)\mu_{C_1}, \mu_{C_2}, (0.4419)\mu_{C_3}, (0.3369)\mu_{C_4}\right]\end{Bmatrix}$$

$$= \min\begin{Bmatrix}\max[(0.3930)(0), (0.7826)(0), 0, (0.8275)(0.3992)], \\ \max[(0.0991)(0), 0, (0.4419)(0), (0.3369)(1)]\end{Bmatrix}$$

$$= 0.3303$$

$$R_6 = \min\{\max\left[(0.0006)\mu_{B_6}, \mu_{B_7}\right], \max\left[\mu_{C_4}\right]\}$$

$$= \min\{\max[(0.0006)(0.3992), 0.6008], \max[1]\}$$

$$= 0.6008$$

$$R_7 = \min\{\max\left[\mu_{B_6}, (0.2246)\mu_{B_7}, \right], \max\left[\mu_{C_4}\right]\}$$

$$= \min\{\max[0.3992, (0.2246)(0.6008),], \max[1]\}$$

$$= 0.3992$$

From the rule calculations, the total rules is seven $(R_i, i = 1 \text{ to } 7)$, and the values of R_1, R_2, R_3 are equal to zero, therefore $n(u) = 4$ and $N(u) = 7$.

Hence,

$$F_{AR_1}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{\sum_{i=1}^{7} M_i}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{(-27.86) + (-22.91) + (-15.79) + (-11.55) + (-5.64) + (-1.27) + 2.81}$$

$$= 0.042$$

$$F_{AR_2}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{\sum_{i=1}^{7} R_i}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{0 + 0 + 0 + 0.1713 + 0.3303 + 0.6008 + 0.3992}$$

$$= -2.319$$

$$F_{AR_3}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{N(u)}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{7}$$

$$= -0.498$$

$$F_{AR_4}(day\ 1) = \frac{\sum_{i=1}^{7} R_i M_i}{n(u)}$$

$$= \frac{\begin{matrix}(0)(-27.86) + (0)(-22.91) + (0)(-15.79) + (0.1713)(-11.55) + \\ (0.3303)(-5.64) + (0.6008)(-1.27) + (0.3992)(2.81)\end{matrix}}{4}$$

$$= -0.871$$

Table 4.29 summarizes the actual and forecasted percent changes of MH-ELD, C_{t+1} values from four defuzzification methods based on M-factor (M=2) WeSuSFTS model.

Universiti Utara Malaysia

Table 4.29

Comparison of C_{t+1} Actual and Forecasted Values from Four Defuzzification Methods in M-factor (M=2) WeSuSFTS

Day	Actual value C_{t+1}	Defuzzification method			
		AR_1	AR_2	AR_3	AR_4
1	-0.140	0.042	-2.319	-0.498	-0.871
2	-7.738	0.0471	-2.303	-0.553	-0.968
3	-17.113	0.168	-11.269	-1.969	-4.595
4	-20.968	0.107	-10.617	-1.254	-2.194
5	-18.029	0.199	-15.807	-2.342	-4.098
6	-17.318	0.317	-17.999	-3.719	-5.207
7	-18.551	0.354	-18.627	-4.153	-5.814

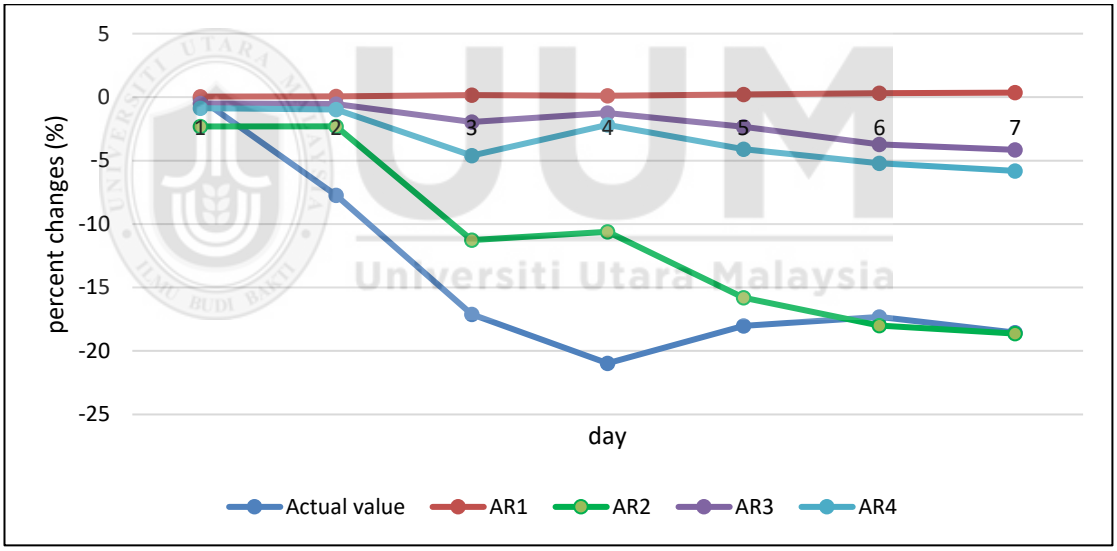


Figure 4.13. Actual and forecasted ELD percent changes values based on M-factor (M=2) WeSuSFTS model

Figure 4.13 graphically illustrates that the forecasted value from AR_2 defuzzification method yielded the nearest values to the actual ones, when compared to AR_1, AR_3, and AR_4. The forecasted value trend from AR_2 defuzzification method adhered to the actual value time series trend. The forecasted C_{t+1} based on AR_1 defuzzification

method gave the worst result, whereas the forecasted C_{t+1} values based on AR_1, AR_3, and AR_4 defuzzification methods appeared close to each other.

Since AR_2 defuzzification method yielded the nearest values to the actual ones, this study analyzes the property of AR_2 defuzzification method by robustness criteria based on Leekwijck and Kerre (1999) numerically. A small variation in any of the degrees of membership should not result in a big change in the defuzzification value (Leekwijck & Kerre, 1999). This means that a small variation of any of the input parameter in defuzzification formula should only result in small changes of the output.

Table 4.30

Changes of MSE

Data set	1 increment	1 decrement	0.5 increment	0.5 decrement
A	0.11	0.20	0.07	0.20
B	0.10	0.20	0.06	0.09
C	0.31	0.25	0.15	0.13
D	0.77	0.69	0.37	0.36
E	1.07	0.97	0.52	0.50
F	0.03	0.07	0.02	0.02
G	0.47	0.39	0.22	0.20

Table 4.30 shows the results of MSE changes for seven data set (A, B, …., G) due to the existence of seven peak point (M) in TMF of dependent variable. Small changes of peak point had been conducted on each input with increment and decrement of 1 and 0.5 respectively, show that the changes of MSE was less than 1.1. This means that small variation in the input contributes to a small changes of the output for the proposed AR_2 defuzzifications. Hence AR_2 defuzzification method is robust.

Universiti Utara Malaysia

4.5.2 Results of Step (2): Forecasting Execution

The ELD forecasted values in MH week were calculated using Equation (3.30), as depicted in Chapter Three.

$$\hat{y}_{t+1} = y_t + \left(\frac{F}{100} \times y_t\right) \tag{3.30}$$

Where $\hat{y}_{t+1}$ is the next day ELD forecasted value, y_t denotes the actual previous ELD for the same type of day in prototype week, and *F* signifies the forecasted next day percentage changes obtained from Step (1) (Defuzzifying fuzzy value to crisp value) in Phase 3 of the WeSuSFTS algorithm; regardless of One-factor or M-factor (M=2) WeSuSFTS model. The results are presented in the next sections.

4.5.2.1 One-factor WeSuSFTS Model

The MH-ELD forecasted values are tabulated in Table 4.31 and Figure 4.14. Based on Figure 4.14, the time series pattern was similar to that of Figure 4.13. All the ELD forecasted values from the four defuzzification methods gradually decreased from the first to the sixth day, and later increased on the seventh day; similar to the actual value time series pattern. Interestingly, all MH-ELD forecasted values from all the defuzzification methods were close to the actual values for day 1. Nonetheless, referring to Figure 4.14 (exclusion of COG defuzzification method), the proposed defuzzification method (AR_2) yielded a graph near similar to the actual MH-ELD. It reveals that the AR_2 defuzzification method performed well to defuzzify the fuzzy output based on WeSuSFTS algorithm for One-factor WeSuSFTS model. It is due to the robustness of AR_2 method.

Universiti Utara Malaysia

The example calculation to obtain the results in Table 4.31 are as follows. Based on results in Table 4.28, by using Equation (3.29), forecasted MH-ELD day 1 are as follows.

$$\hat{y}_{COG,day1} = y_t + \left(\frac{F_{COA}}{100} \times y_t\right) = 17921 + \left(\frac{-2.841}{100} \times 17921\right) = 17411.864$$

$$\hat{y}_{AR_1,day1} = y_t + \left(\frac{F_{AR_1}}{100} \times y_t\right) = 17921 + \left(\frac{0.042}{100} \times 17921\right) = 17928.527$$

$$\hat{y}_{AR_2,day1} = y_t + \left(\frac{F_{AR_2}}{100} \times y_t\right) = 17921 + \left(\frac{-2.319}{100} \times 17921\right) = 17505.412$$

$$\hat{y}_{AR_3,day1} = y_t + \left(\frac{F_{AR_3}}{100} \times y_t\right) = 17921 + \left(\frac{-0.498}{100} \times 17921\right) = 17831.753$$

$$\hat{y}_{AR_4,day1} = y_t + \left(\frac{F_{AR_4}}{100} \times y_t\right) = 17921 + \left(\frac{-0.871}{100} \times 17921\right) = 17764.908$$

Where $\hat{y}_{COG,day1}$, $\hat{y}_{AR_1,day1}$, $\hat{y}_{AR_2,day1}$, $\hat{y}_{AR_3,day1}$ and $\hat{y}_{AR_4,day1}$ are the MH-ELD forecasted value for day 1 based on COG, AR_1, AR_2, AR_3 and AR_4 defuzzification methods respectively. y_t is the previous actual ELD value on the same day-type (Sunday, Monday, Tuesday, …, Saturday) as the forecasted day. F_{COA}, F_{AR_1}, F_{AR_2}, F_{AR_3} and F_{AR_4} are the forecasted *percent changes* value based on COG, AR_1, AR_2, AR_3 and AR_4.

Universiti Utara Malaysia

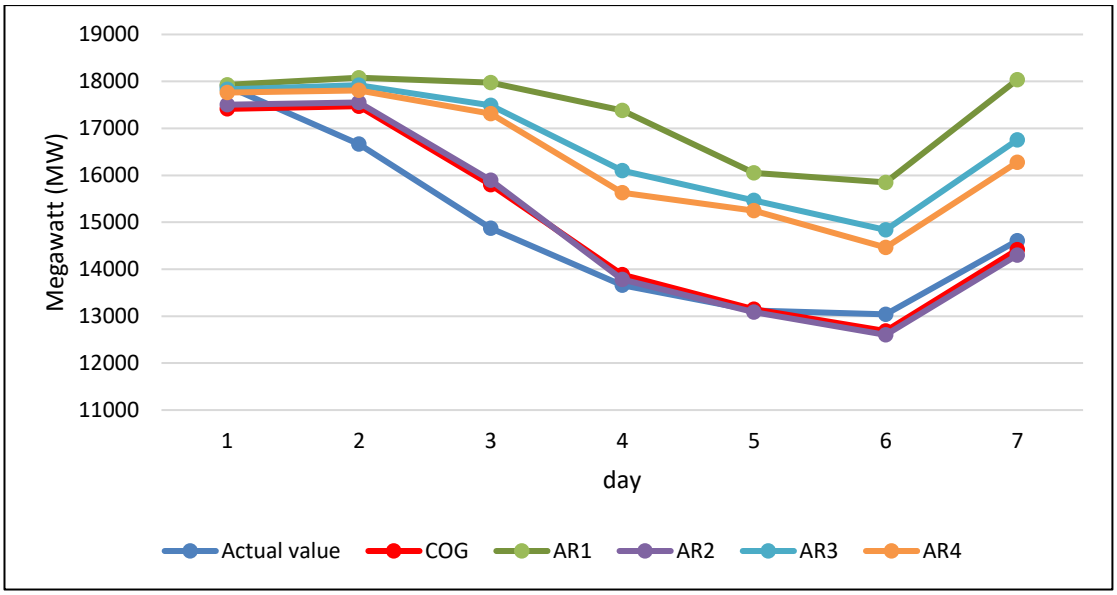


Figure 4.14. Actual and forecasted ELD values based on One-factor WeSuSFTS model

Universiti Utara Malaysia

Table 4.31

Comparison of Actual and Forecasted ELD Values from Five Defuzzification Methods

Day	Actual value ELD	Defuzzification methods				
		COG	$\mathbf{AR_1}$	$\mathbf{AR_2}$	$\mathbf{AR_3}$	$\boldsymbol{AR_4}$
1	17896.000	17411.864	17928.527	17505.412	17831.753	17764.908
2	16668.000	17472.604	18078.576	17551.472	17918.268	17807.469
3	14869.000	15800.635	17977.009	15893.810	17492.507	17313.910
4	13656.000	13886.562	17379.521	13779.782	16098.168	15625.835
5	13122.000	13144.937	16054.117	13088.038	15466.258	15249.562
6	13039.000	12682.739	15849.4713	12601.261	14836.439	14463.015
7	14607.000	14412.964	18034.659	14302.136	16751.549	16278.569

Universiti Utara Malaysia

4.5.2.2 M-factor (M=2) WeSuSFTS Model

The forecasted ELD values based on M-factor (M=2) WeSuSFTS model are presented in Table 4.32 and Figure 4.15. Based on Figure 4.15, all ELD forecasted values from all the defuzzification methods were close to the actual values for day 1. The ELD forecasted values based on AR_2 defuzzification method were very close to the actual ELD values for days 1, and 5-7. The difference between ELD actual values and AR_2 forecasted values was insignificant at 0.05 significance level based on Wilcoxson Rank Signed non-parametric statistical test with *p*-value = 0.237.

The example calculation to obtain the results in Table 4.32 are as follows. Based on results in Table 4.29, by using Equation (3.29) to find forecasted MH-ELD day 7 are as follows.

$$\hat{y}_{AR_1,day7} = y_t + \left(\frac{F_{AR_1}}{100} \times y_t\right) = 17934 + \left(\frac{0.354}{100} \times 17934\right) = 17997.486$$

$$\hat{y}_{AR_2,day7} = y_t + \left(\frac{F_{AR_2}}{100} \times y_t\right) = 17934 + \left(\frac{-18.627}{100} \times 17934\right) = 14593.434$$

$$\hat{y}_{AR_3,day7} = y_t + \left(\frac{F_{AR_3}}{100} \times y_t\right) = 17934 + \left(\frac{-4.153}{100} \times 17934\right) = 17189.201$$

$$\hat{y}_{AR_4,day7} = y_t + \left(\frac{F_{AR_4}}{100} \times y_t\right) = 17934 + \left(\frac{-5.814}{100} \times 17934\right) = 16891.317$$

Where $\hat{y}_{AR_1,day7}$, $\hat{y}_{AR_2,day7}$, $\hat{y}_{AR_3,day7}$ and $\hat{y}_{AR_4,day7}$ are the MH-ELD forecasted value for day 7 based on AR_1, AR_2, AR_3 and AR_4 defuzzification methods respectively. Since the day-type of forecasted day at day 7, $\hat{y}_{day7}$ is Monday, then, y_t is the previous actual ELD value on Monday of prototype week. F_{AR_1}, F_{AR_2}, F_{AR_3} and F_{AR_4} is the forecasted percent changes value based on AR_1, AR_2, AR_3 and AR_4.

Universiti Utara Malaysia

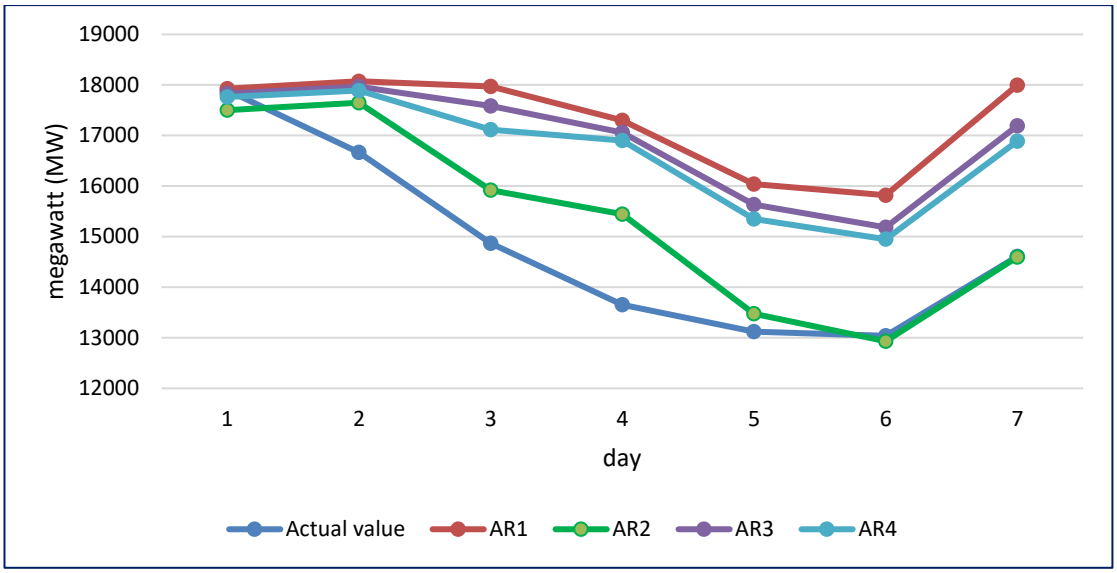


Figure 4.15. Actual and forecasted ELD values based on M-factor (M=2) WeSuSFTS model

Universiti Utara Malaysia

Table 4.32

Comparison of Actual and Forecasted ELD Values from Four Defuzzification Methods Based on M-factor (M=2) WeSuSFTS Model

Day	Actual value ELD	Defuzzification methods			
		$\mathbf{AR_1}$	$\mathbf{AR_2}$	$\mathbf{AR_3}$	$\mathbf{AR_4}$
1	17896	17928.527	17505.412	17831.753	17764.908
2	16668	18074.512	17649.898	17966.035	17891.062
3	14869	17969.082	15917.379	17585.704	17114.643
4	13656	17297.449	15444.461	17062.331	16899.829
5	13122	16039.916	13477.633	15633.176	15352.057
6	13039	15819.937	12931.580	15183.525	14948.935
7	14607	17997.486	14593.434	17189.201	16891.317

Universiti Utara Malaysia

4.6 Results of Phase 4: Model Evaluation

In this step, both forecasting error and absolute percentage forecasting error (APE) were calculated for seven data points in the evaluation part. After that, MAPE, MSE, and RMSE were determined using Equations (3.31) to (3.34) for each WeSuSFTS model with different defuzzification methods and other conventional FTS models. Models proposed by Chen (1996) and Cheng et al. (2008) were adopted in this study, whereby Chen and Cheng's models represented the conventional non-weighted and weighted FTS models, respectively. The results of MH-ELD Chen and Cheng forecasting models are shown in Appendix D. Since the results from Steps (1) and (2) of this phase can be presented in a continuous manner and also very related, the discussion of the results is not segregated into different sections.

Table 4.33 tabulates the forecasting error results derived from One-factor WeSuSFTS model. The defuzzification method recorded the smallest forecasting error measurements value, thus emerging as the best One-factor WeSuSFTS model. Based on Table 4.33, the lowest MAPE, MSE, and RMSE derived from COG defuzzification method, and followed by AR_2, AR_3, AR_4 and AR_1 defuzzification methods. Nonetheless, the proposed defuzzification method, AR_2, appeared to be the best among other proposed defuzzification methods with difference in MAPE by 0.181% only with COG (2.998-2.817%). Table 4.33 shows the consistency of AR_2 results from day 1 to day 7 compared to AR_3, AR_4 and AR_1. Thus, AR_2 emerged as the best defuzzification method in One-factor WeSuSFTS algorithm, when compared to the other defuzzification methods in forecasting the first day of MH event, whereby the fourth day in the MH week was HRA day 1, since the APE value was the lowest among others by only 0.9064%.

Table 4.33

Absolute Percentage Error (APE) for Five Defuzzification Methods and Other Forecasting Error Measurement Results for One-factor WeSuSFTS Model

Day	Defuzzification methods				
	COG	**AR_1**	**AR_2**	**AR_3**	**AR_4**
1	2.705	0.182	2.183	0.359	0.7321
2	4.827	8.463	5.300	7.501	6.8363
3	6.266	20.903	6.892	17.644	16.4430
4	1.688	27.267	0.906	17.884	14.4247
5	0.175	22.345	0.259	17.865	16.2137
6	2.732	21.554	3.357	13.785	10.9212
7	1.328	23.466	2.087	14.682	11.4436
Max-APE	6.266	27.267	6.892	17.865	16.4430
Min-APE	0.175	0.182	0.259	0.359	0.7321
MAPE	2.817	17.740	2.998	12.817	11.0021
MSE	281134.56	7680001.97	326338.23	3962811.64	2931695.08
RMSE	530.22	2771.28	571.26	1990.68	1712.22

Universiti Utara Malaysia

Similarly, the forecasting error measurements in M-factor (M=2) WeSuSFTS models were compared between different defuzzification methods. Here, the COG defuzzification method was again excluded as it turned out to be the best scheme in One-factor WeSuSFTS algorithm. Besides, the MAPE between COG and AR_2 were very close. Hence, it was sufficient to implement M-factor (M=2) WeSuSFTS with AR_2 alone.

By referring to Table 4.34, the best performance of M-factor (M=2) WeSuSFTS model was exerted by the algorithm of M-factor (M=2) WeSuSFTS with AR_2 as defuzzification method with the lowest MAPE (4.550%), and followed by 13.458% WeSuSFTS with AR_3 defuzzification method. Similar to One-factor WeSuSFTS, the M-factor (M=2) WeSuSFTS algorithm with AR_2 defuzzification method successfully

yielded the desired forecasting results, when compared to other defuzzification methods tested in this study. The model gave the lowest forecasting error for the first day of MH that fell on the fourth day in MH week.

Table 4.34

Absolute Percentage Error (APE) and Other Forecasting Error Measurements for Four Defuzzification Methods for M-factor (M=2) WeSuSFTS

Day	Defuzzification methods			
	$\mathbf{AR_1}$	$\mathbf{AR_2}$	$\mathbf{AR_3}$	$\mathbf{AR_4}$
1	0.182	2.183	0.359	0.732
2	8.438	5.891	7.788	7.338
3	20.849	7.051	18.271	15.103
4	26.666	13.097	24.944	23.754
5	22.237	2.710	19.137	16.995
6	21.328	0.824	16.447	14.648
7	23.211	0.093	17.679	15.640
Max-APE	26.666	13.097	24.944	23.754
Min-APE	0.182	0.093	0.359	0.732
MAPE	17.559	4.550	14.946	13.458
MSE	7513245.93	793227.58	5463686.33	4416844.98
RMSE	2741.03	890.63	2337.45	2101.63

Universiti Utara Malaysia

Table 4.35 and Figure 4.16 display the actual and forecasted ELD values from the proposed model and the conventional FTS models. The ELD forecasted values were obtained from One-factor WeSuSFTS with COG and AR_2 defuzzification methods, M-factor (M=2) WeSuSFTS with AR_2 defuzzification method, and two conventional FTS models (Chen and Cheng's models). Based on the pattern analysis displayed in Figure 4.16, all the FTS models adhered to the actual ELD pattern. However, the proposed model yielded a trend that was closer to the actual trend, when compared to the conventional FTS models.

Table 4.35

The Actual and Forecasted ELD Values Based on Three Proposed FTS Models and Two Conventional FTS Models

Day	Actual value ELD	FTS model				
		One-factor WeSuSFTS-COG	One-factor WeSuSFTS-AR_2	M-factor (M=2) WeSuSFTS-AR_2	Chen	Cheng
1	17896	17411.900	17505.390	17505.412	16384.274	16384.274
2	16668	17472.604	17551.472	17649.898	16055.254	16055.254
3	14869	15800.635	15893.810	15917.379	16400.731	16400.731
4	13656	13886.562	13779.782	15444.461	14368.353	14177.420
5	13122	13144.937	13088.038	13477.633	13795.694	13652.156
6	13039	12682.739	12601.261	12931.580	13113.544	12939.285
7	14607	14412.964	14302.136	14593.434	14913.018	14714.847

Universiti Utara Malaysia

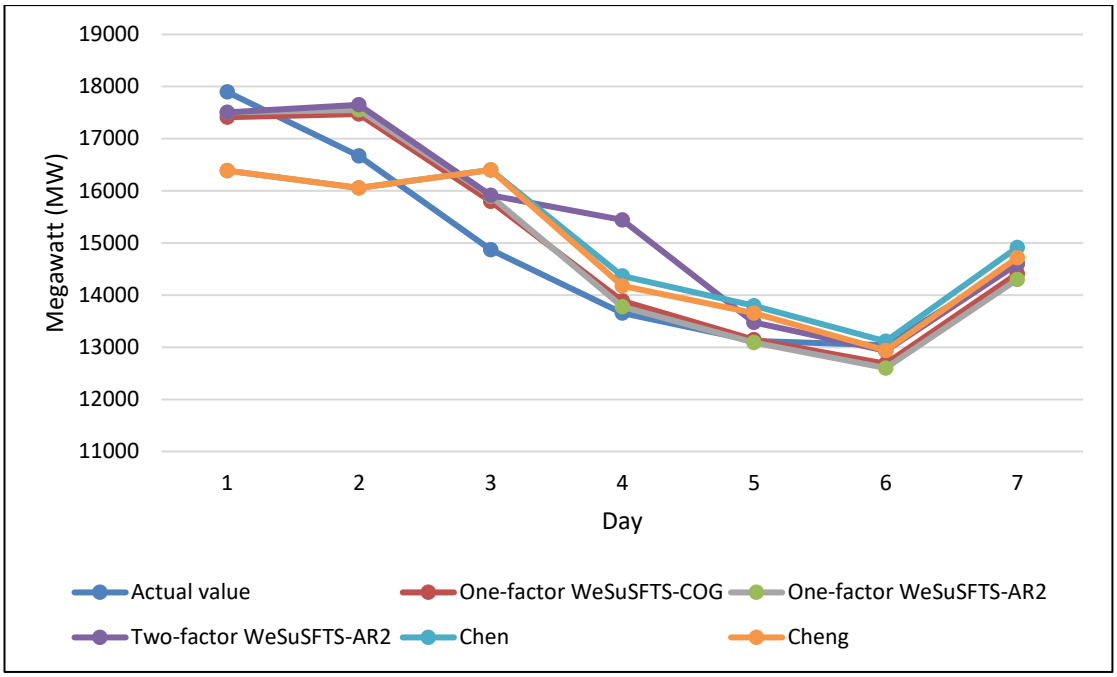


Figure 4.16. Comparison of actual and forecasted ELD values based on three proposed FTS models and two conventional FTS models

Referring to Table 4.36, the best performance of WeSuSFTS model was provided by One-factor WeSuSFTS-COG with the lowest MAPE (2.817%), and followed by 2.998% One-factor WeSuSFTS with the new AR_2 method of defuzzification. Nonetheless, the APE value for day 4 was the lowest based on AR_2, in which day 4 was the first day of MH. Hence, the difference in MAPE values between COG and AR_2 was only 0.181%, which was not huge. Furthermore, the AR_2 defuzzification method is way simpler than COG calculation in term of computationally inexpensive and easy to implement. In other words, AR_2 only requires numeric value from each rule, R_i, by using weighted value and min-max operator; and peak points values of its respective fuzzy output. Compared to COG, it is necessary to find the center of fuzzy sets area and the geometric center of each area. The AR_2 would be chosen as the defuzzification method of WeSuSFTS algorithm, and as a whole the proposed WeSuSFTS algorithm appeared to be successful in yielding the desired forecasting outputs especially for the MH-ELD.

Universiti Utara Malaysia

Table 4.36

FTS Models Performance Results

Day	FTS model				
	One-factor WeSuSFTS-COG	**One-factor WeSuSFTS-AR_2**	**M-factor (M=2) WeSuSFTS-AR_2**	**Chen**	**Cheng**
1	2.705	2.183	2.183	8.447	8.447
2	4.827	5.300	5.891	3.676	3.676
3	6.266	6.892	7.051	10.302	10.302
4	1.688	0.906	13.097	5.216	3.818
5	0.175	0.259	2.710	5.134	4.040
6	2.732	3.357	0.824	0.572	0.765
7	1.328	2.087	0.093	2.095	0.738
Max-APE	6.266	6.892	13.097	10.302	10.302
Min-APE	0.175	0.259	0.093	0.572	0.738
MAPE	2.817	2.998	4.550	5.063	4.541
MSE	281134.6	326338.23	73227.6	866783.6	797355.6
RMSE	530.22	571.26	890.63	931.01	892.95

Universiti Utara Malaysia

4.7 Summary

In order to solve some MH-ELD forecasting problems stipulated in Chapter One, this chapter presents the results of this study phase-by-phase, as detailed in the methodology chapter. The study objectives have been met through the successful implementation of the proposed algorithm. As a summary, this chapter outlines the results of WeSuSFTS forecasting algorithm implemented into nine models;

i. One-factor WeSuSFTS with COG defuzzification method

ii. One-factor WeSuSFTS with AR_1 defuzzification method

iii. One-factor WeSuSFTS with AR_2 defuzzification method

iv. One-factor WeSuSFTS with AR_3 defuzzification method

v. One-factor WeSuSFTS with AR_4 defuzzification method

vi. M-factor (M=2) WeSuSFTS with AR_1 defuzzification method

vii. M-factor (M=2) WeSuSFTS with AR_2 defuzzification method

viii. M-factor (M=2) WeSuSFTS with AR_3 defuzzification method

ix. M-factor (M=2) WeSuSFTS with AR_4 defuzzification method

Initially, the first phase in the WeSuSFTS algorithm had successfully extracted the essential features and patterns of MH-ELD. This was accomplished by reviewing the prototype and MH-ELD weeks, as well as the general performances of ELD variation by percentage changes in data and data presentation, which had been better when compared to the algorithms excluded from this phase.

Universiti Utara Malaysia

Phase 2 consists of the main body of the proposed FTS forecasting algorithm. The WeSuSFTS model in this study was built based on the weighted subsethood algorithm, which appeared to be the main difference between the proposed algorithm and the other FTS algorithms. The proposed WeSuSFTS algorithm is composed of two-stage forecasting approach, as elaborated in Phase 3. The first stage of forecasting is to forecast C_{t+1} using the WeSuSFTS model, and the second stage of forecasting is to forecast the MH-ELD based on the initial forecasted value, the forecasted percent changes of MH-ELD, C_{t+1}. The results showed that the forecasted C_{t+1} aided the WeSuSFTS MH-ELD forecasting model to achieve better performance.

In Phase 4, the advantage of using WeSuSFTS models with AR_2 defuzzification method seemed to be far from overwhelming, when compared to the WeSuSFTS models with COG defuzzification method. However, it is still a promising preliminary outcome in the future. In a nutshell, the One-factor WeSuSFTS forecasting algorithm with COG defuzzification emerged as the best WeSuSFTS forecasting algorithm to forecast MH-ELD.

Based on the results presented in this chapter, the following have been summarised:

i. The WeSuSFTS model offers some meaningful independent fuzzy linguistic terms relationship, such as the important and the most important fuzzy linguistic terms that contribute to the dependent fuzzy linguistic term. This study has highlighted the strength of the fuzzy relationship.

ii. Different defuzzification methods yielded different forecasted results for the same problem.

iii. Different types of WeSuSFTS forecasting models with the same defuzzification method gave different forecasted results.

iv. The One-factor WeSuSFTS forecasting model had successfully outperformed the M-factor (M=2) WeSuSFTS forecasting model due to smaller error. The second factor, current ELD (L_t) in this study did not contribute to increase the model accuracy. There are reasons that require further investigation for future research, for example, by using different variable selection mechanism, or by selecting and deciding different number of intervals in U.

Universiti Utara Malaysia

v. The forecasting error value from the AR_2 defuzzification method is very close to the forecasting error value from the COG defuzzification method with difference 0.181% only. This is because the center of the area value of corresponding fuzzy sets in the COG defuzzification method is very close to the peak point value of corresponding fuzzy sets in the AR_2 defuzzification method. However, one has to bear in mind that AR_2 is a lot simpler in calculation since it only requires to find the numeric value from each rule (R_i), compared to find the corresponding fuzzy set area in COG defuzzification method.

It can be concluded that the enhanced FTS algorithm proposed in this study can be used as an MH-ELD forecasting model with limited MH, nonlinear, and uncertain data. The algorithm used to construct the WeSuSFTS model may be used as an alternative method to extract and to reduce the number of rules in fuzzy reasoning model (Handoyo, 2018; Handoyo et al., 2018).

Referring to the results presented in this chapter, the WeSuSFTS forecasting algorithm had successfully produce both One-factor and M-factor (M=2) WeSuSFTS models with encouraging outcomes. The MAPE value for first-order WeSuSFTS model was below that of M-factor (M=2) WeSuSFTS model, which were 2.998% and 4.550%, respectively. This finding indicates that a simpler model is the best when compared to the other complicated ones. Upon comparing the first-order and high-order WeSuSFTS models, varied outcomes may be yielded. Besides, the comparison between One-factor and high-factors WeSuSFTS models may produce differing outputs. This stems from FTS sensitivity, as mentioned in prior investigations (Duru & Yoshida, 2012; Hauwa, 2012). Some of the factors mentioned above are the number

of fuzzy sets and the number of interval length. This clearly demonstrates that the WeSuSFTS algorithm initiates a new opportunity for WeSuSFTS modelling. Thesis conclusion, further research endeavours, and some shortcomings of this study are presented in the next chapter.

Universiti Utara Malaysia

CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This research is primarily concerned with the enhancement of fuzzy time series (FTS) forecasting algorithm to forecast moving holiday electricity load demand (MH-ELD) by using weighted fuzzy subsethood based algorithm (WSBA). The main contribution and the impact of the thesis is summarized in this chapter. Furthermore, some suggestions for future potential works to be explored are also introduced.

5.2 Research Contribution

This research has achieved the overall research objectives of constructing new modified FTS forecasting algorithm to forecast MH-ELD by considering WSBA. This thesis includes the following contributions:

Universiti Utara Malaysia

5.2.1 Theoretical Contribution

Three contributions were highlighted in theoretical as follow:

- **Weighted Subsethood Segmented Fuzzy Time Series (WeSuSFTS) forecasting algorithm**

In Chapter Three, WeSuSFTS forecasting algorithm has been developed as an enhancement of the idea of FTS conventional algorithms by allowing the segmented FTS data and WSBA in constructing the FTS forecasting model. It has been proven that the WeSuSFTS forecasting algorithm is able to implement One-factor and M-factor segmented FTS as presented in Chapter Four. Basically, the WeSuSFTS

forecasting algorithm has contributed to the construction of weighted fuzzy subsethood value into a form of multiplicative factor in meaningful FTS model.

- **MH-ELD FTS forecasting models**

The WeSuSFTS forecasting algorithm has been employed in ELD data to forecast MH-ELD in Malaysia due to some ELD problems stated in Chapter One. Two types of model were developed which were One-factor and M-factor (M=2) MH-ELD WeSuSFTS forecasting models. This research has validated the One-factor and M-factor (M=2) MH-ELD WeSuSFTS forecasting models by evaluating the models using a part of the sample data. The evaluation results proved that the constructed models are able to give good results based on the mean absolute percentage error (MAPE) achieved (less than 3% and 5% respectively); and the models are able to capture the actual data pattern as discussed and shown in Chapter Four. This signifies the contribution of MH-ELD FTS forecasting model by producing promising accuracy forecasting results with meaningful FTS model interpretation. The new algorithm can model any time series problem without the need for assumption because it is a data-driven approach.

- **Average Rules defuzzification method**

The new defuzzification method presented in Chapter Three is based on WeSuSFTS rules average method. The WeSuSFTS model consists of fuzzy reasoning rule with multiplication factors, and the membership function of the dependent variable is not always symmetric. In this research, the new defuzzification is proposed and named as Average Rules (AR) defuzzification method. Four suggested AR defuzzification methods, namely AR_1, AR_2, AR_3 and AR_4 are discussed in Chapter Three, and the methods were implemented in the proposed One-factor and M-factor (M=2)

WeSuSFTS forecasting models in order to gain the forecasted value. This research found that the accuracy of One-factor WeSuSFTS with AR_2 defuzzification method (WeSuSFTS-AR_2) and WeSuSFTS with COG defuzzification method (WeSuSFTS-COG) are really close, only 0.181% difference in MAPE. Although WeSuSFTS-COG is the best WeSuSFTS for MH-ELD forecasting, WeSuSFTS- AR_2 gives a very close forecasting result with simpler defuzzification calculation. Moreover, the low absolute percentage error value (APE) of only 0.9% demonstrates the high accuracy of WeSuSFTS-AR_2 in forecasting the first day of moving holiday (day four at moving holiday week).

5.2.2 Practical Contribution

Three contributions were highlighted as follow:

- **Scholar**

The WeSuSFTS forecasting algorithm is useful for scholars that are interested to explore the FTS model with high forecasting accuracy. Each step of the algorithm has potential to be explored especially the WSBA since this algorithm is still new in FTS area. Moreover, the AR defuzzification method in this research is an initial idea because currently there is no standard procedure to choose the best defuzzification method especially for FTS forecasting algorithm.

- **Electricity Management**

The MH-ELD forecasting results of this research can be used as guidance for electricity companies in planning the ELD distribution especially in moving holiday situation. They also can use the results as monitoring tool to monitor staff routine task planning in every power plant and electricity sub-station. The meaningful of

WeSuSFTS model interpretation also can be used by executives because the terms used in the WeSuSFTS are closer to normal daily human language.

- **End user customers**

The results of this study also important to industrial end users. The results can help industrial end users who consume big amount of load demand to plan their procurement of load demand every month especially during moving holiday sessions. So that, they can assure the usage does not exceed the purchased load demand to prevent shortage. Consequently, they can reduce the electricity cost.

5.3 Impact of this Study

This study has proposed a forecasting algorithm that is able to reduce the electricity load forecasting error. Consequently, if the electricity management of the electricity companies used the algorithm, it may help them to prevent any shortage or excess of electricity by balancing between electricity generation and load demand especially during moving holiday events. Then, electricity management can reduce production costs by decreasing electricity purchases to avoid unsold electricity load demand. Besides, the customers are happy celebrating their holidays without any disturbance of the electricity power supply.

5.4 Future Research

Some suggestions for future works are summarized as follows:

- **Exploring the effect of size of number of data**

Universiti Utara Malaysia

This research used limited data. For future study, it will be interesting to investigate how the size of the data reacts towards reducing the forecasting error. By doing this, implication of data size to forecasting error can be examined further.

- **Exploring different weighting mechanism**

Different weighting mechanisms or different weight values may produce different fuzzy rules in WeSuSFTS model. In the future, it will be exciting to utilize different weighting mechanisms to inspect whether different weighting mechanisms may yield better forecasting accuracy.

- **Exploring the effect of interval length**

Many previous studies investigated the effect of interval length in their FTS algorithms. This study used *k*-means clustering and Elbow methods to identify the number of fuzzy sets and triangular membership function parameters. Other applications of WeSuSFTS algorithm can also be adopted with different choice of clustering methods. In addition, future works could concentrate on forecasting accuracy by investigating the optimal number of fuzzy sets and types of membership function.

Universiti Utara Malaysia

- **Modifing any step of WeSuSFTS forecasting algorithm**

Although the results of this study are encouraging, the WeSuSFTS algorithm is a good platform for other researchers and practitioners to improve the algorithm further by modifying steps in the algorithm to obtain better performance.

REFERENCES

A'yun, K., Abadi, A. M., & Saptaningtyas, F. Y. (2015). Application of weighted fuzzy time series model to forecast Trans Jogja's passengers. *International Journal of Applied Physics and Mathematics*, *5*(2), 76–85. https://doi.org/10.17706/ijapm.2015.5.2.76-85

Abdullah, L., & Ling, C. Y. (2012). Intervals in fuzzy time series model preliminary investigation for composite index forecasting. *ARPN Journal of Systems and Software*, *2*(1), 7–11.

Abhishekh, Gautam, S. S., & Singh, S. R. (2019). A new type 2 fuzzy time series forecasting model based on three-factors fuzzy logical relationships. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *27*(2), 251–276. https://doi.org/10.1142/S0218488519500120

Abhishekh, & Kumar, S. (2019). A modified weighted fuzzy time series model for forecasting based on two-factors logical relationship. *International Journal of Fuzzy Systems*, *21*(5), 1403–1417. https://doi.org/10.1007/s40815-019-00652-8

Abogaleela, M., El-marsafawy, M., & El-sobki, M. (2013). Optimal scheme with load forecasting for Demand Side Management (DSM) in residential areas. *Energy and Power Engineering*, *5*, 889–896. https://doi.org/10.4236/epe.2013.54B171

Ahmed, J. S., Kasim, M. M., & Chaloob, I. Z. (2017). A defuzzification approach to solve a multi-objective programming problem with fuzzy parameters. *AIP Conference Proceedings*. https://doi.org/10.1063/1.5012192

Arora, S., & Taylor, J. W. (2013). Short-term forecasting of anomalous load using rule-based triple seasonal methods. *IEEE Transactions on Power Systems*, *28*(3), 3235–3242. https://doi.org/10.1109/TPWRS.2013.2252929

Badar, E., & Islam, U. (2011). Comparison of conventional and modern load forecasting techniques based on artificial intelligence and expert system. *IJCSI International Journal of Computer Science Issues*, *8*(5), 504–513.

Benaouda, D., & Murtagh, F. (2006). Electricity load forecast using neural network trained from wavelet-transformed data. *IEEE International Conference on Engineering of Intelligent Systems*, (1), 6–11.

Bessec, M., Fouquau, J., & Meritet, S. (2016). Forecasting electricity spot prices using time-series models with a double temporal segmentation Forecasting electricity spot prices using time-series models with a double temporal segmentation. *Applied Economics*, *48*(5), 361–378.

Boongoen, T., Shen, Q., & Price, C. (2011). Fuzzy qualitative link analysis for academic performance evaluation. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *19*(03), 559–585. https://doi.org/10.1142/S0218488511007131

Brunet, Y. (2013). Energy Storage. In *Solar Engineering of Thermal Processes* (pp.

Universiti Utara Malaysia

373–408). https://doi.org/10.1002/9781118671603.ch8

Buitrago, J., & Asfour, S. (2017). Short-term forecasting of electric loads using nonlinear autoregressive artificial neural networks with exogenous vector inputs. *Energies*, *10*(1), 1–24. https://doi.org/10.3390/en10010040

Bunn, D. W., & Farmer, E. D. (1985). *Comparative models for electrical load forecasting*. New York: John Wiley & Sons.

Cerqueira, V., Torgo, L., & Mozetič, I. (2020). Evaluating time series forecasting models: an empirical study on performance estimation methods. *Machine Learning*, *109*(11), 1997–2028. https://doi.org/10.1007/s10994-020-05910-7

Çevik, H. H., & Çunkaş, M. (2016). A fuzzy logic based short term load forecast for the holidays. *International Journal of Machine Learning and Computing*, *6*(1), 57–61. https://doi.org/10.18178/ijmlc.2016.6.1.572

Chang, J., Liu, Z., & Yu, P. (2019). Forecasting for the total electricity consumption of Taiwan by fuzzy time series model. In *Smart Innovation, Systems and Technologies* (pp. 220–225). https://doi.org/10.1007/978-3-030-03748-2

Chen, S. M. (1996). Forecasting enrollments based on fuzzy time series. *Fuzzy Sets and Systems*, *81*(3), 311–319.

Chen, S. M., & Chen, S. W. (2015). Fuzzy forecasting based on two-factors second-order fuzzy-trend logical relationship groups and the probabilities of trends of fuzzy logical relationships. *IEEE Transactions on Cybernetics*, *45*(3), 391–403. https://doi.org/10.1109/TCYB.2014.2326888

Chen, S. M., & Kao, P. Y. (2013). TAIEX forecasting based on fuzzy time series, particle swarm optimization techniques and support vector machines. *Information Sciences*, *247*, 62–71. https://doi.org/10.1016/j.ins.2013.06.005

Chen, S. M., Lee, S. H., & Lee, C. H. (2001). A new method for generating fuzzy rules from numerical data for handling classification problems. *Applied Artificial Intelligence: An International Journal*, *15*(7), 645–664. https://doi.org/10.1080/088395101750363984

Cheng, C. H., Chen, T. L., & Chiang, C. H. (2006). Trend-weighted fuzzy time-series model for TAIEX. In *Neural Information Processing* (pp. 469–477).

Cheng, C. H., Chen, T. L., Teoh, H. J., & Chiang, C. H. (2008). Fuzzy time-series based on adaptive expectation model for TAIEX forecasting. *Expert Systems with Applications*, *34*(2), 1126–1132. https://doi.org/10.1016/j.eswa.2006.12.021

Cheng, C. H., & Yang, J. H. (2015). Rough-set rule induction to build fuzzy time series model in forecasting stock price. *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery*, 278–284. Retrieved from https://ieeexplore.ieee.org/abstract/document/7381954/

Crone, S. F., & Kourentzes, N. (2011). Segmenting electrical load time series for forecasting? an empirical evaluation of daily uk load patterns. *Proceedings of the*

2011 International Joint Conference on Neural Networks.

Darbellay, G. A., & Slama, M. (2000). Forecasting the short-term demand for electricity. Do neural networks stand a better chance ? *International Journal of Forecasting*, *16*, 71–83.

Davidson, I. (2002). *Understanding K-Means Non-hierarchical Clustering*. Albany.

De Livera, A. M., Hyndman, R. J., & Snyder, R. D. (2011). Forecasting time series with complex seasonal patterns using exponential smoothing. *Journal of the American Statistical Association*, *106*(496), 1513–1527. https://doi.org/10.1198/jasa.2011.tm09771

Department, S. B. (2017). *Single Buyer Operations Manual (Peninsular Malaysia)*. Retrieved from https://www.singlebuyer.com.my/files/Single_Buyer_Operations_Manual_%28Revised_4.417%29_%28clean%29.pdf

Ding, Q. D. Q., Zhang, H. Z. H., Huang, T. H. T., & Zhang, J. Z. J. (2005). A holiday short term load forecasting considering weather information. *2005 International Power Engineering Conference*. https://doi.org/10.1109/IPEC.2005.206879

Ding, Q., Zhang, H., Huang, T., & Zhang, J. (2005). A holiday short term load forecasting considering weather information. *2005 International Power Engineering Conference*, 2–5.

Duru, O., & Yoshida, S. (2012). Modeling principles in fuzzy time series forecasting. *2012 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr)*, (August), 1–7. https://doi.org/10.1109/CIFEr.2012.6327767

Ebrahimi, A., & Moshari, A. (2013). Holidays short-term load forecasting using fuzzy improved similar day method. *International Transactions on Electrical Energy Systems*, *23*(8), 1254–1271. https://doi.org/10.1002/etep.1650

Efendi, R, Deris, M. M., & Ismail, Z. (2016). Implementation of fuzzy time series in forecasting of the non-stationary data. *International Journal of Computational Intelligence and Applications*, *15*(2), 1–10. Retrieved from https://www.worldscientific.com/doi/abs/10.1142/S1469026816500097

Efendi, R, Ismail, Z., & Deris, M. M. (2015). A new linguistic out-sample approach of fuzzy time series for daily forecasting of Malaysian electricity load demand. *Applied Soft Computing Journal*, *28*, 422–430. https://doi.org/10.1016/j.asoc.2014.11.043

Efendi, Riswan, Deris, M. M., & Ismail, Z. (2016). Implementation of fuzzy time series in forecasting of the non-stationary data. *International Journal of Computational Intelligence and Applications*, *15*(2), 1–10.

Egrioglu, E., Bas, E., Yolcu, U., & Yen, M. (2020). Picture fuzzy time series: Defining, modeling and creating a new forecasting method. *Engineering Applications of Artificial Intelligence*, *88*, 103367.

https://doi.org/10.1016/j.engappai.2019.103367

Energy Comission. (2016). Enhancing Energy Efficiency in Malaysia Through Legislation and Policy. Retrieved from http://www.st.gov.my/index.php/en/download-page/category/115-seminar-ke-arah-budaya-bijak-tenaga.html?download=477:enhancing-energy-efficiency-in-malaysia-through-legislation-and-policy

Fallah, S. N., Ganjkhani, M., Shamshirband, S., & Chau, K. wing. (2019). Computational intelligence on short-term load forecasting: A methodological overview. *Energies*, *12*(3). https://doi.org/10.3390/en12030393

Farfar, K. E., & Khadir, M. T. (2018). A two-stage short-term load forecasting approach using temperature daily profiles estimation. *Neural Computing and Applications*, *31*(8), 3909–3919. https://doi.org/10.1007/s00521-017-3324-x

Fathoni, M. Y. (2017). Implementasi Metode Fuzzy Time Series Cheng untuk prediksi Kosentrasi Gas NO2 Di Udara. *Jurnal Sistem Informasi Bisnis*, *7*(1), 17. https://doi.org/10.21456/vol7iss1pp17-23

Fernandes, R. S. S., Bichpuriya, Y. K., Rao, M. S. S., & Soman, S. A. (2011). Day ahead load forecasting models for holidays in Indian context. *2011 International Conference on Power and Energy Systems*, 1–5. https://doi.org/10.1109/ICPES.2011.6156652

Fernandez, A., & a, F. (2012). Linguistic fuzzy rules in data mining : Follow-up Mamdani fuzzy modeling principle. In E. et al. Trillas (Ed.), *Combining Experimentation and Theory* (pp. 103–122). Verlag Berlin Handberg: Springer.

Gahirwal, M. (2013). Inter time series sales forecasting. *Nternational Journal of Computer Sciences and Engineering*, *2*(1).

Gardner, E. S. (2006). Exponential smoothing: The state of the art Part II. In *International Journal of Forecasting* (Vol. 22). https://doi.org/10.1016/j.ijforecast.2006.03.005

Garg, B., & Garg, R. (2016). Enhanced accuracy of fuzzy time series model using ordered weighted aggregation. *Applied Soft Computing*, *48*, 265–280. Retrieved from https://www.sciencedirect.com/science/article/pii/S1568494616303258

Gupta, K. K., & Kumar, S. (2019). A novel high - order fuzzy time series forecasting method based on probabilistic fuzzy sets. *Granular Computing*, *4*(2016), 699–713. https://doi.org/10.1007/s41066-019-00168-4

Hahn, H., Meyer-Nieberg, S., & Pickl, S. (2009). Electric load forecasting methods: Tools for decision making. *European Journal of Operational Research*, *199*(3), 902–907. Retrieved from http://www.sciencedirect.com/science/article/pii/S0377221709002094

Handoyo, S. (2018). The fuzzy inference system with rule bases generated by fuzzy C-means clustering. *Thai Journal of Mathematics*, (December 2018).

Universiti Utara Malaysia

Handoyo, S., Marji, M., & Jie, F. (2018). The fuzzy inference system with rule bases generated by using the fuzzy C-means to predict regional minimum wage in Indonesia. *International Journal of Operations and Quantitative Management*, *24*(4), 101–116.

Haseeb, A. S. M. A. (2018, January 10). Education in the Era of IR 4 . 0. *New Straits Times*. Retrieved from https://www.nst.com.my/education/2018/01/323591/higher-education-era-ir-40

Hauwa, Z. N. (2012). *Effect of triangular and Gaussian membership functions in fuzzy time series forecasting: a case study of electric load forecasting* ((Master's thesis). Ahmadu Bello University Zaria). Retrieved from http://hdl.handle.net/123456789/4649

Hernández, L., Baladrón, C., Aguiar, J., Calavia, L., Carro, B., Sánchez-Esguevillas, A., … Lloret, J. (2014). Artificial neural network for short-term load forecasting in distribution systems. *Energies*, *7*(3), 1576–1598. https://doi.org/10.3390/en7031576

Hidayah, N., Purnamasari, I., & Hayati, M. N. (2017). Penerapan metode fuzzy time series using percentage change. *Jurnal Eksponensial*, *7*(2), 187–192. Retrieved from http://jurnal.fmipa.unmul.ac.id/index.php/exponensial/article/view/67

Hong, T., Gui, M., Baran, M. E., & Willis, H. L. (2010). Modeling and forecasting hourly electric load by multiple linear regression with interactions. *Power and Energy Society General Meeting, 2010 IEEE*, 1–8. https://doi.org/10.1109/PES.2010.5589959

Hongbin, W., & Li, C. W. (2009). Load forecasting for electrical power system based on BP neural network. *1st International Workshop on Education Technology and Computer Science, ETCS 2009*, *1*, 702–705. https://doi.org/10.1109/ETCS.2009.162

Huarng, K. (2001). Effective lengths of intervals to improve forecasting in fuzzy time series. *Fuzzy Sets and Systems*, *123*(3), 387–394. https://doi.org/10.1016/S0165-0114(00)00057-9

Ismail, S., Zulkifli, M., Mansor, R., Mat Yusof, M., & Ismail, M. I. (2016). The role of exploratory data analysis (EDA) in electricity forecasting. *Pertanika Journal of Social Sciences & Humanites*, *24*(S), 111–118.

Ismail, Z., Efendi, R., & Deris, M. M. (2015). Application of fuzzy time series approach in electric load forecasting. *New Mathematics and Natural Computation*, *11*(3), 229–248. Retrieved from https://www.worldscientific.com/doi/abs/10.1142/S1793005715500076

Ismail, Z., & Mansor, R. (2011). Fuzzy logic approach for forecasting half-hourly Malaysia electricity. *International Institute of Forecasters (ISF) 2011 Proceedings (2011)*, 179=180. Retrieved from http://forecasters.org/pdfs/isf/ISF11_Proceedings.pdf

Jarrett, J. E., & Plouffe, J. S. (2011). The fuzzy logic method for simpler forecasting.

International Journal of Engineering Business Management, *3*(3), 25–52.

Javedani, H., Hisyam, M., & Gadelha, F. (2019). Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series. *Energy*, *175*, 365–377. https://doi.org/10.1016/j.energy.2019.03.081

Joshi, B. P., & Kumar, S. (2013). A computational method for fuzzy time series forecasting based on difference parameters. *International Journal of Modeling, Simulation, and Scientific Computing*, *04*(01), 1250023. https://doi.org/10.1142/S1793962312500237

Kamel, N., & Baharudin, Z. (2007). Short term load forecast using Burg autoregressive. *International Conference on Intelligent and Advances Systems IEEE*, 912–916.

Kaushik, A., & Singh, A. K. (2013). Long term forecasting with fuzzy time Series and neural network : a comparative study using sugar production data. *International Journal of Computer Trens and Technology (IJCTT)*, *4*(7), 2299–2305.

Keogh, E., Chu, S., Hart, D., & Pazzani, M. (2003). Segmenting time series : A survey and novel approach. In *Data Mining in Time Series Databases* (p. 57).

Khamis, M. F. I., Baharudin, Z., Hamid, N., Abdullah, M., & Nordin, F. (2011). Short term load forecasting for small scale power system using fuzzy logic. *2011 Fourth International Conference on Modeling, Simulation and Applied Optimization*. https://doi.org/10.1109/ICMSAO.2011.5943733

Khamis, M. F. I., Baharudin, Z., Hamid, N. H., Abdullah, M. F., & Solahuddin, S. (2011). Electricity forecasting for small scale power system using artificial neural network. *5th International Power Engineering and Optimization Conference*, (June), 6–7. https://doi.org/10.1109/PEOCO.2011.5970423

Khosravi, A., Nahavandi, S., & Creighton, D. (2011). Short term load forecasting using interval type-2 fuzzy logic systems. *2011 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2011)*, 502–508. https://doi.org/10.1109/FUZZY.2011.6007450

Khuntia, S. R., Rueda, J. L., & Van der Meijden, M. A. M. M. (2018). Long-term electricity load forecasting considering volatility using multiplicative error model. *Energies*, *11*(12). https://doi.org/10.3390/en11123308

Kim, K. H., Youn, H. S., & Kang, Y. C. (2000). Short-term load forecasting for special days in anomalous Load conditions using neural networks. *IEEE Transactions on Fuzzy Systems*, *15*(2), 559–565.

Kim, M. S. (2013). Modeling special-day effects for forecasting intraday electricity demand. *European Journal of Operational Research*, *230*(1), 170–180. https://doi.org/10.1016/j.ejor.2013.03.039

Kosko, B. (1986). Fuzzy Entropy and Conditioning. *Information Sciences*, *40*, 165–174.

Kown, D., Kim, M., Hong, C., & Cho, S. (2014). *Short term load forecasting based on BPL neural network with weather factors*. *9*(1), 415–424.

Kumar, S., & Gangwar, S. (2015). Intuitionistic fuzzy time series: An approach for handling non-determinism in time series forecasting. *IEEE Transactions on Fuzzy Systems*, *24*(6), 1270–12. https://doi.org/10.1109/TFUZZ.2015.2507582

Lazim, M. A. (2013). *Introductory Business Forecasting: a practical approach* (3rd Editio). UiTM Press.

Lee, M., Efendi, R., & Ismail, Z. (2009). Modified weighted for enrollment forecasting based on fuzzy time series. *Matematika*, *25*(1), 67–78. Retrieved from http://www.matematika.utm.my/index.php/matematika/article/view/260

Leekwijck, W. Van, & Kerre, E. E. (1999). Defuzzifcation: criteria and classifcation. *Fuzzy Sets and Systems*, *108*, 159–178.

Li, S., & Cheng, Y. (2009). An enhanced deterministic fuzzy time series. *Cybernetics and Systems: An International Journal*, *40*(3), 211–234. https://doi.org/10.1080/01969720802715128

Liu, Z., & Zhang, T. (2019). A second-order fuzzy time series model for stock price analysis. *Journal of Applied Statistics*. Retrieved from https://www.tandfonline.com/doi/abs/10.1080/02664763.2019.1601163

Luo, X., Wang, J., Dooner, M., & Clarke, J. (2014). Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*, *137*, 511–536. https://doi.org/10.1016/j.apenergy.2014.09.081

Macqueen, J. (1967). Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Symposium on Mathematical Statistics and Probability*, *1*, 281–297. Retrieved from https://projecteuclid.org/euclid.bsmsp/1200512992

Mandal, P., Srivastava, A. K., Negnevitsky, M., & Park, J. (2009). Sensitivity analysis of neural network parameters to improve the performance of electricity price forecasting. *International Journal of Energy Research*, *33*, 38–51. https://doi.org/10.1002/er

Mansor, R., Kasim, M. M., & Othman, M. (2016a). A weighted subsethood mamdani fuzzy rules based system rule extraction (MFRBS-WSBA) for forecasting electricity load demand - A framework. *Journal of Telecommunication, Electronic and Computer Engineering*, *8*(8), 97–102. https://doi.org/10.1063/1.4960901

Mansor, R., Kasim, M. M., & Othman, M. (2016b). The framework of weighted subset-hood Mamdani fuzzy rule based system rule extraction (MFRBS-WSBA) for forecasting electricity load demand. *International Conference on Applied Science and Technology 2016 (ICAST'16)*, *1761*, 020061. https://doi.org/10.1063/1.4960901

Universiti Utara Malaysia

Mansor, R., Othman, M., & Kasim, M. M. (2016). Fuzzy reasoning based time series forecasting using weighted subsethood model. *International Conference on Science, Engineering, Management and Social Science*. Johor Bahru.

Mansor, R., Othman, M., & Kasim, M. M. (2017). Fuzzy reasoning based time series forecasting using weighted subsethood model. *Advanced Science Letters*, *23*(9), 9094–9097.

Mansor, R., Zaini, B. J., Othman, M., & Kasim, M. M. (2018). The effect of interval length in weighted subsethood fuzzy time series. *AIP Conference Proceeding*, *1974*, 040017-1-040017–7. https://doi.org/10.1063/1.5041691

Mansor, R., Zulkifli, M., Yusof, M. M., & Ismail, M. I. (2014). Performance of fuzzy approach in Malaysia short-term electricity load forecasting. *AIP Conference Proceedings*, *1635*, 817–824. https://doi.org/10.1063/1.4903677

Mansor, R., Zulkifli, M., Yusof, M. M., Ismail, M. I., Ismail, S., & Yin, Y. C. (2014). Performance of fuzzy approach in Malaysia short-term electricity load forecasting. *AIP Conference Proceeding*, *1635*, 817–824. https://doi.org/10.1063/1.4903677

Medeiros, M. C., & Soares, L. J. (2008). Modeling and forecasting short-term electricity load: A comparison of methods with an application to Brazilian data. *International Journal of Forecasting*, Vol. 24, pp. 630–644. https://doi.org/10.1016/j.ijforecast.2008.08.003

Mohamed, N., & Ahmad, M. H. (2012). *Forecasting short term load demand using multilayer feed-forward (MLFF) neural network model*. *6*(108), 5359–5368.

Mohammad, F., & Kim, Y.-C. (2019). Energy load forecasting model based on deep neural networks for smart grids. *International Journal of Systems Assurance Engineering and Management*. https://doi.org/10.1007/s13198-019-00884-9

Musleha, S., Mutalib, A., Ramli, N., & Mohamad, D. (2019). A new method to forecast TAIEX based on fuzzy time series with trapezoidal fuzzy numbers and center of gravity similarity measure approach. *Proceedings of the Third International Conference on Computing, Mathematics and Statistics (ICMS2017)*, 489–495. https://doi.org/10.1007/978-981-13-7279-7

Nagi, J., Yap, K. S., Nagi, F., Tiong, S. K., & Ahmed, S. K. (2011). A computational intelligence scheme for the prediction of the daily peak load. *Applied Soft Computing*, *11*(8), 4773–4788. https://doi.org/10.1016/j.asoc.2011.07.005

Ngoc, H. C., & Nguyen-trang, T. (2018). An improved fuzzy time series forecasting model. In *Econometrics for Financial Applications* (Vol. 760, pp. 474–490). https://doi.org/10.1007/978-3-319-73150-6

Nguyen, H., & Hansen, C. K. (2017). *Short-term electricity load forecasting with Time Series Analysis*. 214–221. https://doi.org/10.1109/ICPHM.2017.7998331

Ningrum, R. W., Surarso, B., & Farikhin. (2019). Modification of triangular member's function (TMF) based on firefly-chen fuzzy time series (FTS) method. *Journal of*

Universiti Utara Malaysia

Physics: Conference Series, *1321*, 022077. Retrieved from https://iopscience.iop.org/article/10.1088/1742-6596/1321/2/022077/meta

Nivetha, S., & Samundeeswari, E. S. (2016). Predicting survival of breast cancer patients using fuzzy rule based system. *International Research Journal of Engineering and Technology (IRJET)*, *03*(03), 962–969.

Nowicka-Zagrajek, J., & Weron, R. (2002). Modeling electricity loads in California: ARMA models with hyperbolic noise. *Signal Processing*, *82*(12), 1903–1915. https://doi.org/10.1016/S0165-1684(02)00318-3

Nurhayadi. (2014). Fuzzy Model Optimization for Time Series Data Using a Translation in the Extent of Mean Error. *Journal of Mathematics and Statistics*, *10*(2), 267–274. https://doi.org/10.3844/jmssp.2014.267.274

Operator, G. S. (2020). System Demand Profile. Retrieved from https://www.gso.org.my/SystemData/SystemDemand.aspx

Othman, M., Khalid, S. A., Abdullah, F., Hamzah, S. H. A., & Mahmud, K. R. K. (2013). Hybrid subjective evaluation method using weighted subsethood-based (WSBA) rule generation algorithm. *Journal of Arts, Science & Commerce*, *IV*(1(1)), 46–54.

Othman, M., Saian, R., Nazri, M. N., Safiah, N., Kamal, A., & Liyana, N. (2013). Fuzzy forecasting for water level of flood warning system in Perlis. *International Symposium on Mathematical Sciences and Computing Research*, 104–109.

Padhy, N. P. (2005). *Artificial Intelligence and Intelligent Syatem*. Oxford University Press.

Papalexopoulos, A. D., & Hesterberg, T. C. (1990). A regreession-based approach to short-term system load forecasting. *IEEE Transactions on Power Systems*, *5*(4), 1535–1550.

Pei, A. O. (2015). Load Forecasting based on Fuzzy Time Series. *3rd International Conference on Material, Mechanical and Manufacturing Engineering (IC3ME 2015)*, *1*, 715–719.

Qiu, X., Ren, Y., Suganthan, P. N., & Amaratunga, G. A. J. (2017). Empirical Mode Decomposition based ensemble deep learning for load demand time series forecasting. *Applied Soft Computing Journal*, *54*, 246–255. https://doi.org/10.1016/j.asoc.2017.01.015

Rahim, N. F., Othman, M., Sokkalingam, R., & Abdul Kadir, E. (2018). Forecasting crude palm oil prices using fuzzy rule-based time series method. *IEEE Access*, *6*, 32216–32224. https://doi.org/10.1109/ACCESS.2018.2846809

Rasmani, K. A., & Shen, Q. (2003). Weighted linguistic modelling based on fuzzy subsethood values. *IEEE International Conference on Fuzzy Systems*. https://doi.org/10.1109/FUZZ.2003.1209451

Rasmani, K. A., & Shen, Q. (2004). Modifying weighted fuzzy subsethood-based rule

Universiti Utara Malaysia

models with fuzzy quantifiers. *IEEE International Conference on Fuzzy Systems*, 1679–1684. Budapest.

Rasmani, K. A., & Shen, Q. (2005). Subsethood-based fuzzy rule models and their application to student performance classification. *The 14th IEEE International Conference on Fuzzy Systems, 2005. FUZZ '05.*, 755–760. https://doi.org/10.1109/FUZZY.2005.1452489

Razak, F. A., Hashim, A. H., Abidin, I. Z., & Shitan, M. (2010). Moving holidays' effects on the Malaysian peak daily load. *2010 IEEE International Conference on Power and Energy*, 906–910. https://doi.org/10.1109/PECON.2010.5697708

Rizwan, M., Kumar, D., & Kumar, R. (2012). Fuzzy logic approach for short term electrical load forecasting. *Electrical and Power Engineering Frontier*, *1*(1), 8–12.

Sachdeva, S., & Verma, C. M. (2008). Load forecasting using fuzzy methods. *2008 Joint International Conference on Power System Technology and IEEE Power India Conference*. https://doi.org/10.1109/ICPST.2008.4745206

Sadaei, H. J. (2013). *Improved models in Fuzzy Time Series for forecasting*. (Doctoral thesis). Universiti Teknologi Malaysia.

Samuel, O., Alzahrani, F. A., Khan, R. J. U. H., Farooq, H., Shafiq, M., Afzal, M. K., & Javaid, N. (2020). Towards modified entropy mutual information feature selection to forecast medium-term load using a deep learning model in smart homes. *Entropy*, *22*(1), 68. https://doi.org/10.3390/e22010068

Saxena, P., Sharma, K., & Easo, S. (2012). Forecasting enrollments based on fuzzy time series with higher forecast accuracy rate. *International Journal of Computer Technology & Applicatin*, *3*(3), 957–961. https://doi.org/10.1016/0165-0114(95)00220-0

Selim, K. S., & Elanany, G. A. (2013). A new method for short multivariate fuzzy time series based on genetic algorithm and fuzzy clustering. *Advances in Fuzzy Systems*, *2013*, 1–10.

Setiawan, A., Koprinska, I., & Agelidis, V. G. (2009). Very short-term electricity load demand forecasting using support vector regression. *2009 International Joint Conference on Neural Networks*, 2888–2894. https://doi.org/10.1109/IJCNN.2009.5179063

Shayeghi, H., Shayanfar, H. A., & Azimi, G. (2009). STLF based on optimized neural network using PSO. *World Academy of Science, Engineering and Technology*, *52*, 1066–1076.

Shrivastava, P., & Sharma, S. (2014). Forecasting lahi production in India using fuzzy time series and diffusion of innovation. *International Journal on Advanced Computer Theory and Engineering (IJACTE)*, *3*(5), 51–56.

Shukur, O. B., Fadhil, N. S., Lee, M. H., & Ahmad, M. H. (2014). Electricity load forecasting using hybrid of multiplicative double seasonal exponential smoothing

model with artificial neural network. *Jurnal Teknologi*, *2*, 65–70.

Silva, P. C. L., Sadaei, H. J., & Guimaraes, F. G. (2017). Interval forecasting with Fuzzy Time Series. *2016 IEEE Symposium Series on Computational Intelligence, SSCI 2016*, (October 2017). https://doi.org/10.1109/SSCI.2016.7850010

Singh, P. (2016). Fuzzy time series modeling approaches : A review. In *Applications of Soft Computing in Time Series Forecasting* (pp. 11–40). https://doi.org/10.1007/978-3-319-26293-2

Singh, Pritpal, & Borah, B. (2014). Forecasting stock index price based on M-factors fuzzy time series and particle swarm optimization. *International Journal of Approximate Reasoning*, *55*(3), 812–833. https://doi.org/10.1016/J.IJAR.2013.09.014

Song, K., Baek, Y., Hong, D. H., & Jang, G. (2005). Short-term load forecasting for the holidays using fuzzy linear regression method. *IEEE Transactions on Power Systems*, *20*(1), 96–101.

Song, Q., & Chissom, B. S. (1993a). Forecasting enrollments with fuzzy time series - Part I. *Fuzzy Sets and Systems*, *54*(1), 1–9. https://doi.org/10.1016/0165-0114(93)90355-L

Song, Q., & Chissom, B. S. (1993b). Fuzzy time series and its models. *Fuzzy Sets and Systems*, *54*(3), 269–277. https://doi.org/10.1016/0165-0114(93)90372-O

Song, Q., & Chissom, B. S. (1994). Forecasting enrollments with fuzzy time series - part II. *Fuzzy Sets and Systems*, *62*(1), 1–8. https://doi.org/10.1016/0165-0114(94)90067-1

Soria, D., Garibaldi, J. M., Green, A. R., Powe, D. G., Nolan, C. C., Lemetre, C., … Ellis, I. O. (2013). A quantifier-based fuzzy classification system for breast canser patients. *Artificial Intelligence in Medicine*, *58*(3), 175–184.

Srinivasan, D., Chang, C. S., & Liew, A. C. (1995). Demand forecasting using fuzzy neural computation, with special emphasis on weekend and public holiday forecasting. *IEEE Transactions on Power Systems*, *10*(4), 1897–1903. https://doi.org/10.1109/59.476055

Srinivasan, D., Liew, A. C., & Chang, C. S. (1995). Applications of fuzzy systems in power systems. *Electric Power Systems Research*, *35*(1), 39–43. Retrieved from https://doi.org/10.1016/0378-7796(95)00985-X

Suhartono, & Lee, M. H. (2011). A hybrid approach based on Winter ' s model and weighted fuzzy time series for forecasting trend and seasonal data. *Journal of Mathematics and Statistics*, *7*(3), 177–183.

Sulandari, W., Subanar, Lee, M. H., & Rodrigues, P. C. (2020). Indonesian electricity load forecasting using singular spectrum analysis, fuzzy systems and neural networks. *Energy*, *190*, 116408. https://doi.org/10.1016/j.energy.2019.116408

Taylor, J. W., de Menezes, L. M., & McSharry, P. E. (2006). A comparison of

Universiti Utara Malaysia

univariate methods for forecasting electricity demand up to a day ahead. *International Journal of Forecasting*, *22*(1), 1–16. https://doi.org/10.1016/j.ijforecast.2005.06.006

Tenaga Nasional Berhad. (2020a). Corporate profile. Retrieved from https://www.tnb.com.my/about-tnb/corporate-profile/

Tenaga Nasional Berhad. (2020b). Maximum Demand. Retrieved from https://www.tnb.com.my/commercial-industrial/maximum-demand/

Tenaga, S. (2011). *Laporan Tahunan 2011*.

Tinh, N. Van. (2019). An improved fuzzy time series forecasting model based on combining k–means clustering with harmony search. *American Journal of Information Science and …*. Retrieved from http://files.aiscience.org/journal/article/pdf/70080118.pdf

Tinh, N. Van, & Dieu, N. C. (2017). Improving the forecasted accuracy of model based on fuzzy time series and k-means clustering. *Journal of Science and …*. Retrieved from https://pdfs.semanticscholar.org/365e/fec534376171cdcfb7de31cd2cf78a521ff9.pdf

Tinh, N. Van, & Duy, N. T. (2019). A novel forecasting model combining the high–order fuzzy time series with particle swam optimization. *American Journal of Information Science and Computer Engineering*, *5*(3), 103–112. Retrieved from http://files.aiscience.org/journal/article/pdf/70080120.pdf

Tinh, N. Van, Vu, V. V., & Linh, T. T. N. (2016). A new method for forecasting enrolments combining time-variant fuzzy logical relationship groups and k-means clustering. *International Research Journal of Engineering and Technology*, *03*(03), 23–30.

Tiwari, A. (2020). Time series forecasting: Build evaluation framework for forecast models. Retrieved February 17, 2021, from Towards data Science Inc. website: https://towardsdatascience.com/build-evaluation-framework-for-forecast-models-fbc1bd775edd

Tiwari, S., Singh, V., & Kumar, R. (2015). An intelligent system for forecasting electric load and price. *International Journal of Computer Sciences and Information Technoligies*, *6*(3), 2121–2126.

Tóth-Laufer, E., Rudas, I. J., & Takács, M. (2014). Operator dependent variations of the Mamdani-type inference system model to reduce the computational needs in real-time evaluation. *International Journal of Fuzzy Systems*, *16*(1), 57–72.

Tsai, M. C., Cheng, C. H., & Tsai, M. I. (2019). A multifactor fuzzy time-series fitting model for forecasting the stock index. *Symmetry*, *11*, 1474. Retrieved from https://www.mdpi.com/2073-8994/11/12/1474

Tsekouras, J. G., Salis, A. D., Tsaroucha, M. A., & Karanasiou, I. S. (2008). Load time-series classification based on pattern recognition methods. In P.-Y. Yin

(Ed.), *Pattern Recognition Techniques, Technology and Applications* (pp. 361–432). https://doi.org/10.5772/711

Unit, M. E. I. H. (2017). *2017 Malaysia Energy Statistics Handbook*. Retrieved from http://www.statcan.gc.ca/pub/57-601-x/57-601-x2012001-eng.pdf%5Cnpapers2://publication/uuid/792EFC7D-A6CF-40B5-A139-8FA59714AA41

Vovan, T. (2018). An improved fuzzy time series forecasting model using variations of data. *Fuzzy Optimization and Decision Making*, *September*, 1–23. https://doi.org/10.1007/s10700-018-9290-7

Wang, C., Xu, Z., & Zhu, T. X. (2005). A method of load forecasting for January and February in China. *IEEE Power Engineering Society General Meeting 2005*. https://doi.org/10.1109/PES.2005.1489376

Wang, H., Wang, H., Guo, J., & Feng, H. (2014). A fuzzy time series forecasting model based on yearly difference of the student enrollment number. *International Conference on Soft Computing in Information Communication Technology (SCICT2014)*, (Scict), 172–175.

Wang, S., & Chaovalitwongse, W. (2011). Evaluating and comparing forecasting models. In *Wiley encyclopedia of operations research and management science*. https://doi.org/10.1002/9780470400531.eorms0307

Wang, Y., Lei, Y., Fan, X., & Yi Wang. (2016). Intuitionistic fuzzy time series forecasting model based on intuitionistic fuzzy reasoning. *Mathematical Problems in Engineering*, *2016*, 1–12.

Wang, Y. M., Chin, K. S., Poon, G. K. K., & Yang, J. B. (2009). Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. *Expert Systems with Applications*, *36*(2 PART 1), 1195–1207. https://doi.org/10.1016/j.eswa.2007.11.028

Wi, Y., Joo, S., & Song, K. (2012). Polynomial regression With weather. *IEEE Transactions on Power Systems*, *27*(2), 596–603.

Yahaya, A. S., Javaid, N., Latif, K., & Rehman, A. (2019). An enhanced very short-term load forecasting scheme based on activation function. *International Conference on Computer and Information Sciences (ICCIS)*. https://doi.org/10.1109/ICCISci.2019.8716384

Yap, K. S., & Yap, H. J. (2012). Daily maximum load forecasting of consecutive national holidays using OSELM-based multi-agents system with weighted average strategy. *Neurocomputing*, *81*, 108–112. https://doi.org/10.1016/j.neucom.2011.12.002

Ye, F., Zhang, L., Zhang, D., Fujita, H., & Gong, Z. (2016). A novel forecasting method based on multi-order fuzzy time series and technical analysis. *Information Sciences*, *367–368*, 41–57. https://doi.org/10.1016/j.ins.2016.05.038

Yolcu, U., Cagcag, O., Hakan, C., & Egrioglu, E. (2014). An enhanced fuzzy time

Universiti Utara Malaysia

series forecasting method based on artificial bee colony. *Journal of Intelligent & Fuzzy Systems*, *26*, 2627–2637. https://doi.org/10.3233/IFS-130933

Yu, H. K. (2004). Weighted fuzzy time series models for TAIEX forecasting. *Physica A: Statistical Mechanics and Its Applications*, *349*, 609–624. https://doi.org/10.1016/j.physa.2004.11.006

Yusuf, S. M., Mohammad, A., & Hamisu, A. A. (2017). A novel two – factor high order fuzzy time series with applications to temperature and futures exchange forecasting. *Nigerian Journal of Technology*, *36*(4), 1124–1134. https://doi.org/10.4314/njt.v36i4.18

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, *8*, 338–353. Retrieved from http://www.sciencedirect.com/science/article/pii/S001999586590241X

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—II. *Information Sciences*, Vol. 8, pp. 301–357. https://doi.org/10.1016/0020-0255(75)90046-8

Zadeh, L. A. (2008). Is there a need for fuzzy logic? *Information Sciences*, *178*(13), 2751–2779. https://doi.org/10.1016/j.ins.2008.02.012

Zakaria, Z., & Shamsuddin, S. (2016). Electricity consumption and economic activity in Malaysia: Co-integration, causality and assessing the forecasting ability of the vector error correction model. *International Journal of Energy Economics and Policy*, *6*(4), 706–713.

Zhang, K., Li, Z., Wang, H., & Wang, H. (2015). Fuzzy time series prediction model and application based on fuzzy inverse. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, *8*(10), 121–128.

Zounemat-Kermani, M., & Scholz, M. (2014). Modeling of dissolved oxygen applying stepwise regression and a template-based fuzzy logic system. *Journal of Environmental Engineering*, *140*(January), 69–76. https://doi.org/10.1061/(ASCE)EE.1943-7870.0000780.

Universiti Utara Malaysia

Appendix A

Data for Figure 4.1

Date	ELD	Day	Event
01-06-17	16752	THU	
02-06-17	16321	FRI	
03-06-17	15389	SAT	
04-06-17	14703	SUN	
05-06-17	17150	MON	
06-06-17	17372	TUE	
07-06-17	17141	WED	
08-06-17	17128	THU	
09-06-17	17041	FRI	
10-06-17	15332	SAT	
11-06-17	15090	SUN	
12-06-17	16174	MON	
13-06-17	17222	TUE	
14-06-17	16867	WED	
15-06-17	16998	THU	
16-06-17	16711	FRI	
17-06-17	14763	SAT	
18-06-17	14407	SUN	
19-06-17	16782	MON	
20-06-17	16886	TUE	
21-06-17	16679	WED	
22-06-17	16205	THU	
23-06-17	14753	FRI	
24-06-17	13252	SAT	
25-06-17	12231	SUN	HRA
26-06-17	12107	MON	
27-06-17	12795	TUE	
28-06-17	14448	WED	
29-06-17	14577	THU	
30-06-17	15398	FRI	
01-07-17	14505	SAT	
02-07-17	14524.5	SUN	
03-07-17	16434.5	MON	
04-07-17	16819	TUE	
05-07-17	16887	WED	
06-07-17	16721	THU	
07-07-17	16373.5	FRI	
08-07-17	14847	SAT	
09-07-17	14642	SUN	
10-07-17	16695	MON	
11-07-17	16510	TUE	
12-07-17	16983.5	WED	
13-07-17	16736	THU	
14-07-17	16036	FRI	
15-07-17	14931	SAT	
16-07-17	14638	SUN	
17-07-17	17012	MON	
18-07-17	17125	TUE	
19-07-17	17080	WED	
20-07-17	16837	THU	
21-07-17	17036	FRI	
22-07-17	15678	SAT	
23-07-17	15462	SUN	
24-07-17	17130	MON	
25-07-17	16951	TUE	

Universiti Utara Malaysia

Appendix B

Data for Figure 4.2

Date	ELD	Day	Event
01-01-17	13016	SUN	NEW YEAR
02-01-17	13655	MON	
03-01-17	15458	TUE	
04-01-17	15756	WED	
05-01-17	16081	THU	
06-01-17	16252	FRI	
07-01-17	14769	SAT	
08-01-17	14449	SUN	
09-01-17	16808	MON	
10-01-17	17045	TUE	
11-01-17	16808	WED	
12-01-17	16737	THU	
13-01-17	16084	FRI	
14-01-17	14766	SAT	
15-01-17	14513	SUN	
16-01-17	16372	MON	
17-01-17	16623	TUE	
18-01-17	16600	WED	
19-01-17	16357	THU	
20-01-17	15786	FRI	
21-01-17	14283	SAT	
22-01-17	13917	SUN	
23-01-17	15554	MON	
24-01-17	15043	TUE	
25-01-17	15187	WED	
26-01-17	14623	THU	
27-01-17	13325	FRI	
28-01-17	11464	SAT	CNY
29-01-17	12405	SUN	
30-01-17	12745	MON	
31-01-17	13800	TUE	
01-02-17	14290	WED	
02-02-17	15054	THU	
03-02-17	15515	FRI	
04-02-17	14653	SAT	
05-02-17	14292	SUN	
06-02-17	16525	MON	
07-02-17	16247	TUE	
08-02-17	16381	WED	THAIPUSAM
09-02-17	15136	THU	
10-02-17	16237	FRI	
11-02-17	14621	SAT	
12-02-17	14087	SUN	
13-02-17	16116	MON	
14-02-17	16053	TUE	
15-02-17	16001	WED	
16-02-17	16212	THU	
17-02-17	15835	FRI	
18-02-17	14815	SAT	
19-02-17	14359	SUN	
20-02-17	16719	MON	
21-02-17	16490	TUE	
22-02-17	16790	WED	
23-02-17	16619	THU	
24-02-17	15859	FRI	
25-02-17	14403	SAT	
26-02-17	14166	SUN	
27-02-17	15837	MON	
28-02-17	15962	TUE	

Universiti Utara Malaysia

Appendix C

Data for Figure 4.3

Date	ELD	Day	Event
31-Jan-18	15358	WED	
1-Feb-18	16348	THU	
2-Feb-18	16282	FRI	
3-Feb-18	15144	SAT	
4-Feb-18	14690	SUN	
5-Feb-18	16575	MON	
6-Feb-18	16169	TUE	
7-Feb-18	16233	WED	
8-Feb-18	16507	THU	
9-Feb-18	16311	FRI	
10-Feb-18	15187	SAT	
11-Feb-18	14727	SUN	
12-Feb-18	16544	MON	
13-Feb-18	16623	TUE	
14-Feb-18	16027	WED	
15-Feb-18	14765	WED	
16-Feb-18	13833	THU	CNY
17-Feb-18	13261	FRI	
18-Feb-18	13856	SAT	
19-Feb-18	15495	SUN	
20-Feb-18	16327	MON	
21-Feb-18	16835	TUE	
22-Feb-18	16849	WED	
23-Feb-18	16331	THU	
24-Feb-18	14937	FRI	
25-Feb-18	14868	SAT	
26-Feb-18	16828	SUN	
27-Feb-18	17073	MON	
28-Feb-18	17406	TUE	

Universiti Utara Malaysia

Appendix D

MH-ELD Chen and Cheng Forecasting Results

Determine the upper and lower limits, and the middle values.				
Interval	**Lower Boundry**	**Upper Boundry**	**Midpoint**	**Fuzzyfication**
1	-30.330	-25.390	-27.86	A1
2	-25.390	-19.350	-22.37	A2
3	-19.350	-13.670	-16.51	A3
4	-13.670	-8.590	-11.13	A4
5	-8.590	-3.450	-6.02	A5
6	-3.450	0.770	-1.34	A6
7	0.770	4.850	2.81	A7

		Fuzzyfication	Determine FLR (Fuzzy Logical Relationship)			
t	**Actual**	**Fuzzyfication**	**FLR1**	**LH**	**RH**	**FLRG**
1	-9.6442	A4				
2	-12.6307	A4	A4 -> A4	A4	A4	G4
3	-17.1537	A3	A4 -> A3	A4	A3	G4
4	-22.3622	A2	A3 -> A2	A3	A2	G3
5	-14.5249	A3	A2 -> A3	A2	A3	G2
6	-22.1537	A2	A3 -> A2	A3	A2	G3
7	-16.9825	A3	A2 -> A3	A2	A3	G2
8	-4.6653	A5	A3 -> A5	A3	A5	G3
9	-11.7168	A4	A5 -> A4	A5	A4	G5
10	-10.235	A4	A4 -> A4	A4	A4	G4
11	-15.1038	A3	A4 -> A3	A4	A3	G4
12	-27.8572	A1	A3 -> A1	A3	A1	G3
13	-24.2272	A2	A1 -> A2	A1	A2	G1
14	-13.3761	A4	A2 -> A4	A2	A4	G2
15	2.8078	A7	A4 -> A7	A4	A7	G4
16	-1.269	A6	A7 -> A6	A7	A6	G7
17	-10.5531	A4	A6 -> A4	A6	A4	G6
18	-15.1922	A3	A4 -> A3	A4	A3	G4
19	-12.6819	A4	A3 -> A4	A3	A4	G3
20	-5.9143	A5	A4 -> A5	A4	A5	G4
21	-6.3407	A5	A5 -> A5	A5	A5	G5
22	-0.1395	A6	A5 -> A6	A5	A6	G5
23	-7.73829	A5	A6 -> A5	A6	A5	G6
24	-17.1136	A3	A5 -> A3	A5	A3	G5

Universiti Utara Malaysia

25	-20.9676	A2	A3 -> A2	A3	A2	G3
26	-18.0285	A3	A2 -> A3	A2	A3	G2
27	-17.3177	A3	A3 -> A3	A3	A3	G3
28	-18.5514	A3	A3 -> A3	A3	A3	G3

Pivot Table

Row Labels	Count of LH	Count of RH
A1	**1**	**1**
A2	1	1
A2	**3**	**3**
A3	2	2
A4	1	1
A3	**5**	**5**
A1	1	1
A2	2	2
A4	1	1
A5	1	1
A4	**7**	**7**
A3	3	3
A4	2	2
A5	1	1
A7	1	1
A5	**2**	**2**
A4	1	1
A5	1	1
A6	**1**	**1**
A4	1	1
A7	**1**	**1**
A6	1	1
(blank)		
(blank)		
Grand Total	**20**	**20**

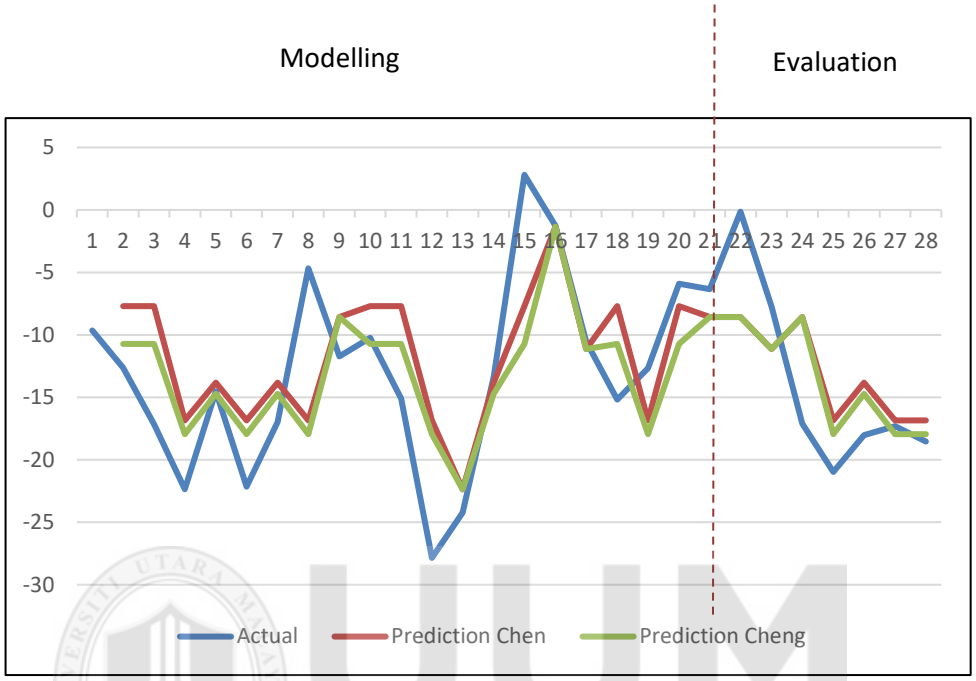
Universiti Utara Malaysia

FLRG	Midpoint	Current State	Next Stage	Total	Prediction Chen	Prediction Cheng
G1	-27.86	A1	A2	1	-22.370	-22.370
G2	-22.37	A2	A3,A4	3	-13.820	-14.717
G3	-16.51	A3	A1,A2,A4,A5	5	-16.845	-17.950
G4	-11.13	A4	A3,A4,A5,A7	7	-7.713	-10.714
G5	-6.02	A5	A4,A5	2	-8.575	-8.575
G6	-1.34	A6	A4	1	-11.13	-11.13
G7	2.81	A7	A6	1	-1.34	-1.34

Prediction	
Prediction Chen	Prediction Cheng
-7.713	-10.714
-7.713	-10.714
-16.845	-17.950
-13.820	-14.717
-16.845	-17.950
-13.820	-14.717
-16.845	-17.950
-8.575	-8.575
-7.713	-10.714
-7.713	-10.714
-16.845	-17.950
-22.370	-22.370
-13.820	-14.717
-7.713	-10.714
-1.340	-1.340
-11.130	-11.130
-7.713	-10.714
-16.845	-17.950
-7.713	-10.714
-8.575	-8.575
-8.575	-8.575
-11.130	-11.130
-8.575	-8.575
-16.845	-17.950
-13.820	-14.717
-16.845	-17.950
-16.845	-17.950

Universiti Utara Malaysia

Graph
Actual vs Prediction (Chen & Cheng)



Universiti Utara Malaysia

Appendix E

List of Publications

1. Mansor, R., Zaini, B.J. & Othman, S. (2021). Moving holiday effects on forecasting electricity load demand. *Productivity Management*, 26(1), 29-45.
2. Mansor, R., Kasim, M. & Othman, M. (2020). Weighted subsethood segmented fuzzy time series for moving holiday electricity load demand forecasting. *Journal of Advanced Research in Dynamical and Control Systems 1*2(Special Issue-02), 686-700.
3. Mansor, R., Othman, M. and Kasim, M.M. (2017). Fuzzy reasoning based time series forecasting using weighted subsethood model. *Advanced Science Letters*, 23(9), 9094-9097.
4. Mansor, R., Kasim, M. M., and Othman, M. (2016). The framework of weighted subset-hood Mamdani fuzzy rule based system rule extraction (MFRBS-WSBA) for forecasting electricity load demand. *Journal of Telecommunication, Electronic and Computer Engineering,* 8(8), 97–102.
5. Mansor, R., Zaini, B.J., Othman, M., Kasim, M.M. (2018). The effect of interval length in weighted subsethood fuzzy time series. *AIP Conference Proceedings* 1974,040017
6. Mansor, R., Kasim, M.M & Othman, M. (2018). The framework of weighted subsethood fuzzy time series (WESUFTS) algorithm. e-P*roceeding of the 1st Young Researchers' Quantitative Symposium 2018*.
7. Mansor, R., Kasim, M. M., & Othman, M. (2016). The framework of weighted subset-hood Mamdani fuzzy rule based system rule extraction (MFRBS-WSBA) for forecasting electricity load demand. In *International Conference on Applied Science and Technology 2016 (ICAST'16). AIP Conference Proceeding,* 1761, 20061.

Universiti Utara Malaysia