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ISSN: 0193-4120 Page No. 832 - 838

M-factors Fuzzy Time Series for Forecasting Stock Price Movement

Rosnalini Mansor[1], Maznah Mat Kasim[2], Mahmod Othman[3], Bahtiar Jamili Zaini[4], Norhayati Yusof[5]

[1, 2, 4, 5] School of Quantitative Sciences, Universiti Utara Malaysia, Sintok, Kedah, Malaysia.
[2]School of Quantitative Sciences, Universiti Utara Malaysia, Sintok, Kedah, Malaysia.

Article Info
Volume 81
Page Number: 832 - 838
Publication Issue:
November-December 2019

Abstract

Forecasting stock price movements is one of the vital activities in assisting to analyze stock market movements technically. However, the forecasting process is inspiring to many researchers in attempting to apply and modify the forecasting methods due to the difficulties and uncertainties of the stock market.One of the continuity innovation forecasting methods in this area is fuzzy time series (FTS). This paper proposed M-factor FTS using weighted subsethood in constructing the FTS model (WeSuFTS model). 1-factor WeSuFTS and 2-factors WeSuFTS models were developed based on WeSuFTS forecasting procedure. Modeling and evaluation part of the data analysis were obtained from the one company listed in Bursa Malaysia website. The daily historical data were selected for two months. The results from step by step algorithm were demonstrated in this paper.Investigation on the accuracy of forecasting results were compared between actual value and M-factor FTS forecast value in evaluation part of the data using absolute percentage error (APE), mean square error (MSE), mean absolute percentage error (MAPE) and root mean squared error (RMSE). The models performance results revealedthe proposed M-factor FTS model can further be improve due to 1-factor WeSuFTS model is the outperform model compared to 2-factors WeSuFTS model to forecast stock price movement with forecasting error from 6.3% - 13.8% (APE), 8.8% (MAPE), 0.0041 (MSE) and 0.0638 (RMSE).

Article History
Article Received: *3 January 2019*
Revised: *25 March 2019*
Accepted: *28 July 2019*
Publication: *25 November 2019*

Keywords: *Fuzzy time series,forecasting, stock price movement, weighted subsethood.*

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I. Introduction

Technical stock market analysts always want to see the nature and pattern of stock market data. The analysts may from the investors, trader or consultants. Their main objective is to attain the return in the correct time with high profit.Therefore, it is important to forecast the future stock price movement before they start to invest.

However, the nonlinearity, complexity and uncertainty in stock price movement is well known problems in stock market forecasting[1], [2]. The uncertainty including the unexpected variation in the stock market fluctuation [3], [4].Interestingly, there are also many factors contribute to stock market analysis problems such aschanges variance in stockprice anddoubtful news exist and shares factors [2].

Therefore, it was a motivation for many researchers to apply a variety of forecasting method to forecast stock price movement. For instance Zaini et al.[5], classify stock market movement using logistic regression with four significant technical indicators and Duta et al. [6] with eight financial ratios in their logistic regression. However, as mention previously, the nonlinear and existing of uncertainty in stock price movement made a rising of many alternative forecasting methods such as neural network [7]–[9], genetic algorithm [10], [11] and fuzzy approach [12]–[15].

However, fuzzy time series (FTS) forecasting method become popular due to the method advantage that the number of historical data are not a constraint in the FTS model building[16].Besides the stock market forecasting problem, FTS forecasting method also successfully applied in other forecasting problems such as in student enrollment [17]–[20], electricity load demand [21]–[23]grain production [24], [25] and country population forecasting [26].

Therefore, the objective of this paper is to forecast stock price movement using our new FTS model namely M-factor weighted subsethood fuzzy time series (M-factor WeSuFTS) Here “M” is equal to one and two due to the number of factors considered in this study were two only. The remainder of this paper is organized as follows: Section II briefly introduce some FTS definition. The proposed M-factor WeSuFTS is presented in Section Methodology. Next section, section IV show the forecasting results and some results discussion. The research conclusion and some recommendations are presented in section V.

II. FUZZY TIME SERIES

Fuzzy time series (FTS) forecasting is the method to solve forecasting problem with the time series data in non-numeric or linguistic value form. Nevertheless, the linguistic time series data cannot be applied in conventional statistical forecasting methods. Interestingly, FTS method also is able to use at the numeric data set by converting the numeric data into fuzzy data using fuzzification process. Essentially, FTS is a data forecasting method that uses basic fuzzy principles developed by Zadeh[27]which was subsequently established by Song and Chissom in 1993[28] as the FTS concept.Song and Chissom[29]employ the FTS definition by applied the FTS concept to solve problems in predicting new student registrations at Alabama University.From that,after years, many FTS models were further developed or modify the Song and Chissom’s model. For instants, the FTS model was further developed by Chen [20]by utilizing arithmetic operations to solve problems with the same case. However, there are several disadvantages to Chen's algorithm, namely not considering the presence of repetition and the absence of weighting that becomes lower in the longer observation[30]. Hence, Cheng et al. [30] implement the weighted concept in their FTS model.

The weighted FTS (WFTS) model can be defined at a certain FTS step in FTS forecasting procedure. Most of the WFTS were based on FTS rules and frequency-weighted method based on fuzzy relationship group[30]–[32]. This paper proposed the new weighted mechanism in FTS stock price movement forecasting based on weighted subsethood algorithm from Rasmani and Shen [33],[34]. The mechanism is based on subsethood fuzzy value. The detail steps of M-Factor WeSuFTS stock price movement forecasting are explained in the next sections.

M-factors WeSuFTS are adopt from M-factors FTS and WeSuFTS. M-factor FTS can be define as follow: Let FTS A_t, B_t, C_t,..., $M_t$be the factors/independent variables of the FTS forecasting problems. If the study uses$A_t$only to address the issues of forecasting problem, then it is called a one-factor FTS. Then, if the study uses the remaining factors B_t, C_t,..., $M_t$with $A_t$to solve the forecastingproblems, then it is called M-factors FTS[35].

III. Methodology

This section explains the methodology to achieve the objectives of the study. This paper proposed two of M-factors WeSuFTS models; 1-factor WeSuFTS and 2-factors WeSuFTS. This studyused the flow of methodology research as presented in Fig. 1 and Fig 2. However, the detail WeSuFTS methodology also discussed at Mansor et. al. [17], [21], [22], [36], [37]. The flow of the WeSuFTS methodology consists of three primary stages including data preprocessing, modeling and model assessment.

In each phase, the detailed steps are:

A. Preprocessing data

Step 1: Dividing the data

The 33 data points in daily basis from 6 August to 25 September 2018 were collected from one company in Bursa Malaysia. Regarding to Fig. 1, the data set were divided into two parts. The first 23 data points were for modelling part while, the rest of 10 data points were for evaluation part.

Step 2: Data preparation

Two models of M-factor WeSuFTS were considered in this study:

Model 1: 1-factor WeSuFTS model.

Model 2: 2-factors WeSuFTS model.

Lets variable $A_t$is the closing price at time t, $B_t$is changes closing price and C_t is percent changes number of share.Therefore, $B_t \rightarrow A_t$is the writing form of 1-factor WeSuFTS model and C_t, $B_t \rightarrow A_t$is the writing form of 2-factors WesuFTS model. We define B_t and C_t as the factors/independent variables and A_t is the dependent variable of the model. B_t and C_t are defined as in (1) and (2).

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$$B_t = A_{t-1} - A_{t-2} \quad (1)$$

$$C_t = \frac{S_{t-1} - S_{t-2}}{S_{t-2}} \times 100 \quad (2)$$

Where $A_{t-1}$and $A_{t-2}$is one and two day(s) previous closing price respectively. S_{t-1} and S_{t-2} is one and two day(s) previous number of shares correspondingly.

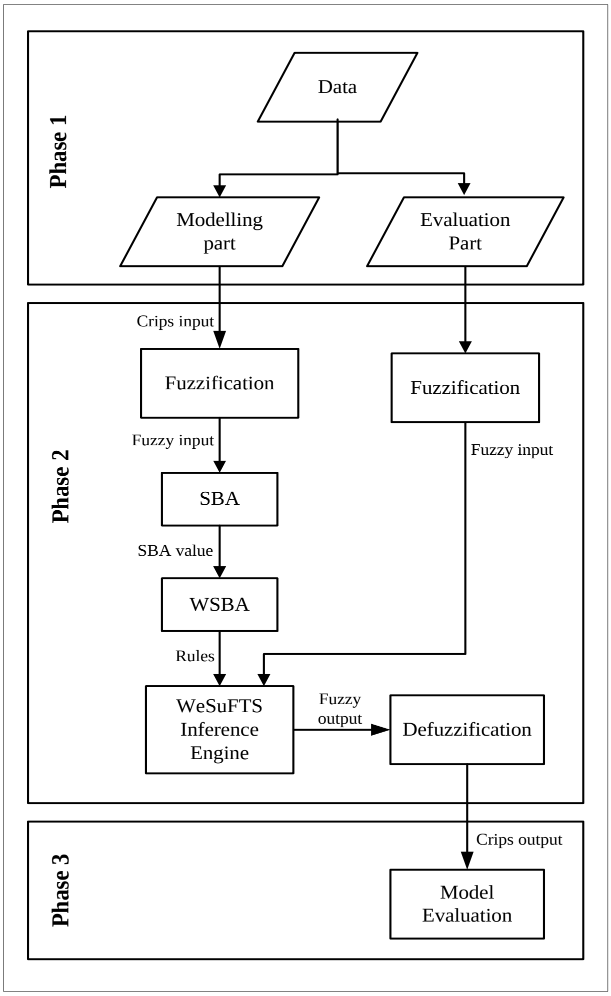

Fig.1: The flowchart of WeSuFTS procedure

Phase 1: Preprocessing data
Step 1: Partitioning the data into modeling and evaluation parts.
Step 2: Data preparation for the M-factor WeSuFTS models.

Phase 2: Modeling and forecast based on WeSuSFTS
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 WeSuFTS model.
Step 8: Defuzzifying fuzzy value into crisp value.

Phase 3: Model evaluation.
Step 1: Defining and calculating forecasting error measurement.
Step 2: Comparing forecasting error measurement with other model.

Fig. 2: The WeSuFTS procedure

B. Model Development

Step 1: Defining and partitioning the universal of discourse, U.

From the data, we define $U_{A_t} = [0.6\,, 0.95]$, $U_{B_t} = [-0.07\,, 0.07]$ and $U_{C_t} = [-250\,, 800\,]$. Then, we partitioned U intofive intervals for U_{C_t} and six intervals for $U_{A_t}$and U_{B_t}.

Step 2: Defining fuzzy set.

Fuzzy sets are defined on the universal set U. Leta_1, a_2, …, a_k, b_1, b_2, …, b_l *and* c_1, c_2, …, c_m be fuzzy set which are linguistic terms of the variable A_t, B_t and $C_t$respectively. We determine some linguistic fuzzy term represented by corresponding fuzzy sets

$$A_t = \{a_1, a_2, \ldots a_6\}$$
$$B_t = \{b_1, b_2, \ldots b_6\}$$
$$C_t = \{c_1, c_2, \ldots c_5\}$$

Therefore, in this study we defining fuzzy set by graphical membership function as shown in Fig.3(a) – (b) respectively.

Step 3: Fuzzifying A_t, B_t and C_t from crisp value into fuzzy value usingrespectivemembership function.

The membership functions constructed in *Model Development Step 2* were used to fuzzify the crisp values in independent and dependent variables into fuzzy linguistic term. Each crisp value is fuzzified according to its highest degree of membership function.

Step 4: Determining fuzzy logical group (FLR) and fuzzy logical relationship group (FLRG)

We grouped the cases which has the same linguistic value dependent variable. The fix number of subgroups are based on the fix number fuzzy set in dependent linguistic variable. We constructed FLR and FLRG by grouped the cases which has the same dependent linguistic fuzzy term.

Step 5: Calculating fuzzy subsethood value using subsethood based algorithm (SBA).

The formula calculation is shown in (3). These values describe the relationship degree between the dependent linguistic fuzzy term (a_i) and every independent linguistic fuzzy term(b_j):

$$S(a_i, b_j) = \frac{\sum_{x \in U} min\left\{\mu_{a_i}(x), \mu_{b_j}(x)\right\}}{\sum_{x \in U} \mu_{a_i}(x)} \quad (3)$$

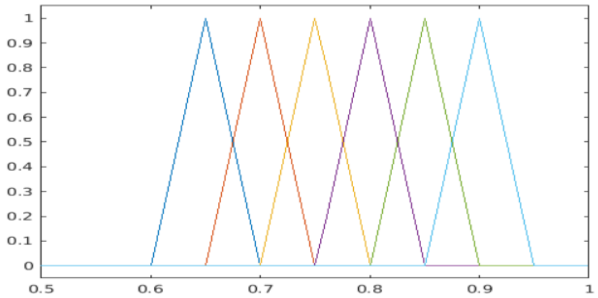

Fig. 3(a) membership function for A_t

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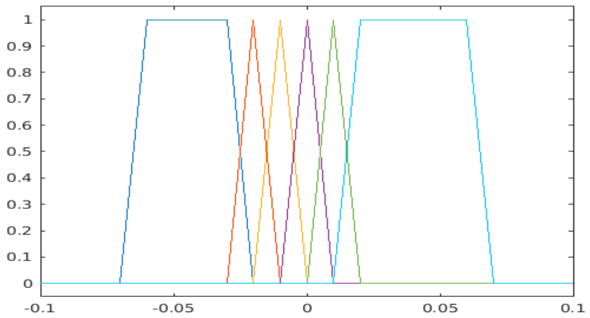

Fig. 3(b) membership function for B_t

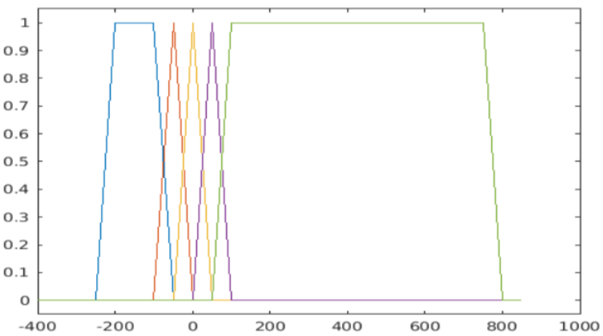

Fig. 3(c) membership function for C_t

Step 6: Calculating weighted fuzzy subsethood value (WSBA)

Calculating WSBA is a calculation of relative weight based on SBA value. The weight mechanism is based on Rasmani and Shen[33][34]. The formula calculation is shown in (4):

$$w(a_i, b_j) = \left(\frac{S(a_i, b_j)}{\max\limits_{j=1,2,\ldots,l} S(a_i, b_j)} \right) \quad (4)$$

Step 7: Constructing WeSuFTS model

We construct **IF-THEN** rule statement to formulate the WeSuSFTS model in this step. The process also refer as WeSuFTS Inference Engine. The WeSuFTS model consist of a set of fuzzy rules in form:

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

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

The condition part involve the WSBA value from *Model Develoment Step 6* and behave as a multiplicative factor for respective independent linguistic variable fuzzy term. The rule set is simplified as any fuzzy term that have multiplicative factor equal to 0 is automatically removed from the model. The general 1-factor WeSuFTS model as shown in Fig. 4(a)If more than one factors use in the study, the model consist of rules with two type operator, **OR** and **AND**. Where operator **OR** apply max operation and operator **AND** apply min operator. Fig. 4(b) shows the general WeSuFTS model for more than one factors.

Rule 1: IF B *is* $w(a_1, b_1)b_1$ OR $w(a_1, b_2)b_2$ OR … OR $w(a_1, b_l)b_l$
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 $w(a_2,$
THEN A *is* a_2.
.
.
.
Rule i: IF B *is* $w(a_i, b_1)b_1$ OR $w(a_i, b_2)b_2$ OR … OR $w(a_i, b$
THEN A *is* a_i.

Fig. 4(a). General model of 1-factor WeSuFTS model

Rule 1: IF B *is* $[w(a_1, b_1)b_1$ OR $w(a_1, b_2)b_2$ OR … OR $w(a$
AND C *is*$[w(a_1, c_1)c_1$ OR $w(a_1, c_2)c_2$ OR … OR $w(a_1, c_m)c$
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 $w(a$
AND C *is* $[w(a_2, c_1)c_1$ OR $w(a_2, c_2)c_2$ OR … OR $w(a_2, c_m)$
THEN A *is* a_2.
.
.
.
Rule i: IF B *is* $[w(a_i, b_1)b_1$ OR $w(a_i, b_2)b_2$ OR … OR $w(a_i,$
AND C *is* $[w(a_i, c_1)c_1$ OR $w(a_i, c_2)c_2$ OR … OR $w(a_i, c_m)c$
THEN A *is* a_i.

Fig. 4(b): General model for M-factors WeSuFTS model

Table 1(a). Fuzzy subsethood value for 1-factor WeSuFTS

		B					
		b_1	b_2	b_3	b_4	b_5	b_6
A	a_1						
	a_2	0.3200	0.2000	0.2000	0.2000	0.2000	0.0000
	a_3	0.2830	0.0943	0.2642	0.2264	0.0943	0.1132
	a_4	0.1923	0.1923	0.3462	0.1923	0.1923	0.0000
	a_5	0.0758	0.2121	0.1515	0.3030	0.1515	0.3485
	a_6						

Table 1(b). Fuzzy subsethood value for 2-factor WeSuFTS

		B						C				
		b_1	b_2	b_3	b_4	b_5	b_6	c_1	c_2	c_3	c_4	c_5
A	a_1											
	a_2	0.320	0.2	0.2	0.2	0.2	0	0	0	0.645	0.385	0
	a_3	0.283	0.094	0.264	0.226	0.094	0.113	0.099	0.368	0.241	0.313	0.131
	a_4	0.192	0.192	0.346	0.192	0.192	0	0.023	0.654	0.07	0	0.346
	a_5	0.076	0.212	0.152	0.303	0.152	0.349	0.085	0.301	0.282	0.206	0.349
	a_6											

Table 2(a). WSBA value for 1-factor WeSuFTS

		B					
		b_1	b_2	b_3	b_4	b_5	b_6
A	a_1						
	a_2	1.0000	0.6250	0.6250	0.6250	0.6250	0.0000
	a_3	1.0000	0.3333	0.9333	0.8000	0.3333	0.4000
	a_4	0.5556	0.5556	1.0000	0.5556	0.5556	0.0000
	a_5	0.2174	0.6087	0.4348	0.8696	0.4348	1.0000
	a_6						

Table 2(b). WSBA value for 2-factor WeSuFTS

		B						C				
		b_1	b_2	b_3	b_4	b_5	b_6	c_1	c_2	c_3	c_4	c_5
A	a_1											
	a_2	1	0.625	0.625	0.625	0.625	0	0	0	1	0.5971	0
	a_3	1	0.333	0.933	0.8	0.333	0.4	0	1	0.655	0.850	0.357
	a_4	0.556	0.556	1	0.556	0.556	0	0.036	1	0.107	0	0.53
	a_5	0.217	0.609	0.4348	0.87	0.435	1	0.245	0.863	0.808	0.592	1
	a_6											

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Step 8: Defuzzifying close price fuzzy value.

In this step, we convert the close price fuzzy value to close price crisp value using peak point defuzzification method. The defuzzification formula is shown in Equation (3)[36].

Where FA_t is the stock market forecast value, R_i is the calculation value from i rules. $M_i$is the midpoint or peak point value for i interval in A_t and n is the number of rules $\neq 0$.

C. Model Evaluation

The M-factors WeSuFTS forecasting model's performance is evaluated with the error forecast measurement.This study consider only four predictive error measures because these error measures were the most common techniques among forecasters. The fourforecasterror measurements are:

i. absolute percentage error (APE),
ii. mean squared error (MSE),
iii. mean absolute percentage error (MAPE)
iv. root mean squared error (RMSE).

IV. RESULTS

This section shows the outcomes of the earlier section's process.After finishing calculation the SBA valueas presented in Table 1(a) and (b) and WSBA value, the 1-factor WeSuFTS model is constructed using information from WSBA value in Table 2(a). Then 2-factors WeSuFTS model constructed using WSBA value in Table 2(b). All the models are shown in Fig. 5(a) and(b).Later, these models were implemented using evaluation part data. Then we forecast closing stock price movement using (5).The results are shown in Table 6 and Figure 6.

In this study, *Rule 1* and *Rule 6* were not appear in both models WeSuFTS. This is because there were no linguistic term a_1 and a_6 data in data set. Therefore no subgroup 1 and 6 in *Phase 2 Step 4*. From the 1-factor WeSuFTS model in Fig. 5(a), some interpretation can be revealed as:

i. B1,B2,B3,B4 and B5 are important to A2 and A4. However, the most important fuzzy term contribute to A2 and A4 is B1 and B3 respectively.
ii. All fuzzy term in B are important to A3 and A5. However, the most important fuzzy term contribute to A3 and A5 is B1 and B6 respectively.

Interestingly, the interpretation of fuzzy term in B and C can combined in 2-factors WeSuFTS model. Based on 2-factors WeSuFTS model in Fig. 5(b), some interpretation can explained as follow:

i. All fuzzy terms in B and C are important to A5. However, B6 and C5 are most important to A5.
ii. All fuzzy terms in B and C except C1 are important to A3. But, B1 and C2 are the most important to A3.
iii. All fuzzy terms in B and C are important to A4 except B6 and C4. However, B3 and C2 are the most important to A4.
iv. Fuzzy terms C3 and C4 and all fuzzy terms in B except B6 are important to A2. However, B1 and C3 are the most important to A2.

From the models performance results in Table 6 shows the 1-factor WeSuFTS model is give more accurate forecast value compared to 2-factors WeSuFTS model with 8.76%, 0.0041 and 0.0638 of MAPE, MSE and RMSE error measurement values respectively.

V. CONCLUSION AND FUTURE RESEARCH

In conclusion, this study shows the implementation of

$$FA_t = \frac{\sum_{i=1}^{n} R_i M_i}{\sum_{i=1}^{n} M_i} \quad (5)$$

M-factors WeSuFTS procedure in the forecasting Malaysia stock price movement. The proposed FTS procedure employsWSBA algorithm in the FLR and FLRG before the WeSuFTS constructed and simple to implement.Two models were constructed; 1-factor and 2-factors WeSuFTS. The interpretability of WeSuFTS models also presented and can contribute more meaningful interpretation such as the relative relationship between dependent variable and each fuzzy term in independent variables. The multiplicative factors in the models also make the model easy to interpret by representing which most fuzzy term dependent variable contribute to fuzzy term in dependent variable.

In general, the M-factors WeSuFTS procedure also shows the data-driven rule generation in WeSuFTS inference engine and could be an alternative fuzzy modelling approach. The inference engine approach can be very useful under the situation where there are no human experts and also can provide information which is not acknowledged by the experts.

Rule 1:	-
Rule 2:	*If* B_t *is* ($B1_t$ *or* $0.625B2_t$ *or* $0.625B3_t$ *or* $0.625B4_t$ *or* $0.625B5_t$) *then* A_t *is* $A2_t$.
Rule 3:	*If* B_t *is* ($B1_t$ *or* $0.333B2_t$ *or* $0.933B3_t$ *or* $0.8B4_t$ *or* $0.333B5_t$ *or* $0.4B6_t$) *then* A_t *is* $A3_t$.
Rule 4:	*If* B_t *is* ($0.556B1_t$ *or* $0.556B2_t$ *or* $B3_t$ *or* $0.556B4_t$ *or* $0.556B5_t$) *then* A_t *is* $A4_t$.
Rule 5:	*If* B_t *is* ($0.218B1_t$ *or* $0.609B2_t$ *or* $0.435B3_t$ *or* $0.870B4_t$ *or* $0.435B5_t$ *or* $B6_t$) *then* A_t *is* $A5_t$.
Rule 6:	-

Fig. 5(a). 1-factor WeSuFTS close price movement model

Rule 1:	-
Rule 2:	*If* B_t *is* ($B1_t$ *or* $0.625B2_t$ *or* $0.625B3_t$ *or* $0.625B4_t$ *or* $0.625B5_t$) *and* C_t *is* ($C3_t$ *or* $0.597C4_t$) *then* A_t *is* $A2_t$.
Rule 3:	*If* B_t *is* ($B1_t$ *or* $0.333B2_t$ *or* $0.933B3_t$ *or* $0.8B4_t$ *or* $0.333B5_t$ *or* $0.4B6_t$) *and* C_t *is* ($C2_t$ *or* $0.645C3_t$ *or* $0.850C4_t$ *or* $0.357C5_t$) *then* A_t *is* $A3_t$.
Rule 4:	*If* B_t *is* ($0.556B1_t$ *or* $0.556B2_t$ *or* $B3_t$ *or* $0.556B4_t$ *or* $0.556B5_t$) *and* C_t *is* ($0.035C1_t$ *or* $C2_t$ *or* $0.107C3_t$ *or* $0.529C5_t$) *then* A_t *is* $A4_t$.
Rule 5:	*If* B_t *is* ($0.218B1_t$ *or* $0.609B2_t$ *or* $0.435B3_t$ *or* $0.870B4_t$ *or* $0.435B5_t$ *or* $B6_t$) *and* C_t *is* ($0.245C1_t$ *or* $0.863C2_t$ *or* $0.808C3_t$ *or* $0.592C4_t$ *or* $C5_t$) *then* A_t *is* $A5_t$
Rule 6:	-

Fig. 5(a). 2-factor WeSuFTS close price movement model

In the side of the future research and improvement, the proposed M-factors WeSuFTS procedure expose much modification and improvement opportunity. For instant, the mechanism to identify the significant or the important factors, named “M” number of factors can employ different methods such as using R^2 values and stepwise variables selection method. The instrument to define the number of fuzzy set also can use other clustering methods such as fuzzy *c*-means clustering and *k*-median clustering. The novel modification of conventional FTS can be seen at the model development by employing weighted fuzzy subsethood algorithm. The performance different weighted mechanism also can suggested for the future research.

Table 6. Models performance

time(t)	Close price Actual value	1-factor WeSuFTS		2-factors WeSuFTS	
		forecasted value	APA	forecasted value	APA
23	0.720	0.7810	8.4745	0.8071	12.0959
24	0.690	0.7850	13.7722	0.7818	13.3034
25	0.700	0.7498	7.1181	0.7692	9.8897
26	0.705	0.7705	9.2953	0.7735	9.7141
27	0.715	0.7850	9.7942	0.7808	9.2073
28	0.725	0.7705	6.2802	0.7672	5.8247
29	0.710	0.7705	8.5256	0.8039	13.2270
30	0.730	0.7810	6.9886	0.8071	10.5604
31	0.720	0.7893	9.6189	0.8088	12.3357
32	0.720	0.7760	7.7783	0.8029	11.5205
MAPE		8.7646		10.7679	
MSE		0.0041		0.0061	
RMSE		0.0638		0.0782	

ACKNOWLEDGMENT

The authors are grateful for the financial support received from Universiti Utara Malaysia under the Research Generating University Grant (S/O Code: 13878).

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AUTHORS PROFILE

Rosnalini Mansoris a lecturer at Department of Mathematics and Statistics, School of Quantitative Sciences, College of Arts and Sciences, Universiti Utara Malaysia. Currently doing PhD at Awang Had Salleh graduated School, Universiti Utara Malaysia. Her research areas mainly focus on forecasting, fuzzy time series, statistical modelling and structural equation model. Among her previous researches were about electricity load demand, stock price movement, soccer tournament and customer loyalty.

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Maznah Mat Kasim is an Associate Professor at Department of Decision Sciences, School of Quantitative Sciences, Universiti Utara Malaysia (UUM). She obtained her PhD in 2008 from Universiti Kebangsaan Malaysia, while her BSc and MSc were from Wichita State University, USA. Her main research work is related to multi-criteria decision modeling whether in crisp or fuzzy environments. Among her previous researches were about performance evaluation in higher learning institutions, allocation problem in hospitals, performance of homestays in tourism industry in Malaysia. She has managed to publish many papers in SCOPUS and ISI journals, and presented many papers in local and international conferences. She has been awarded excellence service award a few times. She also was categorized in top three researcher by UUM in 2014. Lat year, she received a promising book author award given by the UUM Press.

Mahmod Othman is currently an Associate Professor at the Universiti Teknologi PETRONAS, Seri Iskandar, Perak, MALAYSIA since March 2016. Before that, he was an Associate Professor at the Universiti Teknologi MARA, Perlis, MALAYSIA. He has a total of twenty three years (23) of working experience in education industries as an academician where twenty one (21) years with Universiti Teknologi MARA and another two (2) years with Universiti Teknologi PETRONAS until present.His research interests span the fields of Fuzzy Mathematics, Artificial Intelligent, Optimization and Decision Making.

Bahtiar Jamili Zaini is a lecturer at School of Quantitative Sciences, College of Arts and Sciences, Universiti Utara Malaysia. Currently doing PhD at Awang Had Salleh graduated School, Universiti Utara Malaysia. His research interest include data mining involving high dimensional dataset and the application of fuzzy time series. He also has interest in structural equation model, forecasting and statistical modelling.

Norhayati Yusof is a senior lecturer and researcher at School of Quantitative Sciences, College of Arts and Sciences, Universiti Utara Malaysia.She received her PhD from Universiti Utara Malaysia in 2016. Her research areas mainly focus on statistical modelling especially model selection. She also has interest in structural equation modelling, partial least squares, forecasting and data mining.