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A new linguistic out-sample approach of fuzzy time series for daily forecasting of Malaysian electricity load demand

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ABSTRACT

The fuzzy logical relationships and the midpoints of interval have been used to determine the numerical in-out-samples forecast in the fuzzy time series modeling. However, the absolute percentage error is still yet significantly improved. This can be done where the linguistics time series values should be forecasted in the beginning before the numerical forecasted values obtained. This paper introduces the new approach in determining the linguistic out-sample forecast by using the index numbers of linguistics approach. Moreover, the weights of fuzzy logical relationships are also suggested to compensate the presence of bias in the forecasting. The daily load data from National Electricity Board (TNB) of Malaysia is used as an empirical study and the reliability of the proposed approach is compared with the approach proposed by Yu. The result indicates that the mean absolute percentage error (MAPE) of the proposed approach is smaller than that as proposed by Yu. By using this approach the linguistics time series forecasting and the numerical time series forecasting can be resolved.

1. Introduction

In the power management, the forecasting of load demand is the main problem especially in obtaining the high accuracy level. In this decade, the short time load forecasting (STLF) is frequently developed by researchers. Many approaches have been proposed to STLF demand ranging from the statistical to the artificial intelligence approaches [15]. For example, regression method [10,25,36,41], time series [1,9,12,35,54], neural network [2,27,37,38,44], similar day approach [18], expert system [20,40], fuzzy logic [26,49], data mining [16,17], wavelets [33], and evolutionary algorithms [19,21,50]. For the TNB (the largest electricity utility company in Malaysia) data, some previous studies investigated the STLF by using the time series Box–Jenkins method [35,54]. However, these studies do not provide sufficient justification on the results as compared with other approaches. Whereby, this situation encourages us to investigate the STLF for the TNB data by using one artificial intelligence, namely, the fuzzy time series (FTS).

FTS is a new approach which has been developed by Song and Chissom [45,46] in resolving the linguistic time series data problems. This approach is a combination between the fuzzy logic and the time series analysis. Furthermore, its application can be found in some domain problems, such as, enrollment [3,5,11,24,28,30,31,34,39,42,43,45–47,55], the stock index [6–8,11,22,24,48,52,53] temperature [4] and financial prediction [29,32]. The most important thing in the fuzzy time series forecasting is the assumption regarding data that are not needed, which is the main difference from the statistical approaches. In general, the model has been established by using fuzzification, fuzzy logical relationship (FLRs), fuzzy logical group (FLG), and defuzzification.

Many different models have been proposed on the fuzzy time series forecasting by researchers. Huarng [22] initiated a study on heuristic models of the fuzzy time series for forecasting by using the stock index data. In addition, Huarng et al. [23] also continued to analyze a multivariate heuristic model for the fuzzy time series forecasting. On the other hand, Yu [52] enhanced the weighted fuzzy time series models for the Taiwan Stock Index (TAIEX) forecasting. It is assigned by the recurrent FLRs in the FLG. Furthermore, Cheng et al. [7] presented the trend-weighted fuzzy time series model for the TAIEX forecasting. Qiu et al. [39] also presented a generalized approach in the forecasting by using the fuzzy weights. Yu [52] proposed the final forecast was equal to the product of midpoints matrix and the transpose of the weight matrix. However, the approach proposed by Yu is yet to be improved to resolve the linguistic out-sample forecast and also the numerical out-sample forecast.

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In this study, the discussion will be enhanced to design the new linguistic out-sample approach and to determine the weight of FLRs. In the forecasting phase, two types of forecasting phase are used: the linguistics time series forecasting and the numerical time series forecasting. The linguistics time series forecasting is applied to predict the linguistics values by using the index numbers using Box Jenkins procedure. The weights and midpoint intervals will be applied for the numerical time series forecasting. The weights can also be assigned by using index numbers of close relationship in the FLG. In addition, the length of interval and partition number in the universe of discourse will be considered using Sturges and the two powers of p (p is a number interval or class) rules. At the end of this procedure, both of the mean absolute percentage errors (MAPE) from the proposed approach will be compared with the MAPE approach proposed by Yu.

The remainder of the paper is organized as follows: Section 2 presents the basic theory of fuzzy set and fuzzy time series. Section 3 describes the importance of weighted fuzzy time series with few examples. Section 4 proposes weight and forecasting procedures for FLRs. Section 5 describes the empirical analysis using the daily TNB data from 01/01/2006 to 31/08/2006. The final section gives some conclusions of the study.

2. The fundamental theories in the fuzzy time series

This section describes the fuzzy set, fuzzy time series, and some related definitions that can be used in this paper.

2.1. Fuzzy set definition

Let U be the universe of discourse. A fuzzy subset A on the universe of discourse U can be defined as follows:

$$A = \{(u_i, \mu_i(u_i)) | u_i \in U\}$$

where μ_A is the membership function of A, $\mu_A : U \to [0, 1]$, and $\mu_A(u_A)$ is the degree of membership of the element u_i in the fuzzy set A [23]. If U be finite and infinite sets, then fuzzy set A can be expressed as follows:

$$A = \sum \frac{\mu_A(u_i)}{u_i} = \frac{\mu_A(u_1)}{u_1} + \frac{\mu_A(u_2)}{u_2} + \cdots + \frac{\mu_A(u_n)}{u_n}$$

and

$$A = \int \frac{\mu_A(u_i)}{u_i} du, \quad \forall u_i \in U$$

2.2. Fuzzy time series definitions

Song and Chissom [45,46] presented some definitions for fuzzy time series as follows:

Definition 1. Let $Y(t)$ $(t = 0, 1, 2, \ldots)$, a subset of real numbers, be the universe of discourse on which fuzzy sets $f_i(t)$ $(i = 1, 2, \ldots)$ are defined in the universe of discourse $Y(t)$ and $F(t)$ is a collection of $f_i(t)$ $(i = 1, 2, \ldots)$. Then $F(t)$ is called a fuzzy time series defined on $Y(t)$ $(t = 0, 1, 2, \ldots)$. Therefore, $F(t)$ can be understood as a linguistic time series variable, where $f_i(t)$ $(i = 1, 2, \ldots)$, are possible linguistics values of $F(t)$.

Definition 2. Suppose $F(t)$ is caused by $F(t-1)$ denoted by $F(t-1) \to F(t)$, then this relationship can be represented as:

$$F(t) = F(t-1) \circ R(t, t-1)$$

where "$\circ$" represents an operator, $R(t, t-1)$ is a fuzzy relationship between $F(t)$ and $F(t-1)$ and is called the first-order model of $F(t)$.

The other definitions also presented by Yu [52] and Huarng et al. [23] regarding the FLRs and FLG are as follows.

Definition 3. Let $F(t-1) = A_i$ and $F(t) = A_j$. The relationship between two consecutive data (called a fuzzy logical relationship, FLR), i.e., $F(t)$ and $F(t-1)$, can be denoted as $A_i \to A_j$, $i, j = 1, 2, \ldots, p$ (where p is interval or subinterval number) is called the left-hand side (LHS), and A_j is the right-hand side (RHS) of the FLR.

Definition 4. Let $A_i \to A_j$, $A_i \to A_k$, ..., $A_i \to A_p$ are FLRs with the same LHS which can be grouped into an ordered FLG (called a fuzzy logical group) by putting all their RHS together as on the RHS of the FLG. It can be written as bellow:

$$A_i \to A_j, A_i \to A_k, \ldots, A_i \to A_p; \quad i, j, k, \ldots, p = 1, 2, \ldots, n (n \in N)$$

2.3. Fuzzy time series forecasting

The forecasting procedure was developed by Song and Chissom (1993) into several steps as follows:

- Define the universe of discourse (U) and divide it into several equal length intervals.
- Fuzzify each interval into linguistics time series values (A_i, $i = 1, 2, \ldots, p$, p is partition number).
- Establish fuzzy logical relationships among linguistics time series values ($A_i \to A_j$, $i, j = 1, 2, \ldots, p$).
- Establish forecasting rule.
- Determine the forecast value.

3. The importance of weight in the fuzzy time series forecasting

In fuzzy time series, the forecasting model uses fuzzy relationships among the linguistic time series values. Two fuzzy types of relationships are (i) the same-fuzzy logical relationship and (ii) the different-fuzzy logical relationship. Both types of relationships may occur either recurrently or frequently. The occurrence of a particular fuzzy relationship explains the number of its appearances in the past. Some of the reasons for establishing the weight factor are:

i. To compensate for the presence of bias especially when the events are frequently occurred [14].
ii. To raise the influence of the more accurate input data, and to reduce the influence of the less accurate ones [13].

Fundamentally, these are the reasons for finding the weights in the fuzzy relationships. Similar to Yu [52] and Cheng et al. [7] findings, the weight factors are denoted within the weight matrix given in the following definition.

Definition 5. Yager's OWA operator of dimension n is a mapping

$$\emptyset : \mathbb{R}^n \to \mathbb{R}$$

which has an associated of weights $\mathbf{W} = (w_1 \quad w_2 \quad w_3 \cdots w_n)^T$ or can be written as:

$$\mathbf{W} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}$$

such that

i) $w_i \in [0, 1]$

ii) $\sum_{i=1}^{n} w_i = 1$,

$$\emptyset(a) = \emptyset(a_1, \ldots, a_n) = \sum_{i=1}^{n} w_i a_{\sigma(i)}$$

where σ: $\{1, \ldots, n\} \to \{1, \ldots, n\}$ is a permutation function such that $a_{\sigma(i)}$ is the highest value in the set $\{a_1, \ldots, a_n : a_{\sigma(i)} \geq a_{\sigma(i-1)}\}$ [51].

3.1. The existing weight methods in fuzzy time series

Yu [52] considered the recurrence of FLRs in the FLG to be assigned the weighted fuzzy time series. Moreover, the determination of these weights can be described as in Example 1.

Example 1. Let $A_1, A_2, A_1, A_1, A_1, A_1$ be linguistics time series values. By using Definitions 3, 4, and Yu's rule, then the fuzzy logical relationships, fuzzy logical group and weights can be described as follows:

a. Establish the FLRs: $A_1 \to A_2$, $A_2 \to A_1$, $A_1 \to A_1$, $A_1 \to A_1$, $A_1 \to A_1$. Thus, there are five relationships among linguistic time series values.
b. Establish the FLG: $A_1 \to A_2, A_1, A_1, A_1$ is called as the first group and $A_2 \to A_1$ is called as the second group. A_1 has one relationship with A_2, but A_1 has 3 recurrent fuzzy relations with itself. On the other hand, no recurrence of A_2.
c. Determine weights: $A_1 \to A_2$, $w_1 = 1/10$, $A_1 \to A_1$, $w_2 = 2/10$, $A_1 \to A_1$, $w_3 = 3/10$, $A_1 \to A_1$, $w_4 = 4/10$. The sum values of w_2, w_3, and w_4 are more than w_1, because there are three recurrences of A_1, while no recurrence of A_2 in this group. Moreover, no weight can be found for the second group. Yu proposed that the nominators of weights are determined by using the natural number ($i = 1, 2, \ldots$). However, Yus's rule shows that weights are increased following the number of relationships. In addition, these weights are applied to the forecasting approach.

Cheng et al. [7] also considered the trend-weighted recurrence of FLRs in the FLG. Moreover, the assigning of these weights can be described as in Example 2.

Example 2. By using Example 1, the assigning of trend-weighted components for fuzzy relations can be explained as follows:

a. Establish the FLRs: $A_1 \to A_2$, $A_2 \to A_1$, $A_1 \to A_1$, $A_1 \to A_1$, $A_1 \to A_1$. Thus, there are five relationships among the linguistics time series values.
b. Establish the FLG: $A_1 \to A_2, A_1, A_1, A_1$ is called as the first group and $A_2 \to A_1$ is called as the second group. A_1 has one relationship with A_2, but A_1 has 3 fuzzy relations with itself. On the other hand, no recurrence of A_2.
c. Determine the weights: $A_1 \to A_2$, $w_1 = 1/7$, $A_1 \to A_1$, $w_2 = 1/7$, $A_1 \to A_1$, $w_3 = 2/7$, $A_1 \to A_1$, $w_4 = 3/7$. The sum of values w_2, w_3, and w_4 are more than w_1, because there are three recurrences of A_1, while no recurrence of A_2 in this group. In this rule, the numerators of weights are increased following the recurrence and the same left-hand sides of FLRs in FLG. Thus, these weights are called as a trend. As in Yu [52], these numerators are also assigned with the natural numbers.

4. Proposed approach

The new rule in determining the weights of the FLRs are described in this section. Weights are assigned by using index number of close relationship in the FLG. Moreover, the calculations of weights are more simplified as compared with rules proposed by Yu [52] and Cheng et al. [7]. This proposed rule is effective to handle the frequent recurrence of the particular FLRs. The computational weights can be derived as in Section 4.1.

Table 1
The possibilities of index number in the FLG.

No	Conditions in FLG	Index number
1	$A_i \to A_{(-1)}, A_j, A_{(j+1)}$	$[(j-1), j, (j+1)]$
2	$A_i \to A_{(j-1)}, A_{(j+1)}, A_j$	$[(j-1), (j+1), j]$
3	$A_i \to A_{(j+1)}, A_j, A_{(j-1)}$	$[(j+1), j, (j-1)]$
4	$A_i \to A_{(j+1)}, A_{(j-1)}, A_j$	$[(j+1), (j-1), j]$
5	$A_i \to A_j, A_{(j-1)}, A_{(j+1)}$	$[j, (j-1), (j+1)]$
6	$A_i \to A_j, A_{(j+1)}, A_{(j-1)}$	$[j, (j+1), (j-1)]$
7	$A_i \to A_{(j-1)}, A_j$	$[(j-1), j]$
8	$A_i \to A_j, A_{(j+1)}$	$[j, (j+1)]$
9	Otherwise	No weight

4.1. Proposed weight for the fuzzy logical relationships (FLRs)

Suppose that, $A_i \to A_{j-1}, A_j, A_{j+1}$ is an FLG where $(j-1), j, (j+1)$ are the closest index numbers from left and right of A_i, $i = j, i, j \geq 2$ and $i, j \in Z$. By using these indexes, the computational weights values can be assigned mathematically as:

$$W(A_i) = \frac{\text{index number}}{\text{total of index number}}$$

$$\mathbf{W}(A_i) = \left[\frac{(j-1)}{(j-1)+j+(j+1)} \; \frac{j}{(j-1)+j+(j+1)} \; \frac{(j-1)}{(j-1)+j+(j+1)} \right]$$

let $(j-1) = c_1$, $j = c_2$, and $(j+1) = c_3$, and thus,

$$\mathbf{W}(A_i) = \left[\frac{c_1}{(c_1+c_2+c_3)} \; \frac{c_2}{(c_1+c_2+c_3)} \; \frac{c_3}{(c_1+c_2+c_3)} \right]$$

$$= \left[\frac{c_1}{\sum_{h=1}^{3} c_h} \; \frac{c_2}{\sum_{h=1}^{3} c_h} \; \frac{c_3}{\sum_{h=1}^{3} c_h} \right] \qquad (1)$$

where $\sum W_h(A_i) = \frac{\sum_h^3 c_h}{\sum_h^3 c_h} = 1$ has satisfied the condition and Definition 5. Furthermore, weight elements can also be presented in the weight matrix $\mathbf{W}$ as shown below:

$$\mathbf{W}(A_i) = [w_1 \quad w_2 \quad w_3] \qquad (2)$$

In general, there are some conditions and possibilities of the index numbers in the FLG as in Table 1.

Example 3. Let $A_3 \to A_1, A_1, A_2, A_4, A_3, A_3, A_5$ is an FLG. Then, the weights values can be calculated by using three different methods as follows:

(i) Yu's method
Given 7 FLRs from A_3 which $c_1 = 1, c_2 = 2, \ldots, c_7 = 7$, then $w_1 = 1/(1+2+3+4+5+6+7), \ldots, w_7 = 7/(1+2+3+4+5+6+7)$
$\mathbf{W}(A_3) = [w_1 \quad w_2 \ldots w_7] = [1/28 \quad 2/28 \ldots 7/28] = [0.04 \; 0.07 \ldots 0.25]$

(ii) Cheng's method
Given 7 FLRs from A_3 which $c_1 = 1, c_2 = 2, c_3 = 1, c_4 = 1, c_5 = 1, c_6 = 2, c_7 = 1$, then $w_1 = 1/(1+2+1+1+1+2+1), \ldots, w_7 = 1/(1+2+1+1+1+2+1)$
$\mathbf{W}(A_3) = [w_1 \; w_2 \ldots w_7] = [1/9 \; 2/9 \ldots 1/9] = [0.11 \; 0.22 \ldots 0.11]$

(iii) Proposed method
Given 7 FLRs from A_3 which $c_1 = 2, c_2 = 4, c_3 = 3$ (Condition no. 2), then

$w_1 = 2/(2+4+3)$, $w_2 = 4/(2+4+3)$, $w_3 = 3/(2+4+3)$,
$\mathbf{W}(A_3) = [w_1\ w_2\ w_3] = [2/9\ 4/9\ 3/9] = [0.22\ 0.44\ 0.33]$

Example 3 shows that there are some advantages for assigning weights based on index number of close relationship in the FLG as follow:

a. The weights values in the FLG can be calculated directly without take the other representative numbers as presented in Eq. (1), and this approach is more effective when compared with rules proposed by Yu [52] and Cheng et al. [7].
b. The weights values are not monotonously increasing and the forecasting accuracy can be improved by using this approach if compared with methods proposed by Yu [52] and Cheng et al. [7].
c. The proposed rule is able to handle the frequent recurrence of particular FLRs.
d. The maximum number of weight elements is three for each FLG.

4.2. Forecasting approach

In this section, forecasting is divided into two parts, namely, the linguistics time series forecasting and the numerical time series forecasting. Some previous related studies presented the forecast results as based on the FLRs function without transform-back of these linguistics values into numerical values by clearly using out-sample forecast rule. Logically, if the numerical data have been transformed into linguistics then they should be returned back to the numerical values. The linguistics term has been intended to tackle the problem when the numerical time series cannot be forecasted directly. Furthermore, both forecasting types can be described as below:

a. Linguistics time series forecasting

In fuzzy time series forecasting, each numerical data is transformed into linguistic value and is called a fuzzification step. In addition, the forecasted values can be determined by using the fuzzy relation function from the linguistic values. However, some related studies [3,4,7,31,52]; do not present forecasted values in linguistics before transformed into the numerical value. This condition should be considered to avoid the illogicality and fallacy of fuzzy time series forecasting. To minimize both drawbacks, the new procedure is proposed by using the index number of linguistic as below:

Let $A_1, A_2, \ldots, A_p$ $(1, 2, 3, \ldots, p \in N)$ be linguistics time series values after fuzzification step. By taking the index numbers from these values we denote them as new time series data, namely, $1, 2, \ldots, p$. These numbers also describe the chronology of linguistics series. Here, the definition of index number is different with index in economics term. These indices merely express the sequence of the fuzzy interval. The indices are also applied to indicate the location of variable in a list array numbers and usually written as a subscript to the variable. Then, by using the time series approach (Box–Jenkins Method), these data can be forecasted. The results can be used in the linguistics time series forecasting. Furthermore, the forecasted linguistics values are assigned with numerical values as described in part (b).

b. Numerical time series forecasting

In fuzzy time series, the forecasting model is established based on the fuzzy relation function [3,52]. On the other hand, Yu [52] developed the multiplication of the midpoint intervals and the weight vectors as the forecasting model. Moreover, by applying proposed weight and the existing models, then forecasting model can be modified as:

Suppose the forecast of A_i, where A_i has relationships with A_{j-1}, A_j, A_{j+1}, $i = j$, $i, j \geq 2$ and $i, j \in Z$ (perfect condition in FLG). The defuzzified matrix is equal to the matrix of the midpoints of A_{j-1}, A_j, A_{j+1}:

$$\mathbf{M}(A_i) = [m_{A(j-1)} m_{A(j)}\ m_{A(j+1)}]$$

Suppose the corresponding weights for A_{j-1}, A_j, A_{j+1} say, w_1, w_2, w_3 are specified. These weights can be presented in the matrix of the weight as bellow:

$$\mathbf{W}(A_i) = [w_1\ w_2\ w_3]$$

The final forecast is equal to the product of the defuzzified matrix and the transpose of the weight matrix.

$$\widehat{A}_i = \mathbf{M}(A_i) \times \mathbf{W}(A_i)^T \tag{3}$$

where $\times$ is the matrix product operator. Therefore, each forecasted linguistics value is adopted with numerical time series value as described in part (a). Therefore, by using both parts, the forecast in fuzzy time series is more readily grasped. Finally, the proposed procedure of out-sample forecast can be illustrated in Fig. 1.

4.3. The proposed algorithm in the forecasting

In this section, the proposed algorithm for forecasting is described. The algorithm is used in the definition given by Song and Chissom [45,46] and Chen [3] with the improvement mainly at the procedure for determining the interval number and the new rule for the out-sample forecast (testing data). The proposed algorithm is divided into seven essential steps as follows:

Step 1: Determine the universe of discourse U by using Eq. (13) as below:

$$U = [D_{\min} - D_1, D_{\max} + D_2] \tag{4}$$

where $D_{\min}$ and $D_{\max}$ are the minimal and maximal values of the historical data, D_1 and D_2 are proper positive numbers. We can choose any positive numbers independently to get the lower and upper boundary of U which lower boundary is small than $D_{\min}$ and upper boundary is bigger than $D_{\max}$ as common used in the grouped data. Then U is partitioned into p equal intervals, u_1, $u_2, \ldots, u_p$, $(p < n)$ with length l. Referring to the literature review, no standard rule can be followed in determining of the proper partition number. Therefore, we apply Sturges approach or the two power of p rules as follows:

$$p = 1 + 3.3\log(n) \tag{5}$$

$$2^p < n \tag{6}$$

where p is an interval number and n is the number of data or observations.

Step 2: Establish fuzzy sets for observations. Each linguistics observation A_i can be defined by the intervals $u_1, u_2, \ldots, u_p$. Each A_i, $i = 1$, $2, \ldots, p$ can be represented as in the following Eq. (7), and the value, k_j, is determined by:

If $j = i - 1$, then $k_j = 0.5$;
If $j = i$, then $k_j = 1$;
If $j = i + 1$ then $k_j = 0.5$; elsewhere $k_j = 0$.

$$A_i = \sum_{j=1}^{p} \frac{k_j}{u_j} \tag{7}$$

Step 3: Establish the fuzzy logical relationships based on the fuzzified time series data $A_i \to A_1, A_2, \ldots, A_p$ where the fuzzy logical relationship "$A_i \to A_j$" denotes that "if the fuzzified time series data

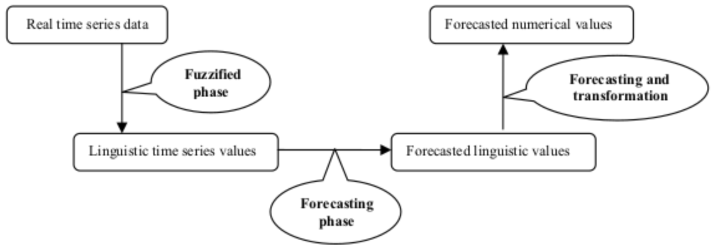

Fig. 1. The new proposed procedure of out-sample forecast.

of time $(t-1)$ is A_i, then the fuzzified time series data of time (t) is A_j".

Step 4: Establish the fuzzy logical groups into corresponding trends. The FLRs with same LHSs (left hand sides) can be grouped to form an FLG. For example, $A_i \to A_j, A_i \to A_k, A_i \to A_m$ can be grouped as $A_i \to A_j, A_k, A_m$.

Step 5: Assignment of the weights elements by using the proposed approach for each FLG as given in Section 4.1.

Step 6: Forecast the linguistics time series values as described in Section 4.2 (a).

Step 7: Forecast the numerical time series values by using two rules as follows:

Rule 1: If there is no weight in FLG then the forecast value is equal to the average of the midpoint intervals of the linguistic time series values.

Rule 2: Otherwise, apply Eq. (3).

Step 7: Verify the MAPE of the proposed approach with the MAPE of existing approaches.

5. Empirical analysis

The proposed approach is applied in forecasting the daily electricity load data from TNB, the period 01/01/2006–31/08/2006 (240 observations) which are used as model building. By using the algorithm given in Section 4.3, the forecast values can be derived as follows:

Step 1: Define the universe of discourse for the daily load data by using Eq. (4) and divide this universe into several intervals based on Eqs. (5) and (6) as illustrated in Table 2.

Table 2 shows that the universe of discourse is defined as $U=[7200.00,\ 9653.34]$ and there are nine equal length intervals obtained by using Sturges rule and two power of k rule. In some related studies, the proper partition number is not clearly explained, such as, no standard rule can be followed. Thus, both rules are appropriate to solve this problem.

Step 2: Establish the fuzzy sets for observations (linguistic time series values) by using Eq. (7) as follows:

$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + \cdots + 0/u_9 \to$ "very very very low"
$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + \cdots + 0/u_9 \to$ "very very low"
$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + \cdots + 0/u_9 \to$ "very low"
$A_4 = 0/u_1 + 0/u_2 + 0.5/u_3 + 1/u_4 + 0.5/u_5 + \cdots + 0/u_9 \to$ "low"
$A_5 = 0/u_1 + 0/u_2 + 0/u_3 + 0.5/u_4 + 1/u_5 + 0.5/u_6 + \cdots + 0/u_9 \to$ "moderate"
$A_6 = 0/u_1 + \cdots + 0/u_4 + 0.5/u_5 + 1/u_6 + 0.5/u_7 + 0/u_8 + 0/u_9 \to$ "high"
$A_7 = 0/u_1 + \cdots + 0/u_5 + 0.5/u_6 + 1/u_7 + 0.5/u_8 + 0/u_9 \to$ "very high"
$A_8 = 0/u_1 + \cdots + 0/u_6 + 0.5/u_7 + 1/u_8 + 0.5/u_9 \to$ "very very high"
$A_9 = 0/u_1 + \cdots + 0/u_7 + 0.5/u_8 + 1/u_9 \to$ "very very very high"

Step 3: Transform the daily load data into the linguistics time series values and the index numbers of these values into the natural number as in Table 3.

Table 3 shows that each actual load is transformed into the linguistics time series value by following the interval given. There are nine linguistics values to represent the actual data in this table. On the other hand, the forecasted indices and linguistics values are also presented in this table. These indices have been predicted by using Box–Jenkins, namely, seasonal ARIMA$(1,0,0)(0,1,1)^7$ model.

Step 4: Establish the FLRs and the FLG as in Tables 4 and 5.

Table 4 shows the first-order of FLRs between the present linguistics A_i and the past linguistics (A_j). This relationship indicates that the present linguistics is influenced by the past linguistics time series values. Each relationship can be grouped by following the index numbers of the linguistics as in Table 5.

Table 5 shows that there are nine groups of linguistics time series values obtained with various FLRs. This table also describes that the recurrence of $A_4, A_5, A_6, A_7, A_8, A_9$ has frequent relationships with other linguistics time series values and itself. These relationships indicate that the present linguistics only has a relationship with the linguistics that is close to itself.

Step 5: Assign weights elements for each group by using the proposed method.

Table 2
Partition number and midpoints of fuzzy sets.

Intervals	Midpoint	Fuzzy sets
[7200.00–7608.89]	7404.45	u_1
[7608.89–8017.78]	7813.34	u_2
[8017.78–8426.67]	8222.23	u_3
[8426.67–8835.56]	8631.12	u_4
[8835.56–9244.45]	9040.01	u_5
[9244.45–9653.34]	9448.90	u_6
[9653.34–10062.23]	9857.79	u_7
[10062.23–10471.12]	10,266.68	u_8
[10471.12–10880.00]	10,675.56	u_9

Table 3
Fuzzification and forecast of A_i.

Day	Actual data	Fuzzified	Index of A_i	Forecasted index of A_i	Forecast of A_i
1	7681.77	A_2	2	*	*
2	7919.07	A_2	2	*	*
3	9395.66	A_6	6	*	*
4	9651.72	A_7	6	*	*
5	9859.63	A_7	7	*	*
6	9634.88	A_6	6	*	*
7	8876.23	A_5	5	*	*
8	7981.16	A_2	2	3	A_3
9	8781.00	A_4	4	5	A_5
10	7306.09	A_1	1	5	A_5
11	9091.44	A_5	5	3	A_3
12	9719.24	A_7	7	6	A_6
13	9810.20	A_7	7	7	A_7
14	9249.16	A_6	6	5	A_5
15	8397.34	A_3	3	4	A_4
⋮	⋮	⋮	⋮	⋮	⋮
233	10,494.57	A_9	9	8	A_8

Table 4
FLRs.

Day	Fuzzified	FLRs
1	A_2	
2	A_2	$A_2 \rightarrow A_2$
3	A_6	$A_2 \rightarrow A_6$
4	A_7	$A_6 \rightarrow A_7$
5	A_7	$A_7 \rightarrow A_7$
6	A_6	$A_7 \rightarrow A_6$
7	A_5	$A_6 \rightarrow A_5$
8	A_2	$A_5 \rightarrow A_2$
9	A_4	$A_2 \rightarrow A_4$
10	A_1	$A_4 \rightarrow A_1$
⋮	⋮	⋮
232	A_5	$A_7 \rightarrow A_5$
233	A_9	$A_5 \rightarrow A_9$

Table 5
Fuzzy logical groups (FLG).

Fuzzy logical groups (FLG)
$A_1 \rightarrow A_5, A_1, A_1, A_2$
$A_2 \rightarrow A_2, A_6, A_4, A_4$
$A_3 \rightarrow A_7, A_1, A_7, A_7, A_7, A_3, A_8$
$A_4 \rightarrow A_1, A_7, A_6, A_3, A_8, A_8, A_8, A_8, A_8, A_8, A_7, A_7, A_3, A_8, A_8, A_8, A_8, A_7, A_8, A_7$
$A_5 \rightarrow A_2, A_7, A_3, A_8, A_8, A_8, A_8, A_8, A_8, A_9, A_8, A_8, A_9, A_9, A_8$
$A_6 \rightarrow A_7, A_5, A_3, A_4, A_3, A_5, A_4, A_4, A_5, A_4, A_4, A_4, A_4, A_4, A_6, A_4, A_4, A_4, A_4, A_4, A_5, A_4, A_5$
$A_7 \rightarrow A_7, A_6, A_7, A_6, A_7, A_8, A_7, A_7, A_7, A_6, A_8, A_4, A_8, A_6, A_4, A_4, A_6, A_5, A_8, A_5, A_4, A_8, A_5, A_8, A_5, A_5, A_5, A_8, A_5, A_5, A_5$
$A_8 \rightarrow A_8, A_8, A_6, A_8, A_8, A_7, A_8, A_8, A_7, A_8, A_8, A_8, A_8, A_6, A_9, A_7, A_8, A_8, A_8, A_8, A_7, A_9, A_8, A_8, A_6, A_8, A_8, A_8, A_8, A_6, A_8, A_8, A_8, A_7, A_9, A_6, A_9, A_6, A_8, A_8, A_8, A_7, A_9, A_8, A_8, A_6, A_9, A_6, A_9, A_8, A_8, A_7, A_8, A_9, A_6, A_8, A_9, A_3, A_8, A_8, A_8, A_8, A_6$
$A_9 \rightarrow A_9, A_9, A_8, A_8, A_9, A_9, A_8, A_8, A_9, A_9, A_9, A_7, A_9, A_8, A_8, A_9, A_8, A_9, A_8, A_9, A_9, A_8, A_9, A_9, A_9, A_7, A_9, A_9, A_7, A_9, A_9, A_9, A_9, A_7, A_9, A_9, A_8, A_8, A_9, A_9, A_8, A_9, A_9, A_9, A_9, A_7, A_9, A_9, A_9, A_8, A_8$

Tables 6a and 6b show the number of weight elements per group. On the other hand, no weight can be found for group 2–5 because no close relationship can be found within itself. It can be seen that the number and the computational time of weights are simpler to generate by using our proposed method than the methods used by Yu [52] and Cheng et al. [7]. This table also demonstrates that frequent recurrence of the FLRs can be handled efficiently by using this proposed rule. Moreover, the time complexity of proposed method and methods proposed by Yu [52] and Cheng et al. [7] are also presented in Table 6b.

Step 6: Calculate the forecasted values by using Eq. (3), in which the numerical time series forecasting is done. For example, the forecasted value for A_6 can be derived as below:

Table 6a
Weight values.

Linguistics	Weights
A_1	$w_1 = 0.33$, $w_2 = 0.67$
A_2	No weight
A_3	No weight
A_4	No weight
A_5	No weight
A_6	$w_1 = 0.39$, $w_2 = 0.28$, $w_3 = 0.33$
A_7	$w_1 = 0.33$, $w_2 = 0.29$, $w_3 = 0.38$
A_8	$w_1 = 0.33$, $w_2 = 0.29$, $w_3 = 0.38$
A_9	$w_1 = 0.53$, $w_2 = 0.47$

The given weights for A_6 are $w_1 = 0.39$, $w_2 = 0.28$, $w_3 = 0.33$ from Tables 6a and 6b. The related midpoints of A_5, A_6, A_7 are 9040.01, 9448.90, and 9857.79, and the forecasted value for A_6 can then be derived as below:

The other forecasted values are 7686.94 for A_1, 7820.83 for A_2, 8226.58 for A_3, 8632.33 for A_4, 9038.08 for A_5, 9886.10 for A_7, 10,291.86 for A_8, and 10,470.39 for A_9. As no weight can be computed for A_2, A_3, A_4, A_5, their midpoints are then used as the forecast values as described in Section 4.3. Moreover, in Box–Jenkins methods, the first or the second differencing (Δd_t) process of actual data are done to remove the trend in the data. However, for this step, Box–Jenkins method is applied to obtain a more accurate forecast and also to avoid the same forecasted value for the same linguistic time series values as in methods proposed by Chen [3], Yu [52] and Cheng et al. [7].

Table 7 shows that the numerical forecasted values which have been determined by using the proposed method. In column 3, these values declare the first-differencing of actual data. In column5, these linguistics time series values are predicted by using the seasonal ARIMA(1,0,0)(0,1,1)^7 model, and applying of this procedure has not yet been clearly described in some previous studies. This model indicates that the trend of electricity load demand is repeated every 7 days. By using this model, many of linguistics values can be predicted more precisely. Consecutively, the numerical forecasted values are also obtained accurately. The forecast value started at $t = 8$ (Day 8). Moreover, the pre-forecasted values are presented in column 6 and these values obtained using Eq. (3). Finally, pre-forecasted values are added with first-differencing values as final forecasted values.

Step 7: Verify the MAPE of proposed method and the MAPE of methods proposed by Chen [3], Yu [52] and Cheng et al. [7] as in Table 8.

Table 8 shows the comparison of the MAPE between the proposed method and methods proposed by Chen [3], Yu [52] and Cheng's et al. [7] using various number (10, 9, 8, 7, 6, 5) of testing

Table 6b
Time complexity in determining weight values.

Proposed method	Yu's method	Cheng's method
Input; a) Index number of linguistic values (A_i) ($i = 1, 2, \ldots, p$). b) All index numbers of others linguistic values (A_j) ($j = 1, 2, \ldots, p$) which have relationships with (A_i). **Process;** a) Choose the closest index numbers ($j-1, j, j+1$) to (A_i) from input (b). b) Compute $w_1 = j-1/[(j-1)+j+(j+1)]$, $w_2 = j/[(j-1)+j+(j+1)]$, $w_3 = j+1/[(j-1)+j+(j+1)]$ **Output;** W(A_i) = w_1, w_2, w_3 **Time complexity;** $T(n) = 3n$, thus complexity is O(n).	**Input;** a) Index number from main linguistic value (A_i) ($i = 1, 2, \ldots, p$). b) All index numbers of others linguistic values (A_j) ($j = 1,2, \ldots, p$) which have relationships with (A_i). **Process;** a) Choose all index numbers in input (b). b) Assign $c_1 = 1, \ldots, c_r = r$. (r is a number of FLRs). c) Compute $w_1 = c_1/(c_1 + \cdots + c_r), \ldots, w_r = c_1/(c_1 + \cdots + c_r)$ **Output;** W(A_i) = w_1, w_2, ..., w_r **Time complexity;** $T(n) = n^2$, thus complexity is O(n^2).	**Input;** a) Index number from main linguistic value (A_i) ($i = 1, 2, \ldots, p$). b) All index numbers of others linguistic values (A_j) ($j = 1,2, \ldots, p$) which has relationship with (A_i). **Process;** a) Choose all index numbers in input (b). c) Assign trend $c_1 = 1$ for one time occur of index number, $c_2 = 2$ for two times occur of index number, ..., r. (r is a number of FLRs). c) Compute $w_1 = c_1/(c_1 + \cdots + c_r), \ldots, w_r = c_1/(c_1 + \cdots + c_r)$ **Output;** W(A_i) = w_1, w_2, ..., w_r **Time complexity;** $T(n) = n^2$, thus complexity is O(n^2).

Table 7
The forecasted results based on the proposed method.

Day	Actual data	Diff 1	Fuzzified	Forecasted of Ai	Pre-forecasted	Final forecasted
1	7681.77		A_2	*	*	
2	7919.07	237.3	A_2	*	*	*
3	9395.66	1476.6	A_6	*	*	*
4	9651.72	256.1	A_7	*	*	*
5	9859.63	207.9	A_7	*	*	*
6	9634.88	−224.7	A_6	*	*	*
7	8876.23	−758.7	A_5	*	*	*
8	7981.16	−895.1	A_2	A_3	9040.01	8144.9
9	8781.00	799.8	A_4	A_5	7813.34	8613.2
10	7306.09	−1474.9	A_1	A_5	8631.12	7156.2
11	9091.44	1785.4	A_5	A_3	7404.45	9189.8
12	9719.24	627.8	A_7	A_6	9040.01	9667.8
13	9810.20	91.0	A_7	A_7	9857.79	9948.7
14	9249.16	−561.0	A_6	A_5	9857.79	9296.7
15	8397.34	−851.8	A_3	A_4	9424.36	8572.5
16	9719.24	1321.9	A_7	A_6	8222.23	9544.1
17	10,036.98	317.7	A_7	A_7	9857.79	10,175.5
18	10,113.61	76.6	A_8	A_7	9857.79	9934.4
19	10,178.28	64.7	A_8	A_8	10,266.68	10,331.4
20	10,126.91	−51.4	A_8	A_7	10,288.68	10,237.3
⋮	⋮	⋮	⋮	⋮	⋮	⋮
232	9029.16	−872.3	A_5	A_7	9886.10	8985.40
233	10,494.57	1465.4	A_9	A_5	9038.08	10,505.40

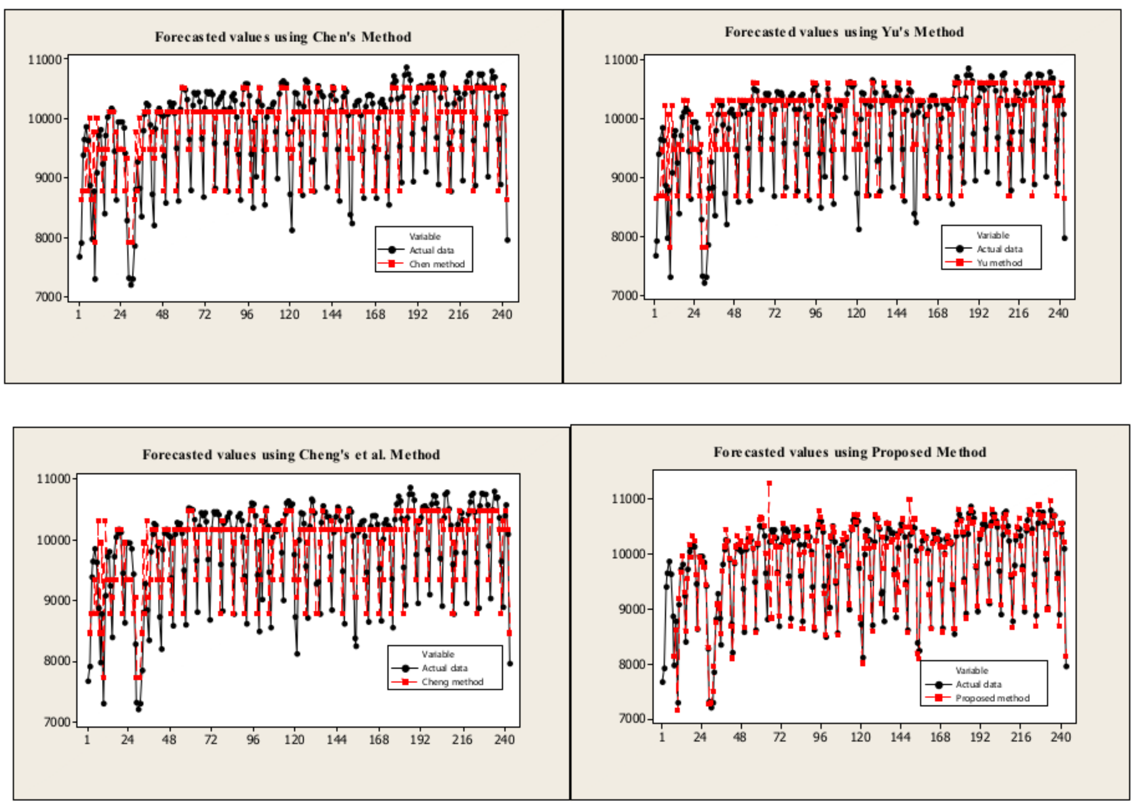

Fig. 2. The actual load and forecasted values based on Chen, Yu, Cheng and proposed methods.

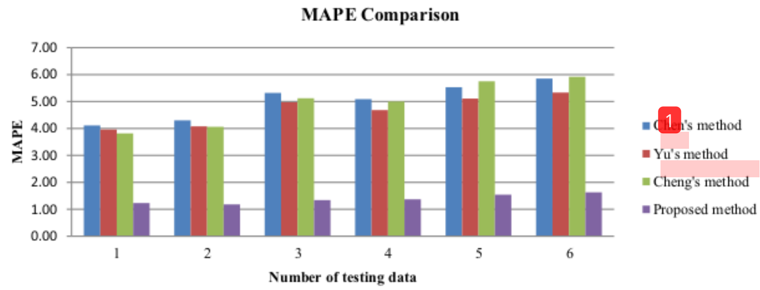

Fig. 3. MAPE comparison of various number of testing data.

data. In the general, all percentages of MAPE increase gradually following the decrease of testing data number in Table 8, but the percentages of MAPE from proposed method are smallest if compared with these existing methods. Moreover, in the forecasting, MAPE value will be increased to the decrease of number testing data. On the other hand, MAPE of training data show that proposed method is also smallest among them. Thus, by comparing these percentages of MAPE, the proposed method is better than methods proposed by Chen [3], Yu [52] and Cheng et al. [7]. The actual data and forecasted values are also illustrated in Fig. 2 using the proposed method, Chen's method, Yu's method and Cheng's method, respectively.

Fig. 2 shows the actual data, training data, and testing data which are derived from the proposed method and methods proposed by Chen [3], Yu [52] and Cheng et al. [7]. In general, the training data are able to capture the trend of the actual data. However, this figure shows that the training data which are determined using the existing methods do not capture the trend of the actual data generally. Many of the training data are out of the trend line of the actual data. Furthermore, Chen's, Yu's and Cheng's et al., methods present the same forecasted values for the same linguistic values when the load consumption is bigger than 10,000 MW. Therefore, the forecasted values do not fluctuate following time generation. This is due to the fact that these existing methods do not consider the forecasting of linguistic time series as shown in Fig. 1. Thus, these existing methods cannot be applied to investigate the seasonal or trend-seasonal time series values. Moreover, in the end of each graph on Fig. 2, there are ten testing data, but they are not close to the actual data if existing methods are used. Meanwhile, using the proposed method, the testing data are similar with the actual data. Through this figure, the capability of the proposed method in forecasting of testing data (out-sample) can be improved. In general, methods proposed by Chen [3], Yu [52] and Cheng et al. [7] have shown the same value in each day

Table 8
MAPE comparison of proposed method and the existing methods.

Training data	Chen's method	Yu's method	Cheng's method	Proposed method
233	4.50%	4.90%	4.80%	1.33%[a]
Testing data	**Chen's method**	**Yu's method**	**Cheng's method**	**Proposed method**
10	4.11%	3.96%	3.82%	1.23%[a]
9	4.30%	4.08%	4.06%	1.18%[a]
8	5.32%	4.97%	5.12%	1.34%[a]
6	5.09%	4.68%	5.00%	1.37%[a]
7	5.53%	5.11%	5.75%	1.54%[a]
5	5.85%	5.33%	5.92%	1.63%[a]

[a] The smallest percentage.

for the testing data. Thus, the forecasted values are not influenced by the time generation, unlike forecasted values obtained using the proposed method as depicted in Fig. 2. This indicates that the types of time series data and out-sample forecast are not clearly described by Chen [3], Yu [52] and Cheng et al. [7]. Fig. 3 shows the performance comparisons between the proposed method and the methods proposed by Chen, Yu and Cheng et al.

Fig. 3 shows that the MAPE of the proposed approach and that by Yu's approach which are based on various numbers of testing data. These numbers are 5–10 data. The bars of the MAPE from the proposed method increase gradually with the percentage interval from 1.23% until 1.63%. In contrast, the MAPE of Chen's, Yu's and Cheng's methods increase sharply from 4.11% to 5.65%, 3.96% to 5.33%, and 3.82% to 5.92%. Thus, the interval range of the MAPE from the proposed method is smaller than the MAPE's range of methods proposed by Chen, Yu and Cheng. Therefore, by using these numbers of testing data, it can be revealed that the proposed method can yield a better than three existing methods above.

6. Conclusion

In this paper, we assigned the weight of the FLRs in the FLG as based on the closest relationship of linguistic index number method. Through this method, the frequent recurrence of FLRs is easy to handle and to calculate if compared with methods proposed by Yu [52] and Cheng et al. [7]. Thus, the computational time can be reduced significantly. Moreover, Sturges approach and the two-power of *p* rules might be considered to determine the proper partition number of the universe of discourse. These rules are chosen in order to avoid the trial-error procedure because no previous studies have been able to mention the number of partition rule in fuzzy time series properly.

In the forecasting procedure, the consideration of the index numbers from the linguistics time series could be revealed as a promising way to handle the out-sample forecast. Furthermore, by using this approach, the linguistic time series values can be forecasted, and then these values can be transformed into the numerical time series values. Thus, the out-sample forecast can be obtained logically and properly by following time generation. Therefore, this new procedure presents the clearly contribution in determining of out-sample forecast on fuzzy time series.

In the verification, the MAPE of the proposed approach is smaller than that of Yu's approach. The result shows that our proposed approach is better than methods proposed by Chen [3], Yu [52] and Cheng et al. [7]. Finally, in fuzzy time series, there are three essential factors should be concerned in achieving the high level forecasting accuracy such as interval length or partition number of universe of discourse, weight of FLRs, and forecasting procedure for in-out sample.

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