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Implementation of Fuzzy Time Series in Forecasting of the Non-Stationary Data

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To forecast the non-stationary data is quite difficult when compared with the stationary data time series. Because their variances are not constant and not stable like the second data type. This paper presents the implementation of fuzzy time series (FTS) into the non-stationary time series data forecasting, such as, the electricity load demand, the exchange rates, the enrollment university and others. These data forecasts are derived by implementing of the weightage and linguistic out-sample methods. The result shows that the FTS can be applied in improving the accuracy and efficiency of these non-stationary data forecasting opportunities.

Keywords: Fuzzy time series; non-stationary data; electricity load; exchange rates; enrollment.

1. Introduction

Many soft computing approaches are presented in the forecasting and prediction of non-stationary time series data by researchers in this decade. For example, genetics algorithm, neural network, fuzzy logic, fuzzy neural network and evolutionary algorithm, etc. These approaches aimed to solve the limitations of classical time series approaches, especially the linearity assumptions.[1] Moreover, the main reason why the fuzzy time series (FTS) concept was introduced because the statistical assumptions are not required strictly in this concept.[2] This reason is very beneficial in the forecasting with limited data and the data are not normally distributed.

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Therefore, FTS approaches have been widely implemented to forecast the real data, such as enrollment,[2–14] stocks index prices,[15–22] temperature,[23] financial prediction[24,25] and electricity load.[26–28] These approaches are developed to produce the forecasting rules, procedures, and systems by using three components, namely, the partition number of the universe of discourse, the weight fuzzy logical relationship (FLRs), and the mathematical models in determining in–out sample linguistic and numerical time series values. In this paper, the implementation of weightage and out-sample linguistics model is applied to forecast the non-stationary time series data.

The rest of paper is organized as follows: in Sec. 2, the fundamental theories in FTS are described. The proposed method is presented in Sec. 3. In Sec. 4, the algorithm for enrollment forecasting is explained. The discussion and a brief conclusion are explored in the final section.

2. The Fundamental Theories in FTS

By using Refs. 2–5, and 17, the basic concept of FTS can be explained in Definitions 1–5, respectively.

Definition 1 (FTS). Let $Y(t)$ $(t = \ldots, 0, 1, 2, \ldots)$, a subset of real numbers, be the universe of discourse on which the 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 a FTS defined on$Y(t)$ $(t = \ldots, 0, 1, 2, \ldots)$. Therefore, $F(t)$ is the linguistic time series variable, where $f_i(t)$ $(i = 1, 2, \ldots)$, are the possible linguistic values of $F(t)$.

Definition 2 (First-order fuzzy relation[2–4]). Suppose $F(t)$ is caused by $F(t-1)$ denoted by $F(t-1) \to F(t)$, then this relationship can be represented by:

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

where "0" represents an operator, $R(t,\ t-1)$ is a fuzzy relationship between $F(t)$ and $F(t-1)$. $F(t-1)$ is the first-order model of $F(t)$.

Definition 3 (FLRs[5]). Let $F(t-1) = A_i$ and $F(t) = A_j$. The relationship between two consecutive data (called a FLR), i.e., $F(t)$ and $F(t-1)$, can be denoted by $A_i \to A_j$, $i, j = 1, 2, \ldots, p$ (where p is the interval or the subinterval number) is called the left-hand side (LHS) of the FLR, and A_j is the right-hand side (RHS) of the FLR.

Definition 4 (Fuzzy logical groups (FLG)[17]). Let $A_i \to A_j$, $A_i \to A_k, \ldots, A_i \to A_p$ be the FLRs with the same LHS which are grouped into an ordered FLG by putting all their RHS together as on the RHS of the FLG. It can be written as below:

$$A_i \to A_j, A_k, \ldots, A_p \quad i, j, k, \ldots, p = 1, 2, \ldots, n(nN). \tag{2}$$

In Ref. 1, the basic of forecasting steps can be presented by the following steps in Fig. 1.

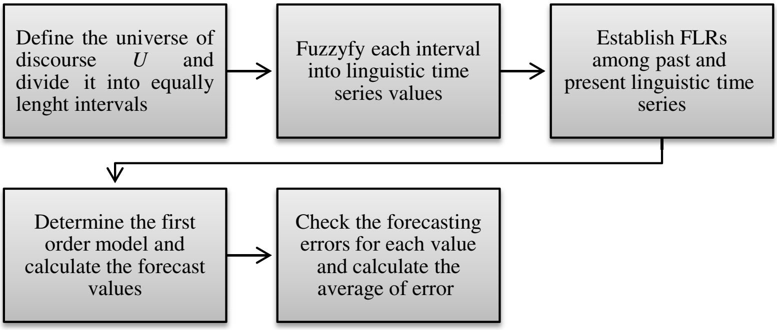

Fig. 1. The basic of forecasting steps.

3. The Procedure of FTS Approach in the Forecasting

From our literature (Ref. 26), there are three components that should be considered in the forecasting as follows:

(a) Component 1: The partition number of universe of discourse (U).

Step 1. Find the max–min data from data set and compute U by using Eq. (3):

$$U = [D_{\text{minimum}} - D_1, D_{\text{maximum}} + D_2], \tag{3}$$

where D_1 and D_2 are proper positive numbers. Both numbers can be chosen independently.

Step 2. Divide U into equally length intervals by Eqs. (4) and (5):

$$p = 1 + 3.3\ \log(n), \tag{4}$$

$$2^p < n, \tag{5}$$

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

(b) Component 2: The weight values based on FLRs.

Step 1. Define fuzzy sets for observations. Each linguistics observation A_{i} can be defined by intervals $u_1, \ldots, u_p$, respectively. Each A_i can be represented as in the following Eq. (6), 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 $k_j = 0$.

$$A_i = \sum (k_j / u_j). \tag{6}$$

Step 2. Transform each actual data into linguistic time series values, establish FLRs, and establish FLG.

Step 3. Calculate the weight values for each FLG.

(c) Component 3: The forecasting models for series of linguistic and the final forecast values.

Step 1. From Component 2, assume the series of linguistics as new time series data. By using statistical approaches, these series can be modelled and forecasted, respectively. This step can be clearly illustrated in Fig. 2.

Step 2. The final forecast value is equal to the product of the defuzzified matrix and the transpose of the weight matrix. This step can be presented in Fig. 3.

At the end of the forecasting step, the accuracy of forecasting error can be verified by comparison of mean square error (MSE) and mean absolute percentage (MAPE) errors with the existing approaches as follows:

$$\mathrm{MSE} = \sum_{t=1}^{n} \frac{(x_t - \hat{x}_t)^2}{n}, \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \times 100\%, \tag{8}$$

where x_t and $\hat{x}_t$ are the actual and the forecast values time series at $t = 1, 2, \ldots, n$.

4. The Implementation of FTS to Forecast the Real Non-Stationary Data

In this section, all components mentioned in Sec. 3 are applied to forecast the real time series data. There are some historical data from some sectors such as energy, economics–finance, education and others sectors.

4.1. *Implementation in energy forecasting*

For the energy sector, Malaysian, Taiwan electricity load data and Malaysian oil consumption are used to examine the performance of FTS approach. By following all calculation steps, the forecasting accuracy for each data sets can be presented in Tables 1–3, respectively.

Table 1 shows the performance of forecasting accuracy of the daily electricity load data from TNB Malaysia which period 01/01/2006–31/08/2006. Both MAPE of training and testing data which are derived by the approach proposed in Ref. 26 have smaller errors when compared with approaches proposed in Refs. 5, 17 and 19. Here,

Table 1. Comparison of MAPE for Malaysian electricity load data.

Approach	MAPE of training data (233 data)	MAPE of testing data (10 data)	Rank
Chen (1996)	4.50%	4.11%	4
Yu (2005)	4.90%	3.96%	3
Cheng *et al.* (2008)	4.80%	3.82%	2
Efendi *et al.* (2015)	1.33%	1.23%	1

Table 2. Comparison of MAPE for Taiwan electricity load data.[27]

Approach	Northern (%)	Southern (%)	Central (%)	Eastern (%)
SVRCAS	1.30	1.45	1.70	2.22
SVRCGA	1.35	2.01	1.72	2.57
SVRCPSO	1.31	1.49	1.81	2.19
ANN	*1.06	2.48	1.73	3.62
Regression	2.45	8.29	8.52	4.10
FTS	1.42	*0.69	*1.24	*1.95

Table 3. Comparison of MSE for Malaysian oil production and consumption.

Approach	Oil production	Oil consumption	Rank
Regression time series (RTS)	8666.020	6855.874	3
FTS (20 intervals)	2328.861	1881.947	2
FTS (48 intervals)	232.6588	521.5041	1

some illustrations of the time series plots for Malaysian electricity load are presented in Figs. 5–7, respectively.

In Table 2, the various approaches are implemented to forecast the yearly electricity load data of Taiwan, during 1981 to 2000. The smaller percentage of MAPE is obtained by the FTS approach except in the Northern region. From this table, the performance FTS is a better approach when compared with the existing approaches.

In Table 3, the forecasting of yearly oil production and consumption from 1965 to 2012 is derived by RTS and FTS approaches. The comparison of MSE indicates that FTS approach with 48 intervals has smaller error than FTS (20 intervals) and RTS approaches. In this case, FTS is better than RTS approach.

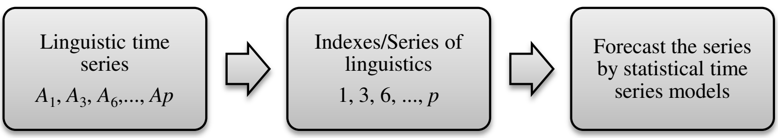

Fig. 2. Forecasting of the linguistic series.

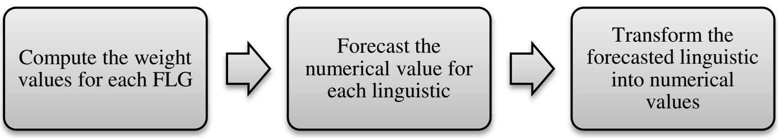

Fig. 3. Forecasting of the numerical values of linguistics.

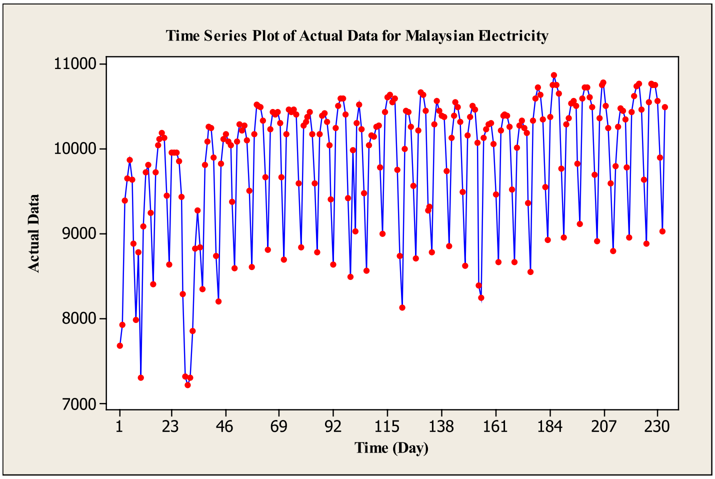

Fig. 4. Plotting of actual data for Malaysian electricity load.

4.2. *Implementation in economics–finance forecasting*

This section explores the implementation of FTS approach to forecast the real-time series data especially the exchange rates data. Some daily exchange rate data are chosen from several countries randomly such as Philippines Peso (PHP), Malaysian, Japanese Yen (JPY) and Hong Kong Dollar (HKD) from 01/08/2011 to 27/03/2012 (www.bnm.gov.my). The comparison of forecasting accuracies by FTS and the existing approaches is shown in Tables 4 and 5, respectively.

In Tables 4 and 5, MAPE for training and testing data which is obtained by the approaches proposed are smaller when compared with the proposed approaches in

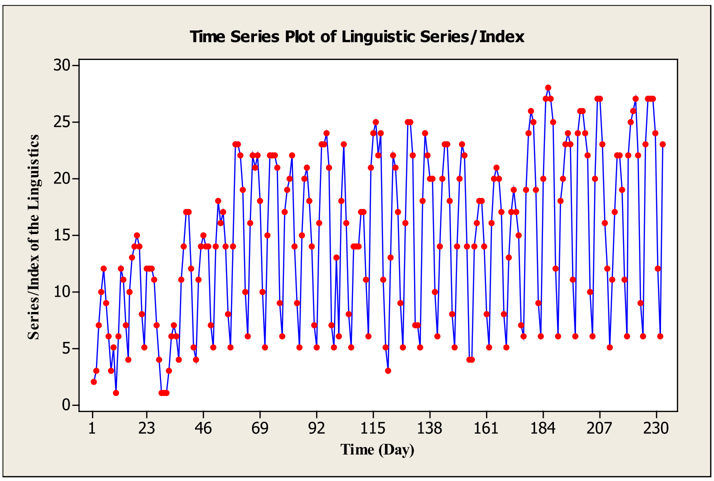

Fig. 5. Plotting of index/series of linguistics for Malaysian electricity load.

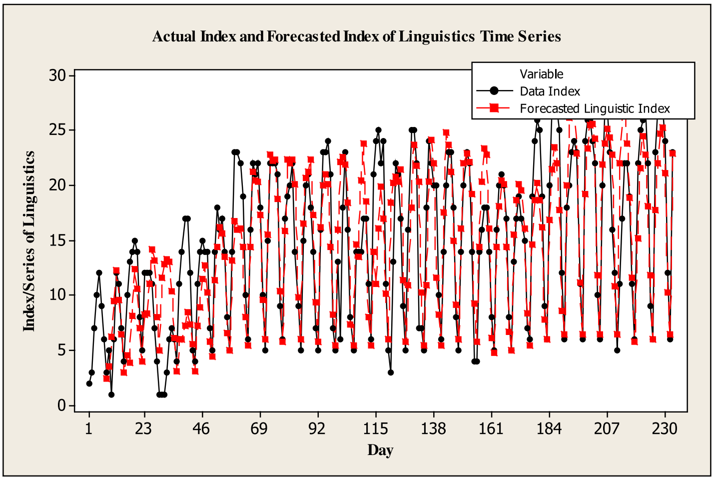

Fig. 6. Plotting of actual index and forecasted index of linguistics for Malaysian electricity load.

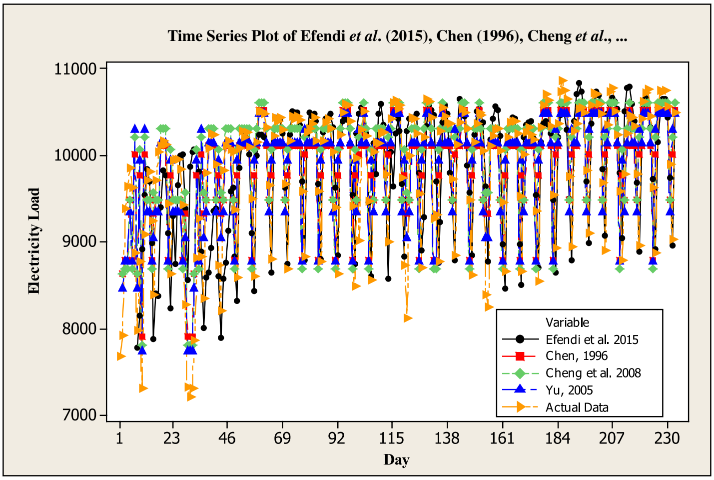

Fig. 7. Forecasted values based on various approaches.

Table 4. Comparison of MAPE for training data.

Exchange rate	Efendi *et al.*	Yu (2005)	Cheng *et al.* (2008)
MYR	*0.04%	0.05%	0.05%
PHP	*0.53%	1.81%	1.70%
HKD	*0.53%	1.81%	1.70%
JPY	*0.81%	0.89%	0.82%

Table 5. Comparison of MAPE for testing data.

Exchange rate	Proposed approach	Yu (2005)	Cheng *et al.* (2008)
MYR	*0.60%	0.63%	0.62%
PHP	*0.04%	0.97%	0.05%
HKD	*0.60%	0.63%	0.62%
JPY	*0.39%	0.40%	0.49%

Table 6. MAPE of training and testing data for Alabama enrollment.

Alabama enrollment	Training data (%)	Testing data (%)
Efendi *et al.* (2015)	*2.32	*0.92
Yu (2005)	2.62	12.79
Cheng *et al.* (2008)	2.36	0.97

Table 7. MAPE of training and testing data for UTM enrollment.

UTM enrollment	Training data (%)	Testing data (%)
Efendi *et al.* (2015)	*5.39	*2.42
Yu (2005)	5.47	2.99
Cheng *et al.* (2008)	5.43	2.48

Refs. 17 and 19. By proposed approach, the forecasting accuracy can be improved and the forecasted values are better than both the existing approaches.

4.3. *Implementation in education forecasting*

In the third implementation, FTS approach is tempted to forecast the university enrollment, two data sets are used, namely, enrollment of Alabama University from 1971 to 1992, and undergraduate enrollment of University Technology Malaysia (UTM) from 1990 to 2008. The performance of the forecasting accuracy for both data sets is shown in Tables 6 and 7, respectively.

From Tables 6 and 7, the approaches proposed in Ref. 26 will be able to achieve the higher forecasting accuracy when compared with approaches proposed in Refs. 17 and 19. For testing and training data, the MAPE are not too sharply different among the three approaches.

5. Conclusion

In this section, there are some components that can be highlighted to improve the forecasting accuracy by FTS approach. Firstly, the partition number of discourse universe, this component is a very significant component to obtain the better forecast results. The adjustment of partition number influences the interval length. Moreover, the increase in the partition number contributes to the midpoint interval values also. Furthermore, these midpoint values affect the forecast model because the model is formed by midpoint matrix. From this explanation, the optimization of the partition number is a key point in FTS forecasting model.[29]

The weight fuzzy relationship is a second component. In Refs. 17 and 19 already mentioned, the importance of weight FLRs is to improve the forecasting error. In this paper, the weightage method is adopted by using Ref. 26. The computational steps and time are more effective when compared with the existing methods. Based on the results obtained from Tables 1–7, the proposed approaches in Refs. 26 and 27 are able to achieve the better forecasted values when compared with the existing approaches.

Third component is the forecasting model for the linguistic time series. This model is very important to determine the numerical forecast of time series values Because we need to forecast the series of each linguistics before the real values are calculated. In Ref. 26, this condition has been solved clearly. While, some of forecasting accuracies are not quite different significantly because the same partition number is applied into the approaches in Refs. 17 and 19. The role of these three components is very reasonable to improve the forecast performance and to reduce the forecasting error.

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