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Stock Market Forecasting Model Based on AR(1) with Adjusted Triangular Fuzzy Number Using Standard Deviation Approach for ASEAN Countries

Muhammad Shukri Che Lah, Nureize Arbaiy and Riswan Efendi

Abstract Traditional autoregressive (AR) time series models have been extensively applied to predict various stationary data sets based on single point data. However, real-world system involves uncertainty due to human behaviours and incomplete information. Since the single point data is not able to represent the nature of data, fuzzy approach is necessary to deal with such uncertainties in the analysis. This paper proposes AR(1) model building based on triangular fuzzy numbers. A procedural step for building triangular fuzzy number based on standard deviation approach is provided, to handle the existence of uncertain information and the biasness during data collection. The proposed model is applied to forecast buying–selling stock market prices by using real data sets from five ASEAN countries. The results from this study show that the proposed method with triangular fuzzy numbers exhibits smaller error. That is, the proposed method is able to achieve almost similar accuracy performance as obtained by the traditional autoregressive approach, yet it also solves the uncertainties issue in the analysis.

Keywords Left–right spread · Triangular fuzzy number · AR(1) · Standard deviation · Stock market

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1 Introduction

The stock market refers to public markets that issuing, buying and selling stocks that trade on a stock exchange [1]. Forecasting the stock market is aiming to develop approaches which successfully predict index values or stock prices at high profits using well-defined trading strategies. Economic analysis usually obtains the result based on the time series data. Autoregressive [2], Moving average [3], Multiple Kernel Learning [4] and Support Vector Machines [5] are an example of a widely used technique to analyze the behaviour of the stock market based on market history data. Among this, most of the models for the time series of stock prices have centred on autoregressive (AR) processes. The results obtained, assist people to select the best stock market. It makes forecasting model is importantly crucial to predict the stock market. The more accurate result implies the better model.

Stock market forecasts are constantly attracting researchers as it is extremely volatile and dynamic [6]. The most challenging task in stock prediction lies in the complexities of modelling market dynamics and uncertainty in stock market [7]. The existence of risk and uncertainty in economic brings a primary concern in this field [8]. Even if the traditional method can produce an impressive result, however, it is unable to cope with uncertainty. The traditional method is difficult to forecast accurately the stock market from the history of price with uncertain behaviour co-exist [5]. The existing models use single input for building univariate forecasting models. Since most of the data are obtained from secondary sources, it may contain validity, biasness, and representation issues which contributes to less accurate forecasting models [9]. Accordingly, Traders make predictions based on incomplete vague data, imperfect and uncertain [10]. Fuzzy logic provides a natural way to deal with subject observed in most financial time series models. Most of the fuzzy financial models that have been proposed to forecast stock market sectors, such as, fuzzy time series [10–14], fuzzy regression [15], fuzzy random [16] and fuzzy random auto-regression [17, 18]. However, the procedure to build a symmetric triangular fuzzy number (TFN) is not yet discussed clearly in the previous works.

In a conventional time series, the recorded values are represented by crisp numerical values, while fuzzy time series uses fuzzy numbers to represent such values. However, the procedure to construct TFN from crisp value is not discussed deeply. Most of the existing approach is focused on the forecasting model itself, while fuzzy data preparation is not thoroughly explained. Though data preparation, which involves fuzzy data transformation is important to obtain appropriate values for forecasting, i.e. the original meaning behind the crisp value is not abandoned. Motivated from the situation and previous studies [10–17, 19–23], this study proposes systematic steps to handle uncertainty in the development of model forecasts. Specifically, the triangular fuzzy number is used to represent the uncertainty in buying–selling data. The standard deviation approach is utilized to construct the TFN since it is able to measure the spread of scores within a set of data stock market using Fuzzy Autoregressive approaches. The concentration in fuzzy data preparation and model forecasting for both are very important to be investigated in improving the forecasting values and achieving the forecasting accuracy. The main contribution of this paper is to provide a better forecasting model for stock market using Fuzzy Autoregressive approach.

This paper is organized as follows: in Sect. 2, the fundamental theories in forecasting are described. The proposed method is presented in Sect. 3. In Sect. 4, the numerical experimental and analysis are explained. The discussion and a brief conclusion are explored in the final section.

2 Fundamental Theories

This section gives fundamental theories about AR, Fuzzy Number and Triangular Fuzzy Number in Sects. 2.1, 2.2, and 2.3, respectively.

2.1 Autoregressive

Based on [24], AR model predicts future behaviour based on past behaviour. It is used for forecasting when there are some correlations between values in time series and their lead and successful values. In the AR model, the value of result (Y axis) at some point t in time directly related to variable predicator (X axis). AR model is different with linear regression where Y depends on X and previous values of Y. An AR (p) model is an AR model where specific lagged values of y_t are used as predictor variable. The lag shows the outcome of a time period affecting the following periods. The value 'p' is called order.

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t \quad (1)$$

where c is constant, e_t is white noise (error), and $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$ are past series. The outcome variable in AR(1) is the process at some point in time, t is related only to line periods that are one period apart. Figure 1 shows an example of AR(1) graph.

From Eq. (1), the expected value of y_t for AR(1) is defined as:

$$y_t = c + \emptyset_1 y_{t-1} + e_t \quad (2)$$

where c is constant, e_t is white noise (error) and y_{t-1} is past series.

2.2 Fuzzy Number (FN)

Zadeh [25] defines the definition of fuzzy set as follows:

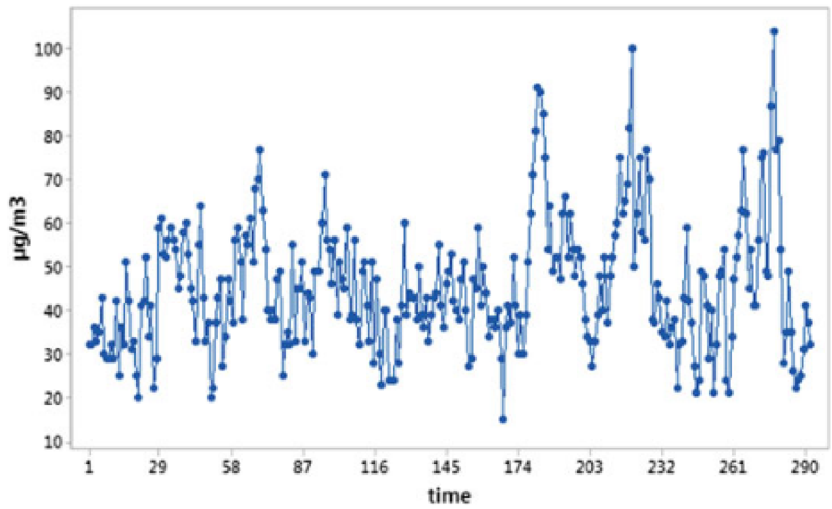

Fig. 1 Example of AR(1) model graph

Definition 1 Let U denote the universal set of the discourse. Then a *fuzzy set A* on U is defined in terms of the *membership function* m_A that assigns to each element of U a real value from the interval [0, 1]. A fuzzy set A in U can be written as a set of ordered pairs in the form $A = \{(x, m_A(x)) : x \in U\}^{\{1\}}$, where $m_A : U \to [0, 1]$.

The value $m_A(x)$, expresses the degree to which x verifies the characteristic property of A. Thus, the nearer is the value $m_A(x)$ to 1, the higher is the membership degree of x in A. The fuzzy number (FN) is a special form of fuzzy sets of real number sets on R. FNs plays an important role in fuzzy math, similar to the role played by ordinary numbers in classical mathematics.

Definition 2 A fuzzy set A on U with membership function $y = m(x)$ is said to be *normal*, if there exists x in U, such that $m(x) = 1$.

Definition 3 Let A be as in definition 2 and let x be a real number of the interval [0, 1]. Then the x-*cut* of A, denoted by A^x, is defined to be the set

$$A^x = \{y \in U : m(y) \geq x\}. \quad (3)$$

2.3 *Triangular Fuzzy Number (TFN)*

TFN is a fuzzy number represented with three points as follows: $A = (a, b, c)$.

Definition 4 Let a, b and c be real numbers with $(a < b < c)$. Then, the Triangular Fuzzy Number (TFN) $A = (a, b, c)$ is the FN with membership function:

$$y = m(x) = \begin{cases} \frac{x-a}{b-a}, & x \in [a, b] \\ \frac{c-x}{c-b}, & x \in [b, c] \\ 0, & x < a \, and \, x > c \end{cases} \quad (4)$$

From Eq. (4), we can define TFN as

$$TFN = y = [\alpha_l, c, \alpha_r] \tag{5}$$

From Eq. (5), if TFN is symmetry, $\alpha_2 - \alpha_1 = \alpha_3 - \alpha_2$, then y can be written as

$$y = [c, \alpha] \tag{6}$$

where a is spread of TFN and y is non-fuzzy number if $a = 0$.

3 Proposed Method: Forecasting Model Based on AR(1) with Standard Deviation Based TFN

This section discusses the systematic steps used for building forecasting model based on AR(1) with standard deviation based TFN (Δ_{σ^2}). The standard deviation approach is used to identify the spread value for building TFN. The proposed forecasting procedure serves as a guideline process in building forecasting model. Additionally, in this proposed procedure, times series model identification is provided to identify the model of Times Series before constructing TFN from crisp value. This step is important to ensure that only compliant dataset AR(1) model is selected. The flow of the proposed forecasting model based on AR(1) with Δ_{σ^2} is shown in Fig. 2.

The systematic steps for building AR(1) with Δ_{σ^2} is as follows:

Step 1. Select n times series datasets in a form of input data as shown in Table 1.
Step 2. Times Series model identification.

i. Prepare datasets. Refer to Table 1.

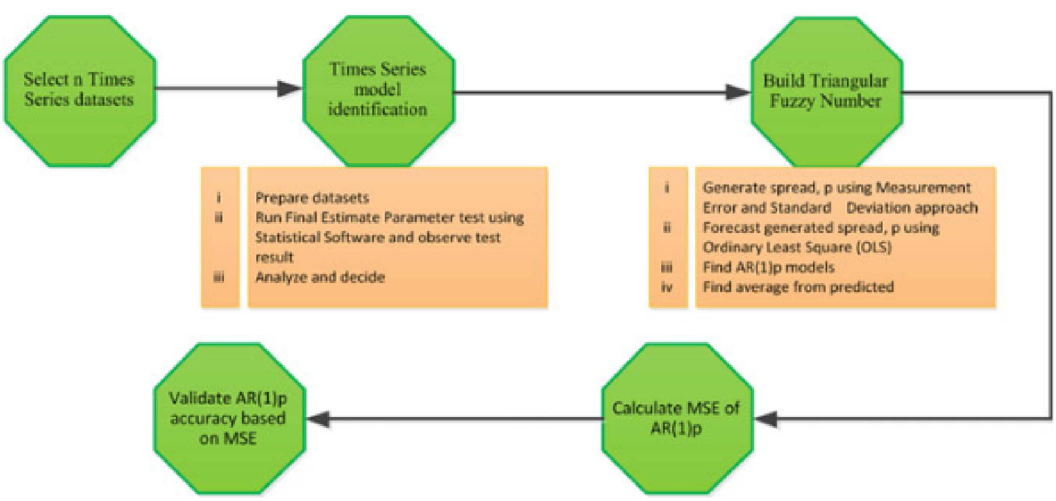

Fig. 2 Flow chart for forecasting model based on AR(1) with Δ_{σ^2}

Table 1 Format for input data

Data	1	2	…	n
Input	y_1	y_2	…	y_n

ii. Run Final Estimate Parameter test using Statistical Software to obtain Coefficient, Standard Error of the Coefficient (SE Coefficient), T-value and P-value.
iii. Check the result from estimate parameter to decide the AR(1) Times Series model. The p-value for each term tests the null hypothesis that the coefficient is equal to zero. The lowest p-value mean it is more meaningful to the model because changes in the predictor's value are related to the changes in the response variable.

Step 3. Build Triangular Fuzzy Number using Standard Deviation (SD).

i. Generate spread, s.

SD is a deviation that can be left or left from the centre. SD of the data is used as a spread because it leads to nature of SD.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}} \tag{7}$$

where σ, is standard deviation for population, x_i is each values of the data, $\bar{x}$ is the mean of x_i and n is the number of data points.

$$\tilde{y}_t^s = [y_t - s, y_t, y_t + s] \tag{8}$$

where $\tilde{y}_t^s$ is a fuzzy time series data at time, t with triangular fuzzy number data format. y_t is a time series data at time, $t\,(t = 1, 2, \ldots, n)$.

ii. Forecast generated spread, s using Ordinary Least Square (OLS).
iii. Find AR(1) models.

$$y_t = \beta_1 - \beta_2 y_{t-1} \tag{9}$$

where y_t is times series, β_1 is constant, β_2 is coefficient and y_{t-1} is past times series.

$$y_t^s = \left(\beta_1^L, \beta_1^R\right) - \left(\beta_2^L, \beta_2^R\right) y_{t-1} \tag{10}$$

where times series for standard deviation based models, $\left(\beta_1^L, \beta_1^R\right)$ is left and right constant, $\left(\beta_2^L, \beta_2^R\right)$ is left and right coefficient, y_{t-1} is past times

Table 2 Data format for average, $\bar{\bar{y}}_t^s$

y_t	y_1	y_2	…	y_n
$\bar{\bar{y}}_t^s$	$\bar{\bar{y}}_1^s$	$\bar{\bar{y}}_2^s$	…	$\bar{\bar{y}}_n^s$

series and $\bar{\bar{y}}_t^s$ is average predicted value. Table 2 shows the data format for average, ($\bar{\bar{y}}_t^s$).
Equation 9 is the traditional model that can be build using OLS approach. While Eq. 10 presents AR(1) model with fuzzy data which is produced by SD approach.

iv. Find average for predicted values, $\bar{\bar{y}}_t^s$.

$$\bar{\bar{y}}_t^s = \frac{\left(\overleftarrow{y}_t^s + s\right) + \left(\overrightarrow{y}_t^s - s\right)}{2} \tag{11}$$

where $\overleftarrow{y}_t^s$ is a left predicted value, $\overrightarrow{y}_t^s$ is a right predicted value and spread of TFN uses SD, s of y_t. Table 2 shows the data format for average, $\left(\bar{\bar{y}}_t^s\right)$.

Step 4. Calculate the Mean Square of Error (MSE) of AR(1) with s-spread.
After all stock market datasets have been tested, we need to compare the result of training and testing. To get total MSE for each y_t^s.

$$\text{MSE} = \frac{\sum_{i=1}^{n}\left(y_t - \bar{\bar{y}}_t^s\right)^2}{n} \tag{12}$$

where y_t is a time series data and $\bar{\bar{y}}_t^s$ is a predicted times series data at time, $t(t = 1, 2, \ldots, n)$ and n is sample size.

Step 5. Validate AR (1) accuracy based on MSE value.

The systematic steps presented here explains how to construct fuzzy number from crisp value, where the spread is derived from standard deviation. This step is important [16, 17] during data preparation since the crisp value which is observed as single points is insufficient to interpret such the financial or economic systems.

4 Numerical Experiment and Analysis

For the purpose of the experiment, stock market from five countries have been selected, namely, Malaysia (Kuala Lumpur Stock Exchange), Indonesia (Jakarta Stock Exchange), Singapore (Stock Exchange of Singapore), Philippines (Philippines Stock Exchange) and Thailand (Stock Exchange of Thailand). The data used was taken from 1 January to 26 March 2018.

Table 3 Datasets from five regions

Data	Input				
	Kuala Lumpur (57 data)	Philippines (58 data)	Thailand (58 data)	Indonesia (59 data)	Singapore (61 data)
1	1859.91	1328.30	1801.10	6200.17	3412.46
2	1865.22	1334.41	1794.21	6210.70	3421.39
…	…	…	…	…	…
56	1792.79	1795.45	1487.41	6353.74	3512.18
57	1782.70	1791.02	1477.91	6292.32	3489.45
58	–	1778.53	1477.18	6251.48	3501.16
59	–	–	–	6339.24	3464.28
60	–	–	–	–	3430.30
61	–	–	–	–	3402.92

Table 4 Kuala Lumpur stock market dataset

t	1	2	3	…	57
y_t	1782.70	1792.79	1803.45	…	1859.91

Table 5 Final estimation of parameters for Kuala Lumpur stock market

Stock market	Final estimates of parameters				
Kuala Lumpur	Type	Coefficient	SE coefficient	T	P
	AR(1)	0.9287	0.0659	14.09	0.00
	Constant	130.861	1.4330	91.33	0.00
	Mean	1835.88	20.10		

Step 1. Select five times series datasets as shown in Table 3.

Step 2. The following steps show times series model identification by using a Malaysia's stock market data as example.

i. Prepare datasets as in Table 4.
ii. Run Final Estimate Parameter test using Statistical Software and identify Coefficient, SE Coefficient, T-value and P-value as in Table 6.
iii. From the result shown in Table 5, Kuala Lumpur stock market fulfills AR(1). This is based on the p-value that is 0.00.

Step 3. Build Triangular Fuzzy Number.

i. Determine spread, s.
The spread to build TFN are determined by using SD approach. The SD is calculated based on Eq. 7 and the value is 20.1057.

Table 6 The possibilities spread, s of TFN

n	y_t	$\overleftarrow{y}_t^s$	$\overrightarrow{y}_t^s$
y_1	1782.7	1762.594	1802.806
y_2	1792.79	1772.684	1812.896
y_3	1803.45	1783.344	1823.556
…	…	…	…
y_{57}	1859.91	1839.804	1880.016

Table 7 Predicted result for spread, s of TFN

n	$\tilde{y}_t$	$\overleftarrow{\tilde{y}}_t^s$	$\overrightarrow{\tilde{y}}_t^s$
y_1	–	–	–
y_2	1786.45	1766.34	1806.55
y_3	1795.82	1775.71	1815.93
…	…	…	…
y_{57}	1863.09	1842.98	1883.19

Using the SD value, the TFN is constructed as $\left(\overleftarrow{y}_t^s, y_t, \overrightarrow{y}_t^s\right)$ and is as shown in Table 6.
The spread to build TFN are generated using SD approach as shown in Table 7. Using the spread, TFN is written as $\left(\overleftarrow{y}_t^s, y_t, \overrightarrow{y}_t^s\right)$.

ii. OLS is used to obtain the forecast model. The predicted result using spread s as shown in Table 7.
iii. Find AR(1) models

$$y_t = 130.861 - 0.9287 y_{t-1} \tag{13}$$

$$y_t^S = (129.427, 132.294) - 0.9287 y_{t-1} \tag{14}$$

From Table 7, two equations are obtained which is Eqs. 13 and 14 that representing traditional and SD approach, respectively.

iv. Find single data point by taking the average $\bar{\tilde{\mathbf{y}}}_{\mathbf{t}}^{\mathbf{S}}$ from predicted values based on Eq. (11). This is to transform the predicted values from TFN into a single point to measure the error. The forecasting result is shown in Table 8.
To get the average, $\bar{\tilde{\mathbf{y}}}_{\mathbf{t}}^{\mathbf{S}}$ we will use Eq. 11. This is to transform the predicted values from TFN into a single point to measure the error.

Step 4. The result of MSE for Kuala Lumpur stock market is obtained based on Eq. 12 and presented in Table 9.

Table 8 Average predicted value for spread, s of TFN

$\mathbf{y_t}$	y_1	y_2	...	y_{57}
$\bar{\mathbf{y}}_t^s$	1786.45	1795.82	...	1863.09

Table 9 MSE for Kuala Lumpur stock market

	Kuala Lumpur stock market MSE	
TFN	Training (46 data)	Testing (11 data)
yt	2.5424	[a]2.5188
y_t^S	[a]2.5342	2.5593

[a]Smallest MSE

Table 10 Summary of MSE

TFN	Stock Market MSE							
	Kuala Lumpur		Indonesia		Singapore		Thailand	
	Training (46 data)	Testing (11 data)	Training (48 data)	Testing (11 data)	Training (49 data)	Testing (12 data)	Training (47 data)	Testing (11 data)
yt	2.5424	[a]2.5188	5.6368	10.9316	4.4731	7.0399	[a]2.5847	2.6257
y_t^S	[a]2.5342	2.5593	[a]5.6367	[a]6.6593	[a]4.4727	[a]3.5830	2.7520	[a]2.0127

[a]Smallest MSE

Step 5. Validate AR(1) p accuracy based on Mean Square Error (MSE).

In the early stage, five stock markets are evaluated. However, only four stock markets fulfill the requirement of AR(1) after AR(1) identification in Step 1. The accuracy of forecasting error can be verified by comparing MSE. Table 10 shows the summary of MSE.

In the validation step, although a result of MSE for training data is better, we consider the testing data results as MSE for testing forecast is made using its own data whilst training MSE uses previous data to forecast. By referring to Table 10, Training SD approach to Kuala Lumpur is better than traditional approach but when it comes to testing, the decision suggests otherwise. Additionally, other testings for Indonesia, Singapore and Thailand shows impressive result because the SD approach is better than traditional approaches.

5 Conclusions

This study presents a procedure to build an adjusted Triangular Fuzzy Number for AR(1) forecasting. The proposed procedure is important in handling uncertainty contained in the data used for forecasting. This procedure also suggests the technique to identify the spread of TFN clearly as compared with other approaches. The experiment result concludes that the proposed procedure is able to compete efficiently with the traditional approach, yet it solves the uncertainty issues in the input data.

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References

1. What is the Stock Market? [Online]. Available https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/stock-market/
2. Grunwald GK, Hyndman RJ, Tedesco LM (1996) A unified view of linear AR(1) models, pp 1–26
3. Lauren S, Harlili S (2015) Stock trend prediction using simple moving average supported by news classification. In: Proceeding—2014 International conference of advanced informatics: concept, theory and application, ICAICTA 2014, no 1, pp 135–139
4. Sirohi AK, Mahato PK, Attar V (2014) Multiple Kernel learning for stock price direction prediction. In: 2014 International conference on advances in engineering and technology research, ICAETR 2014, pp 2–5
5. Kaya M (2010) Stock price prediction using financial news articles. In: 2010 2nd IEEE international conference on information and financial engineering, ICIFE, pp 478–482
6. Schumaker RP, Chen H (2009) Textual analysis of stock market prediction using breaking financial news. ACM Trans Inf Syst 27(2):1–19
7. Sugumar R, Rengarajan A, Jayakumar C (2014) A technique to stock market prediction using fuzzy clustering. Comput Inf 33:992–1024
8. Barker KN (1980) Data collection techniques: observation. Am J Hosp Pharm 37(September):1235–1243
9. Efendi R, Samsudin NA, Arbaiy N, Deris MM (2017) Maximum-minimum temperature prediction using fuzzy random auto-regression time series model. In: 2017 5th International symposium on computational business intelligence, pp 57–60
10. Neenwi SL, Kabari G, Asagba P (2012) Nigerian stock market investment using a fuzzy strategy. J Inf Eng Appl 2(8):18–28
11. Chen MY, Chen BT (2015) A hybrid fuzzy time series model based on granular computing for stock price forecasting. Inf Sci (Ny) 294:227–241
12. Atsalakis GS, Protopapadakis EE, Valavanis KP (2016) Stock trend forecasting in turbulent market periods using neuro-fuzzy systems. Oper Res 16(2):245–269
13. Chang P-C, Wu J-L, Lin J-J (2016) A Takagi-Sugeno fuzzy model combined with a support vector regression for stock trading forecasting. Appl Soft Comput 38:831–842
14. Maciel L, Gomide F, Ballini R (2016) Evolving fuzzy-GARCH approach for financial volatility modeling and forecasting. Comput Econ 48(3):379–398

15. Kahraman C, Beskese A, Bozbura FT (2006) Fuzzy regression approaches and applications. In: Fuzzy Regression Model. Beyond Fuzzy Rule Base Model, vol 201, no 1, pp 589–615
16. Efendi R, Arbaiy N, Deris MM (2017) Indonesian-Malaysian stock market models using fuzzy random time series, pp 18–19
17. Efendi R, Arbaiy N, Deris MM (2018) A new procedure in stock market forecasting based on fuzzy random auto-regression time series model. Inf Sci (Ny) 441:113–132
18. Efendi R, Arbaiy N, Deris MM (2017) Estimation of confidence-interval for yearly electricity load consumption based on fuzzy random auto-regression model. In: Computational intelligence in information systems, vol 532
19. Singh P (2017) An efficient method for forecasting using fuzzy time series. In: Emerging research on applied fuzzy sets and intuitionistic fuzzy matrices, IGI Global, p 18
20. Efendi R, Ismail Z, Deris MM (2015) A new linguistic out-sample approach of fuzzy time series for daily forecasting of Malaysian electricity load demand. Appl Soft Comput J 28:422–430
21. Ismail Z, Efendi R, Deris MM (2015) Application of fuzzy time series approach in electric load forecasting. New Math Nat Comput 11(03):229–248
22. Efendi R, Deris MM, Ismail Z (2016) Implementation of fuzzy time series in forecasting of the non-stationary data. Int J Comput Intell Appl 15(02):1650009
23. Efendi R, Deris MM (2017) Prediction of Malaysian-Indonesian oil production and consumption using fuzzy time series model. Adv Data Sci Adapt Anal 9(1):1–17
24. Hyndman RJ, Athanasopoulos G (2014) Forecasting : principles and practice. [Online]. Available http://otexts.com/fpp/
25. Zadeh LA (1965) Fuzzy Sets. Inf Control 8:338–353

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