Comparison of Two Partitioning Methods in a Fuzzy Time Series Model for Composite Index Forecasting

Lazim Abdullah
Department of Mathematics
Faculty of Science and Technology
University Malaysia Terengganu
21030 Kuala Terengganu
Malaysia
lazim_m@umt.edu.my

Yoke Ling
Department of Mathematics
Faculty of Science and Technology
University Malaysia Terengganu
21030 Kuala Terengganu
Malaysia
haley_yokeling@yahoo.com

Abstract—Study of fuzzy time series has increasingly attracted much attention due to its salient capabilities of tackling vague and incomplete data. A variety of forecasting models have devoted to improve forecasting accuracy. Recently, Fuzzy time-series based on Fibonacci sequence has been proposed as a new fuzzy time series model which incorporates the concept of the Fibonacci sequence, the framework of basic fuzzy time series model and the weighted method. However, the issue on lengths of intervals has not been investigated by the highly acclaimed model despite already affirmed that length of intervals could affects forecasting results. Therefore the purpose of this paper is to propose two methods of defining interval lengths into fuzzy time-series based on Fibonacci sequence model and compare their performances. Frequency density-based partitioning and randomly chosen lengths of interval partitioning were tested into fuzzy time-series based on Fibonacci sequence model using stock index data and compared their performances. A two-year weekly period of Kuala Lumpur Composite Index stock index data was employed as experimental data sets. The results show that the frequency density based partitioning outperforms the randomly chosen length of interval. This result reaffirms the importance of defining the appropriate interval lengths in fuzzy time series forecasting performances.

Keywords-forecasting; fuzzy sets; time series; composite index

I. INTRODUCTION

In the midst of market volatility and risk, it is imperative to minimize losses by embarking in stock price forecasting. Realizing the importance of stock price forecasting, researchers have explored number of methods in the hope to search for one which could give the most accurate prediction. For many decades, researchers have formed various new approaches and methods to increase the accuracy of stock price forecasting. The most common and widely used method is time series. The most popular method in stock price forecasting is Box-Jenkins model which was introduced by Box and Jenkins [1]. In econometrics, the Box–Jenkins methodology, applies autoregressive moving average model to find the best fit of a time series to make forecasts. However the classical time series methods fail to deal with forecasting problems which the values of time series are linguistic terms [2]. With new emergence of fuzzy theory and also challenges to face the uncertainty in stock price forecasting, new efforts have been geared up to incorporate the fuzziness in stock price and time series. Time-series models have successfully utilized the fuzzy theory to solve various domains of forecasting problems, such as university enrolment forecasting [3]-[6] and temperature forecasting [9]. However, most of the researches concentrated on fuzzy time series models in the domain of stock price forecasting. To name a few, stock prices forecasting using fuzzy time series was extensively researched by [10]-[12].

The development of fuzzy theory in stock prices forecasting was further developed. Recently, reference [13] developed a new forecasting model which the intention to improve forecasting results. They proposed fuzzy time-series with Fibonacci sequence forecasting and asserted that their method has surpassed the three conventional fuzzy time-series models of Chen [5], Yu [14] and Huarng [15]. They have implied the Elliott wave principle into the general fuzzy time-series. This principle has been played an important role in stock analysis for more than six decades. According to reference [17], the theory is closely related to stock price time series because it applies the Fibonacci sequence to predict the timing of stock price fluctuations. Despite the success of Chen et al. [13] in surpassing the three fuzzy time series models, the choice of partitioning intervals in the first step of their algorithm warrants further attentions. Reasonably define the universe of discourse and decide into how many intervals the universe will be partitioned in the first step is an arbitrary matter. Therefore interval length in fuzzy time series is widely open for a new exploratory. Apart from that, it was noticed that length of intervals somehow affects the performance of fuzzy time series. Reference [15] has asserted that different lengths of intervals lead to different forecasting results and forecasting errors. Reference [15] also added that there will be no fluctuations in the fuzzy time series when an effective length of intervals is too large. On the other hand, when the length is too small, the meaning of fuzzy time series will be diminished. Therefore, he suggested that a key point in choosing effective lengths of intervals is that they should not be too large or small. It shows that the length of interval is a loosely defined despite their important role in fuzzy time series.

The size of intervals was first coined by Song and Chissom [3] and nothing has been critically examined the appropriate length of interval in the first step of the algorithm. Reference [13] acknowledged two common flaws exist in fuzzy time series models and one of them was partitioning the universe of discourse subjectively. Therefore, it is imperative that we need to decide the length of each interval for the partitioning based on recent development in portioning methods. In the studies of Song and Chissom [3] for enrolment forecasting, they chose 1000 as the length of intervals without specifying any reasons. Since then, 1000 has been used as the length of intervals in their studies. This is what normally referred as the randomly chosen length intervals (RCLI). Then some years later, Huarng [15] found that different length of intervals used offer different forecasting results. In his studies, he has proposed heuristic time-invariant fuzzy time series forecasting models to cope this issue. Recently, reference [16] proposed a new partitioning method to improve the forecasting accuracy of conventional fuzzy time series. The frequency density-based partitioning (FDBP) was proposed as part of efforts to improve forecasting accuracy. This method involved further partitioning of the intervals which have been initially partitioned by using the randomly chosen length. The method employed sub-partitioning the equal length intervals based on frequency density within each existing interval to get the new number of intervals. There are four sub-partitions of the interval having the highest frequency density, three partitions for the interval with second highest frequency density and two partitions for third highest frequency density. They have concluded that this proposed FDBP can improve forecasting accuracy.

Based on these premises, we utilized the model of [13] by incorporating the effect of interval in composite index forecasting. We take the RCLI and FDBP as the interval lengths determination methods for a comparison. Also, we utilize linguistic definition of sixteen and twenty two for each partitioning methods as part of elucidating the effect of interval lengths to forecasting performances. There are no specific reasons for choosing this sixteen and twenty two as number of interval. It is merely to show the effect of larger number of interval to forecasting accuracy. In empirical analysis, we employ an experimental datasets of Kuala Lumpur Composite Index (KLCI) to test the two interval length methods into the model.

The rest of the paper is organized as follows. Section II introduces the related definitions on fuzzy time series and the portioning methods. Section III proposes a computational framework which incorporates two methods of finding interval length. Section IV evaluates the performance of KLCI under two methods of interval lengths. The paper ends with a short conclusion in Section V.

II. PRELIMINARIES

The concept of fuzzy set theory was introduced to cope with the ambiguity and uncertainly of most of real-world problems. The basic concepts of fuzzy set theory and fuzzy time series are given in books of Song and Chissom [3]. Some of the essentials are being reproduced to make this paper self-contained. The basic concepts of fuzzy time series are defined by four definitions (Definition 1 to 4). The definitions of the two partitioning methods are given in Definition 5 and Definition 6. Fibonacci sequence that made up the key improvement of [13] model is given in Definition 7.

Definition 1**.** Let $Y(t)(t = \ldots,0,1,2\ldots)$, be the universe of discourse and $Y(t) \subseteq R$. Assume that $f_i(t), i = \ldots,0,1,2,\ldots$ is defined in the universe of discourse $Y(t)$ and $F(t)$ is a collection of $f_i(t),(i = \ldots,0,1,2,\ldots)$, then $F(t)$ is called a fuzzy time series of $Y(t)$, $i = 1,2,\ldots$ Using fuzzy relation, we define $F(t) = F(t-1) \circ R(t,t,-1)$ where $R(t,t,-1)$ is a fuzzy relation and "$\circ$" is the max–min composition operator, then $F(t)$ is caused by $F(t-1)$ where $F(t)$ and $F(t-1)$ are fuzzy sets.

Definition 2**.** Let $F(t)$ be a fuzzy time series and let $R(t,t,-1)$ be a first-order model of $F(t)$. If $R(t,t-1) = R(t-1,t-2)$ for any time t, then $F(t)$ is called a time-invariant fuzzy time series. If $R(t,t,-1)$ is dependent on time t, that is, $R(t,t,-1)$ may be different from $R(t-1,t-2)$ for any t, then $F(t)$ is called a time-variant fuzzy time series.

Definition 3. Let $F(t)$ be a fuzzy time series. If $F(t)$ is caused by $F(t-1), F(t-2), \ldots, F(t-n)$, then the nth-order fuzzy logical relationship is represented by

$$F(t-1), F(t-2), \ldots, F(t-n) \rightarrow F(t)$$

where $F(t-1), F(t-2), \ldots, F(t-n)$ and $F(t)$ are all fuzzy sets, where $F(t-1), F(t-2), \ldots, F(t-n)$ is called the antecedent and $F(t)$ is called the consequent of the nth-order fuzzy logical relationship. When

$$F(t-1) = A_i \text{ and } F(t) = L_j;$$

the relationship between $F(t-1)$ and $F(t)$ (called a fuzzy logical relationship) is denoted by $L_i \rightarrow L_j$.

Definition 4. Fuzzy logical relationships with the same fuzzy set on the left-hand side can be further grouped into a fuzzy logical relationship group. Suppose there are fuzzy logical relationships such that

$$L_i \rightarrow L_{j1},$$
$$L_i \rightarrow L_{j2},$$
$$\ldots$$

They can be grouped into a fuzzy logical relationship group

$$L_i \rightarrow L_{j1}, L_{j2}, \ldots$$

Following Chen [5] model, the same fuzzy sets can only show up once on the right-hand side of the fuzzy logical relationship group.

Definition 5. Randomly Chosen Length of Intervals (RCLI)

The randomly chosen length of intervals method has been commonly practiced by [3], where they randomly choose an interval length for partitioning. Here, the length must not be larger than the length of the universe of discourse, U. The universe of discourse is then divided equally by the length chosen into n number of intervals.

For example, if the minimum and maximum KLCI stock price in the training dataset from 2007/01/01 to 2008/12/29 is 20 and 50, respectively, the universe of discourse to be defined as $U = [20,50]$. By randomly choosing an interval length of 10, we have three intervals $u_1 = [20,30)$, $u_2 = [30,40)$ and $u_3 = [40,50)$. On the other hand, if we chose 6 as the interval length, then the universe of discourse will have five intervals of $u_1 = [20,26)$, $u_2 = [26,32)$, $u_3 = [32,38)$, $u_4 = [38,44)$, $u_5 = [44,50)$.

Definition 6. Frequency-Density-Based Partitioning (FDBP)

The universe of discourse, $U = [U_{min} - U_1, U_{max} + U_2]$ is first partitioned into equal length intervals $u_1, u_2, \cdots, u_n$, by using the RCLI. Number of observations falling within each interval is counted. Using this method, sub-partition the equal length intervals based on frequency density within each interval can be obtained.

By doing this, a new number of intervals $u'_1, u'_2, \cdots, u'_n$ and new fuzzy sets $L_1, L_2, \ldots, L_k$ of U where

$$L_1 = a_{11}/u'_1 + a_{12}/u'_2 + \cdots + a_{1n}/u'_n$$
$$L_2 = a_{21}/u'_1 + a_{22}/u'_2 + \cdots + a_{2n}/u'_n$$
$$\vdots$$
$$L_k = a_{k1}/u'_1 + a_{k12}/u'_2 + \cdots + a_{kn}/u'_n$$

is obtained.

Definition 7. Fibonacci sequence Model

In mathematics, the Fibonacci numbers are the sequence of numbers which is defined by

$$F_n = \left\{ \begin{array}{ll} 0 & \text{if} \quad n = 0 \\ 1 & \text{if} \quad n = 1 \\ F_{n-1} + F_{n-2} & \text{if} \quad n > 1 \end{array} \right\}_{n=1}^{\infty}$$

The Fibonacci sequence also can be expressed by the general second-order linear recurrence equation (where A and B are constants with arbitrary x_1 and x_2), which is defined as

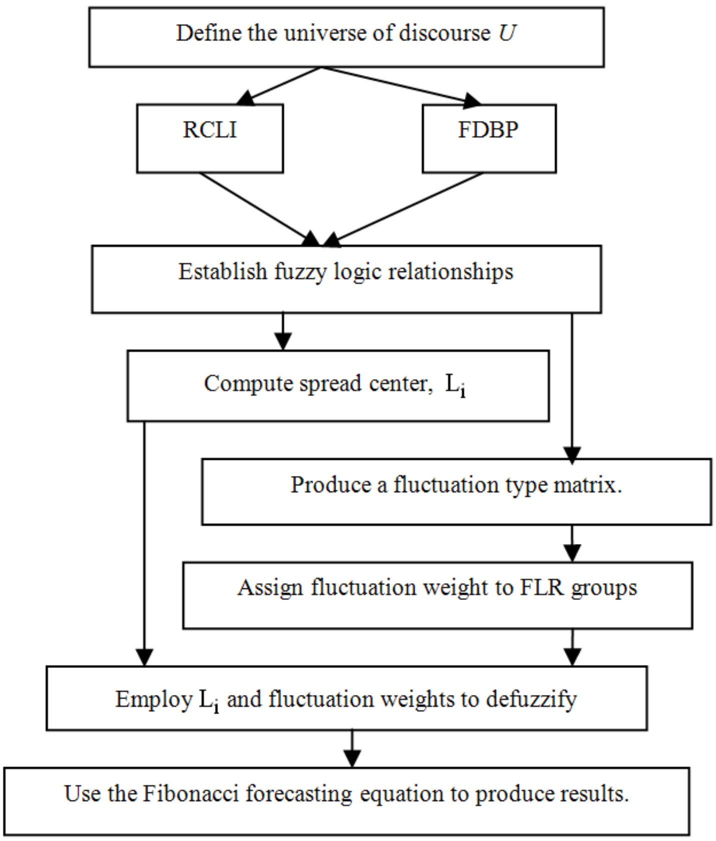
$$x_n = Ax_{n-1} + Bx_{n-2}$$

The application of the Fibonacci sequence, $F_n = F_{n-1} + F_{n-2}$, is extended to the forecasting process.

III. COMPUTATIONAL FRAMEWORK

The fuzzy timeseries model based on the Fibonacci sequence employs eight-step algorithm which is not to be presented in this paper. Details of the algorithms can be retrieved from [13] . The paper aims to verify the algorithm with two different partitioning methods with KLCI stock index. In the first step, universe of discourse is defined as $U = [U_{min} - U_1, U_{max} + U_2]$,where U_{min} and U_{max} are the minimum and maximum values in U and U_1, U_2 are two real positive numbers. Numbers of intervals are determined by randomly chosen interval (Definition 5) or frequency density based partitioning (Definition 6). The next steps account the establishment of linguistic values and its fuzzy logical relations. The following steps engage with assigning weights and linguistics spread centre matrix. The step generates the initial forecasting prior to using Fibonacci sequence to yield forecasted indexes. Summarily, the computational framework can be seen in Fig I.

FIG I COMPUTATIONAL FRAMEWORK OF THE MODEL



This computational framework is tested to the KLCI.

IV. MODEL VERIFICATION AND COMPARISON

The weekly datasets of 105 KLCI from the period of 2007/01/01 to 2008/12/29 were tested to the model. The data were set to verify the model in term of forecasting accuracy for two partitioning methods that lead to the number of intervals.

A. *Forecasting with RCLI*

In this section, we demonstrate how the algorithm of the proposed model with randomly chosen interval be used to produce forecast for our KLCI training datasets.

From the KLCI datasets, the minimum and maximum stock price is 838.28 and 1507.04 respectively, the universe of discourse is hence to be defined as $U = [800,1600]$. By using the fuzzy method, the low bound can be expanded by 38.28 smaller than 838.28, making Low 800, and up bound can be expanded by 92.96 larger than 1507.04, making Up 1600. As a result, the defined universe of discourse of $U = [800,1600]$ can cover every occurring stock price in the KLCI dataset.

The fuzzy sets, $L_1, L_2, \ldots, L_{16}$ for the universe of discourse are defined. Part of the fuzzy sets for the training datasets are described as follows:

$$L_1 = 1/u_1 + 0.5u_2 + 0/u_3 + ... + 0/u_8 + 0/u_9 + 0/u_{10} ... + 0/u_{15} + 0/u_{16}$$

$$L_2 = 0.5/u_1 + 1u_2 + 0.5/u_3 + ... + 0/u_8 + 0/u_9 + 0/u_{10} ... + 0/u_{15} + 0/u_{16}$$

$$L_3 = 0/u_1 + 0.5u_2 + 1/u_3 + ... + 0/u_8 + 0/u_9 + 0/u_{10} ... + 0/u_{15} + 0/u_{16}$$

$\cdots$

$$L_{16} = 0/u_1 + 0u_2 + 0/u_3 + ... + 0/u_8 + 0/u_9 + 0/u_{10} ... + 0.5/u_{15} + 1/u_{16}$$

Each observation in the KLCI datasets can be classified by the sixteen partitioned intervals For each KLCI indices, its values are assigned to its belonging linguistic value based on the linguistic intervals. For example at time $t = 1$, the KLCI index value is assigned to L_6. This is because its value, 1096.24 falls under the interval range of $[1050,1100)$. Next, we randomly chose the length of intervals to be 50. Hence, there are sixteen intervals for this universe of discourse where, $u_1 = [800,850)$, $u_2 = [850,900)$, $u_3 = [900,950)$, $u_4 = [950,1000)$, $u_5 = [1000,1050)$, $u_6 = [1050,1100)$, $u_7 = [1100,1150)$, $u_8 = [1150,1200)$, $u_9 = [1200,1250)$, $u_{10} = [1250,1300)$, $u_{11} = [1300,1350)$, $u_{12} = [1350,1400)$, $u_{13} = [1400,1450)$, $u_{14} = [1450,1500)$, $u_{15} = [1500,1550)$, $u_{16} = [1550,1600]$

The fuzzy logical relationships (FLRs) are formed. Part of the FLRs for the KLCI index datasets are established as

$$L_6(t = 1) \to L_7(t = 2)$$
$$L_7(t = 2) \to L_7(t = 3)$$
$$L_7(t = 3) \to L_7(t = 4)$$
$$L_7(t = 4) \to L_8(t = 5)$$
$$L_8(t = 5) \to L_9(t = 6)$$
$$L_9(t = 6) \to L_9(t = 7)$$
$$L_9(t = 7) \to L_{10}(t = 8)$$
$$\vdots$$

The FLRs formed are then used to establish FLR groups. According to Definition 4 of fuzzy time series, the FLRs with the same left hand side (LHS) linguistic value can be grouped into one FLR group. Suppose there are fuzzy logical relationships such that

$$L_2 \to L_1,$$
$$L_2 \to L_2,$$
$$L_2 \to L_3$$

they can be grouped into a fuzzy logical relationship group such as

$$L_2 \rightarrow L_1, L_2, L_3$$

By applying Chen's theory[5], all the FLRs produces FLR groups as below:

$L_1 \rightarrow L_2$	$L_9 \rightarrow L_8, L_9, L_{10}$
$L_2 \rightarrow L_1, L_2, L_3$	$L_{10} \rightarrow L_8, L_9, L_{10}, L_{11}$
$L_3 \rightarrow L_2, L_3$	$L_{11} \rightarrow L_9, L_{10}, L_{11}, L_{12}$
$L_5 \rightarrow L_3, L_5$	$L_{12} \rightarrow L_{11}, L_{12}, L_{13}$
$L_6 \rightarrow L_5, L_6, L_7$	$L_{13} \rightarrow L_{12}, L_{13}, L_{14}$
$L_7 \rightarrow L_6, L_7, L_8$	$L_{14} \rightarrow L_{13}, L_{14}$
$L_8 \rightarrow L_7, L_8, L_9, L_{10}$	

All FLR groups will construct a fluctuation-type matrix and fluctuation-weighted matrix. Standardized weights for the fuzzy sets, $L_1, L_2, \ldots, L_{16}$ are computed and gives as

$$W_1(t) = [0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0]$$

$$W_2(t) = \left[\frac{1}{17}, \frac{15}{17}, \frac{1}{17}, 0,0,0,0,0,0,0,0,0,0,0,0,0\right]$$

$$\vdots$$

$$W_{16}(t) = [0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0]$$

By using the linguistic spread-centre matrix, and the standardized weight matrix, we generated the initial forecasts. Lastly, we apply the Fibonacci forecasting equation into the initial forecasted results to produce final forecasting results.

B. Forecasting with FDBP

The second forecasting indexes employ refined FDBP into the model.

For this reason, we now employ the universe of discourse, $U = [800,1600]$ and its 22 intervals established by the refined FDBP (Definition 6) into the algorithm of the proposed model. The new intervals are $u'_1 = [800,850)$, $u'_2 = [850,900)$, $u'_3 = [900,950)$, $u'_4 = [950,1000)$, $u'_5 = [1000,1050)$, $u'_6 = [1050,1100)$, $u'_7 = [1100,1150)$, $u'_8 = [1150,1200)$, $u'_9 = [1200,1250)$, $u'_{10} = [1250,1267)$, $u'_{11} = [1267,1283)$, $u'_{12} = [1283,1300)$, $u'_{13} = [1300,1325)$, $u'_{14} = [1325,1350)$, $u'_{15} = [1350,1363)$, $u'_{16} = [1363,1375)$, $u'_{17} = [1375,1388)$, $u'_{18} = [1388,1400)$, $u'_{19} = [1400,1450)$, $u'_{20} = [1450,1500)$, $u'_{21} = [1500,1550)$ and $u'_{22} = [1550,1600]$.

With about the similar fashion as Section IV.A, we could generate the forecasting results.

The two forecasted indexes are further investigated. The trends of RLCI partitioning method forecasting indexes (Forecasted 1), FDBP forecasting indexes (Forecasted 2) and actual indexes can be seen in Fig. II.

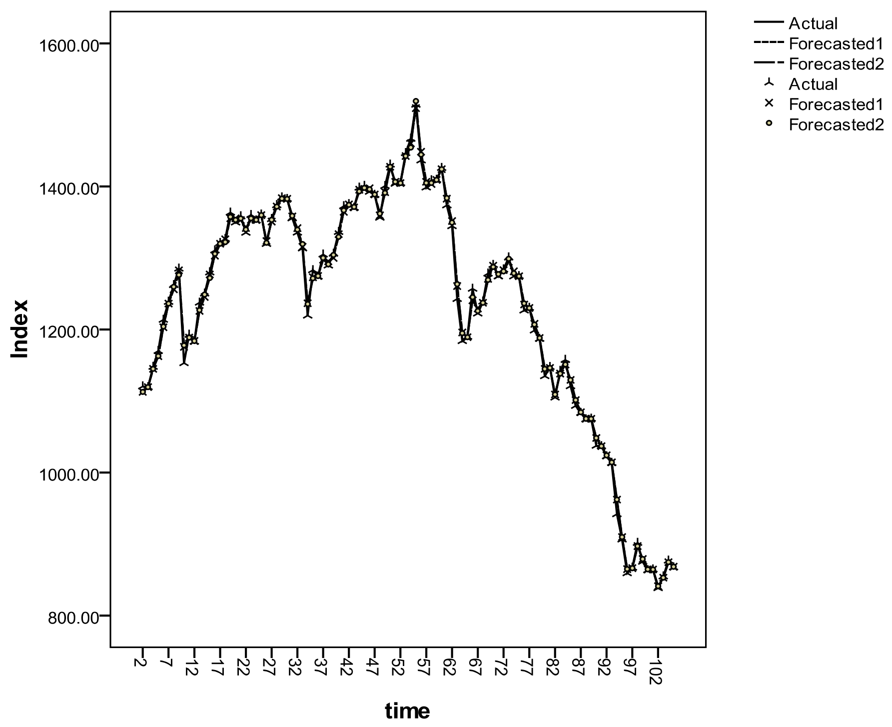


FIG II TRENDS OF ACTUAL INDEXES VERSUS TWO FORECASTED INDEXES.

It can be seen that the trends of two forecasted indexes and observed indexes are very close to each other. Therefore it is anticipated that the model is worked well to the tested data. Furthermore, the trends also conjectured that the two partitioning methods are marginally differed toward the model. Performances of the two portioning methods are further discussed in the following sub section.

C. Forecasting Performance

The performance of the two interval methods is further explored. The two methods of partitioning are compared to investigate forecasting efficacy.

We examine the performance of the model using two methods of length intervals. We compare the difference in error term of mean square error (MSE). The equation for MSE is defined as

$$\mathrm{MSE} = \frac{\sum_{t=1}^{n} |\,\mathrm{actual}(t) - \mathrm{forecast}(t)\,|^2}{n}$$

If the actual and forecasted values are closer to each other the calculated MSE would be smaller. Logically, smaller distance between the actual and forecasted value implicates the forecasted value are more accurate. Root of mean square error (RMSE) is another error term which denotes the square root of MSE. We also use percentage of average forecasting error rate (AFER) to check the performance of forecasting results. The average errors is defined as

$$\mathrm{AFER} = \left(\frac{\sum |\mathrm{actual}(t) - \mathrm{forecast}(t)\,| / \mathrm{actual}}{n}\right)100\% \ .$$

By using sixteen and twenty two linguistic intervals for each partitioning method respectively, we produced performance indicators as shown in Table I.

TABLE I MODEL'S PERFORMANCE

Error term	Forecasted 1	Forecasted 2
MSE	44.21	42.55
RMSE	6.65	6.52
AFER (%)	0.396	0.389

From the Table I, it is obvious that the model of fuzzy time series based on Fibonacci sequence with FDBP (Forecasted 2) has surpasses the fuzzy time series based on Fibonacci sequence with RCLI (Forecasted 1) with very small margin. Although it is a small difference but it is undeniably that the employment of FDBP does improve the forecasting accuracy.

V. CONCLUSION

In this paper we chose fuzzy time series model proposed by Chen et al [13] as a testing platform for two partitioning methods. The randomly chosen length interval and frequency density-based partitioning methods are applied to the model in forecasting the performance of KLCI stock index. Experimental results on the KLCI stock index demonstrate that the partitioning methods are not differ substantially in term of forecasting performances but it is suffice to verify the efficacy of the forecasting model. It can also be concluded that the proposed model of fuzzy time series based on Fibonacci sequence with the employment of frequency density-based partitioning is an improved model to forecast the performance of KLCI stock index. Higher number of intervals defined in the frequency density-based partitioning may contribute to better forecasting accuracy but it sometimes creates computational complexities. This issue probably stimulates a new venture into unraveling the computational risk in fuzzy time series especially in the event of higher number of interval.

ACKNOWLEDGMENT

The authors thank to the University Malaysia Terengganu and Ministry of Higher Education Malaysia under the fundamental research grant scheme, no. 59148 for financing this project.

REFERENCES

[1] G.E.P.Box and G. Jenkins, Time Series Analysis: Forecasting and Control, Holden-Day. 1976.
[2] L.A. Zadeh, Fuzzy Sets, Information Control, 8,1965, pp. 338-358.
[3] Q. Song and B.S. Chissom, Forecasting enrolments with fuzzy time- series. Part I, Fuzzy Sets Syst. 54 ,1993, pp. 1–10.
[4] Q. Song and B.S. Chissom, Forecasting enrolments with fuzzy time- series. Part II, Fuzzy Sets Syst. 62, 1994, pp. 1–8.
[5] S.M. Chen, Forecasting enrollments based on fuzzy time-series, Fuzzy Sets Syst. 81, 1996, pp. 311–319.
[6] S.M. Chen, Forecasting enrollments based on high-order fuzzy time series, Cybern. Syst. 33, 2002, pp. 1–16.
[7] S.M. Chen and C.C. Hsu, A new method to forecast enrolments using fuzzy time series, Appl. Sci. Eng. 2, 2004, pp. 234–244.
[8] S.M. Chen and N.Y. Chung, Forecasting enrollments using high-order fuzzy time series and genetic algorithms, Int. J. Intell. Syst. 21, 2006, pp. 485–501.
[9] S.M. Chen and J.R. Hwang, Temperature prediction using fuzzy time series, IEEE Transactions on Syatems, Man, and Cybernetics-part B:Cybernetics, 30, 2000, pp. 263-275.
[10] R.W. Faff, R.D. Brooks and Y.K. Ho, New evidence on the impact of financial leverage on beta risk: a time-series approach, North Am. J. Econ. Finance 13, 2002, pp. 1–20. |
[11] H.K. Yu, Weighted fuzzy time-series models for TAIEX forecasting, Physica A 349, 2004, pp. 609–624.
[12] C.H. Leon Lee, A. Liu and W.S. Chen, Pattern discovery of fuzzy time series for financial prediction, IEEE Trans. Knowl. Data Eng. 18, 2006, pp. 613–625.
[13] T.L. Chen, C.H. Cheng and H.J. Teoh, Fuzzy time-series based on Fibonacci sequence for stock price forecasting, Physica A 380, 2007, pp. 377–390.
[14] H.K. Yu, Weighted fuzzy time-series models for TAIEX forecasting, Physica A , 349 , 2004, pp. 609–624.
[15] K.H. Huarng and H.K. Yu, A type-2 fuzzy time-series model for stock index forecasting, Physica A 353, 2005, pp. 445–462.
[16] T.A. Jilani, S.M.A. Burney and C. Ardil, Fuzzy metric approach for fuzzy time series forecasting based on frequency density based partitioning, International Journal of Computational Intelligence 4 (1) , 2007, pp. 112–117.
[17] R. Fischer, The New Fibonacci Trader: Tools and Strategies for Trading Success, Wiley, New York, 2001.

AUTHORS' PROFILE

Mohd Lazim Abdullah holds undergraduate B Sc (Hons) in Mathematics at University of Malaya in Jun 1984. He obtained masters degree in Mathematics Education at University of Science Malaysia, Penang in 1999 and Doctorate (Ph.D.) at University of Malaysia Terengganu, in Information Technology Development, September 2004. He is currently an Associate Professor at Faculty of Science and Technology, University of Malaysia Terengganu, Ministry of Higher Education Malaysia. His researches are dealt with fuzzy sets theory and its application to social ecology, health sciences, economics, environmental sciences and education. He is interested about measurement of social, health and education indicators by inserting computational intelligence of fuzzy knowledge. His interest also lies towards profiling social and educational constructs using statistical software. He is an editor of books, conferences' proceedings and also a reviewer and editorial board of International Journals. He is a member of IEEE Computational Intelligence Society and Malaysian Mathematical Society.

Chai Yoke Ling holds Bachelor degree in Financial Mathematics at University Malaysia Terengganu in Jun 2008. She is currently attached to a stock broking company at Kula Lumpur, Malaysia.