Fuzzy Time Series Model Based on Fitting Function for Forecasting TAIEX Index

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Abstract

Many traditional time series model has been widely applied in forecasting Problem. However, the previous time series methods still have some constraints: (1) conventional time series models only considered single variable; (2) traditional fuzzy time series model determined the interval length of linguistic value subjectively; (3) selecting variables depended on personal experience and opinion. Hence, this paper proposes a novel hybrid fuzzy time series model based on fitting function to forecast TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock index). The proposed model employed Pearson's correlation to select important technical indicators objectively, and the proposed model utilized fitting function to forecast TAIEX Index. In verification, the collected TAIEX datasets from 1998/01/03 to 2002/12/31 are used as experimental dataset and the root mean square error (RMSE) as evaluation criterion. The results show that the proposed model outperforms the listing models in accuracy.

Keywords: *Forecast Stock index, Fuzzy time series, Technical Indicator, TAIEX*

1. Introduction

In the past, many time series models such as ARIMA (autoregressive moving average) [1] and GARCH (generalized autoregressive conditional heteroskedasticity) [2] have been applied to forecast stock price and trends in the financial market. However, these models only can deal with linear forecasting model and variables must obey statistical normal distribution. In order to overcome these limitations, many researchers [3-7] utilized the fuzzy time series model to solve non-linearity and uncertainty problems. At first, Song and Chissom proposed fuzzy time series model [8-10]. Fuzzy time series had many applications such as in forecasting university enrollment [6, 11-13] and forecasting stock index [3-5, 7]. However previous fuzzy time series models had two shortcomings: (1) subjective way to determine interval length of linguistic value and (2) only considered single variable. As stated above, these situations can cause a decrease in accuracy of forecasting stock index.

Technical indicators analysis has become important approach for analyzing patterns and trends of stock price [1, 14]. Moreover, selecting technical indicators as input variables depended on personal experience and opinion in former studies. In order to improve the

drawback of selecting variables subjectively, this study utilized Pearson correlation [20] to select two important factors. In contribution of model, this study utilized objective technique to automatically determine the lower bound and upper bound of discourse of universe [15]. Furthermore, this study used the spread-partition algorithm to determine linguistic intervals objectively [15]. The proposed model can provide to investors for determining timing on buying and selling stock.

The rest of this paper is organized, as follows: Section 2 introduces the related works; Section 3 demonstrates the proposed model and algorithm; Section 4 evaluates the performance of the proposed model. Finally, the conclusion and future work are discussed in Section 5.

2. Related Works

This section introduces some important literatures, which includes fuzzy set, fuzzy time series, and technical analysis.

2.1. Fuzzy Set

Traditionally, it is difficult to solve uncertainty problem with binary logic. However, Zadeh [16] introduced the fuzzy set theory which can be used in a wide range of domains in which information is incomplete or imprecise. The membership in a fuzzy set is not a matter of affirmation or denial (crisp sets), but rather a matter of a degree. In crisp sets, the transition for an element in the universe between membership and non-membership in a given set is abrupt and well defined (said to be "crisp"). That is, the element cannot be partially belonged to a crisp set. Let U be the universe of discourse. A crisp set A in U can be described as [25]

$$\mu_A(x) = \begin{cases} 1, & if \ x \in A \\ 0, & if \ x \notin A \end{cases} \tag{1}$$

where $\mu_A(x), \forall x \in U$ maps an element x in the universe of discourse U to either zero or one.

Define U as the universe of discourse, where $U = \{u_1, u_2, \ldots, u_n\}$. The fuzzy set $\tilde{A}$ can be expressed as

$$\tilde{A} = \sum_{i=1}^{n} \mu_{\tilde{A}}(u_i)/u_i = \mu_{\tilde{A}}(u_1)/u_1 + \mu_{\tilde{A}}(u_2)/u_2 + \cdots + \mu_{\tilde{A}}(u_n)/u_n \tag{2}$$

where the symbol "+" denotes the union operator, and "/" denotes the separator.

Define two fuzzy sets, $\tilde{A}$ and $\tilde{B}$, on the universe of discourse U. For a given element x of the universe, the three set-theoretic operations are as follows [25]:

Intersection:

$$\mu_{\tilde{A} \cap \tilde{B}}(x) = \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x), \qquad \forall x \in U \tag{3}$$

Union:

$$\mu_{\tilde{A} \cup \tilde{B}}(x) = \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x), \qquad \forall x \in U \tag{4}$$

Complement

$$\mu_{\tilde{A}}(x) = 1 - \mu_{\tilde{A}}(x), \qquad \forall x \in U \qquad (5)$$

2.2. Fuzzy Time Series

If there exists a fuzzy relationship $R(t-1,t)$, the relationship can be expressed as $F(t) = F(t-1) \times R(t-1,t)$, where $R(t,t-1)$ represents a fuzzy relationship between $F(t)$ and $F(t-1)$, $\times$ is an operator, the $F(t)$n is said to be caused by $F(t-1)$. When $F(t-1) = A_i$ and $F(t) = A_j$, the fuzzy logical relationship between $F(t)$ and $F(t-1)$ can be denoted as $A_i \rightarrow A_j$, where A_i and A_j are the left-hand side (LHS) and right-hand side (RHS) of the FLR.

Fuzzy theory [14] was developed to deal with problems involving linguistic terms. Song and Chissom [8-10] considered the application of this theory to define fuzzy time-series model. They applied the model to forecast the enrollments of the University of Alabama. Further, a first-order time-invariant fuzzy time series model was proposed by Song and Chissom to forecast the enrollments and a step-by-step procedure is presented to develop and utilize the time-variant model [11].

The evaluated fuzzy time-series model which applied simplified arithmetic operations in forecasting algorithms rather than the complicated max-min composition operations was proposed by Chen [6]. In addition, Chen's method can generate more precise forecasting results than those of Song and Chissom [8]. Chen's method consists of the following major steps:

Step 1: Define the universe of discourse U.

Step 2: Divide U into several equal-length intervals.

Step 3: Define the fuzzy sets on U and fuzzify the historical data.

Step 4: Derive the fuzzy logical relationships based on the historical data.

Step 5: Classify the derived fuzzy logical relationships into groups.

Step 6: Utilize three defuzzification rules to calculate the forecasted values.

2.3. Technical Analysis

Technical analysis can be used to forecast price trends and trading signals on historical stock data. In particular, technical analysis evaluates the performance of securities by analyzing statistics generated from various marketing activities such as past prices and trading volumes [14]. A technical indicator consists in a formula that is normally applied to stock's prices and volumes [17]. From the previous studies, the technical indicators are collected and illustrated in Table 1.

Technical analysis explores internal market information and assumes that all the necessary factors are in the stock exchange information [18]. Technical analysis is one of the most popular methods in use by stock traders [1]. The general goal of technical analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data [19].

Table 1. The Technical Indicators are Collected from the Previous Studies

Indicator	Explanation
MA5	MA5 (moving average for 5 days) = $\frac{p_c + p_{c-1} + \cdots + p_{c-i-1}}{i}$, $i = 5$ and p_c is the closing index of the current day [26]
MA10	MA10 (moving average for 10 days) = $\frac{p_c + p_{c-1} + \cdots + p_{c-i-1}}{i}$, $i = 10$ and p_c is the closing index of the current day [26])
5BIAS	The difference between the closing value and MA5, which uses the stock price nature of returning back to average price to analyze the stock market [27]
10BIAS	The difference between the closing value and MA10, which uses the stock price nature of returning back to average price to analyze the stock market [27]
RSI	RSI compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset [27]
12PSY	PSY12 (psychological line for 12 days) = $(D_{up12}/12) * 100$, D_{up12} means the number of days when price going up within 12 days [26]
10WMS%R	Williams %R is usually plotted using negative values. For the purpose of analysis and discussion, simply ignore the negative symbols. It is best to wait for the security's price to change direction before placing your trades [27]
MACD9	MACD shows the difference between a fast and slow exponential moving average (EMA) of closing prices. Fast means a short-period average, and slow means a long period one [27]
MO1	$MO1(t) = price(t) - price(t - n), n = 1$ [28]
MO2	$MO2(t) = price(t) - price(t - n), n = 2$ [28]
DIFN	$DIFF(t) = price(t) - NASDAQ(t)$, NASDAQ stands for NASDAQ Composite Index
DIFF	$DIFF(t) = price(t) - TAIFEX(t)$, TAIFEX stands for Taiwan Futures Exchange
DIFE	$DIFN(t) = price(t) - US\ Exchange\ rate(t)$

Murphy [23] summarizes the basis for technical analysis into the following three premises:

(1) Market action discounts everything

The assumption here is that the price action reflects the shifts in demand and supply which is the basis for all economic and fundamental analysis and everything that affects

the market price is ultimately reflected in the market price itself. Technical analysis does not concern itself in studying the reasons for the price action and focuses instead on the study of the price action itself.

(2) Prices move in trends.

This assumption is the foundation of almost all technical systems that try to identify trends and trading in the direction of the trend. The underlying premise is that a trend in motion is more likely to continue than to reverse.

(3) History repeats itself

This premise is derived from the study of human psychology which tends not to change over time. This view of behavior leads to the identification of chart patterns that are observed to recur over time, revealing traits of a bullish or a bearish market psychology.

The selection of technical and economic indicators to be used in the prediction system will depend on the following factors [24]:

(1) Availability: The data must be easily obtained.

(2) Sufficiency of the Historical Databases: There must be enough sample data for the machine learning and system testing process.

(3) Correlation of the Indicators to the Price: The data should have some relevancy to the price of the security (whether it is lagging, leading, coincidental or noise).

(4) Periodicity of the Data: The data must be available in a predictable frequency (daily, weekly, monthly, and annually).

(5) Reliability of the Data: The fast changing pace of today's global financial world and the increased in financial market volatility has resulted in difficulty to obtain reliable economic data.

3. Proposed Method

In the past, many investors and researchers focus on selecting important technical indicators for forecasting stock's price and trends. However, these technical indicators were based on their subjective experiences or opinions rather than on objective techniques. In order to gain confidence about selection of technical indicators, we must adopt other objective techniques. Hence, this study uses Pearson correlation to choose larger correlation coefficient among these technical indicators for forecasting stock's price and trends.

Many traditional time series model such as ARIMA (autoregressive moving average) and GARCH (generalized autoregressive conditional heteroskedasticity) have been used widely before. But these statistical models can't satisfy all assumption in different datasets, and they must obey the statistical distributions (Cheng et al., 2010). In some

cases, these methods can't forecast stock's price effectively, because stock price variation is nonlinear. Hence, this study uses fuzzy time series to forecast price of stock and employs Granular Spread Partition (GSP) to define and partition the universe of discourse.

In former studies, the most conventional time series forecast model considered only one variable to forecast stock's price and trends. Actually, there are more influential factors or technical indicators, such as economic indicators or financial ratios, could impact forecasting performance. Accordingly, this study proposed multi-factor model and objective technique to improve the shortcomings of the former studies.

In summary, there are main drawbacks about forecasting stock market in former studies as follows: (1) most researches about selecting important technical indicators depend on subjective experiences and opinions; (2) statistical models must satisfy assumptions about variables in data analysis; and (3) most time series models considered only one variable to forecast stock's price and trends. As a result, this study proposes a novel time series model to overcome above shortcomings.

From above reasons, this study proposed a novel fuzzy time series model. The process of proposed model is divided to three phases. At first phase, convert daily stock index into various technical indicators. Then, using bivariate correlation selected the two most important technical indicators. This study utilized fuzzy time series model to fuzzify the stock index, build fuzzy logical relationships, produce linguistics based on weight FLR, and defuzzify initial forecasts. At second phase, combined the transferred variables to build fuzzy time series model and trained adaptive parameters α, β and γ based on minimal RMSE. At final phase, we calculated performance of each model and compared with other models. The research processes of proposed model are shown in Figure 1.

Proposed Algorithm

For introducing proposed model, this section proposes an algorithm to explain the proposed model. The proposed algorithm contains six steps, and each step is described step-by-step as follows:

Step 1. Transform data into technical indicators: This step transforms the five fundamental quantities (opening price, the highest price, the lowest price, closing price and volume) into technical indicators [18]such as moving average (MA), psychology line (PSY), relative strength index (RSI), BIAS, Williams Overbought/Oversold Index (WMS%R) , and so on. Besides, this study also considers other indicators such as the exchange rate for NT dollars to US dollars and momentum of stock price.
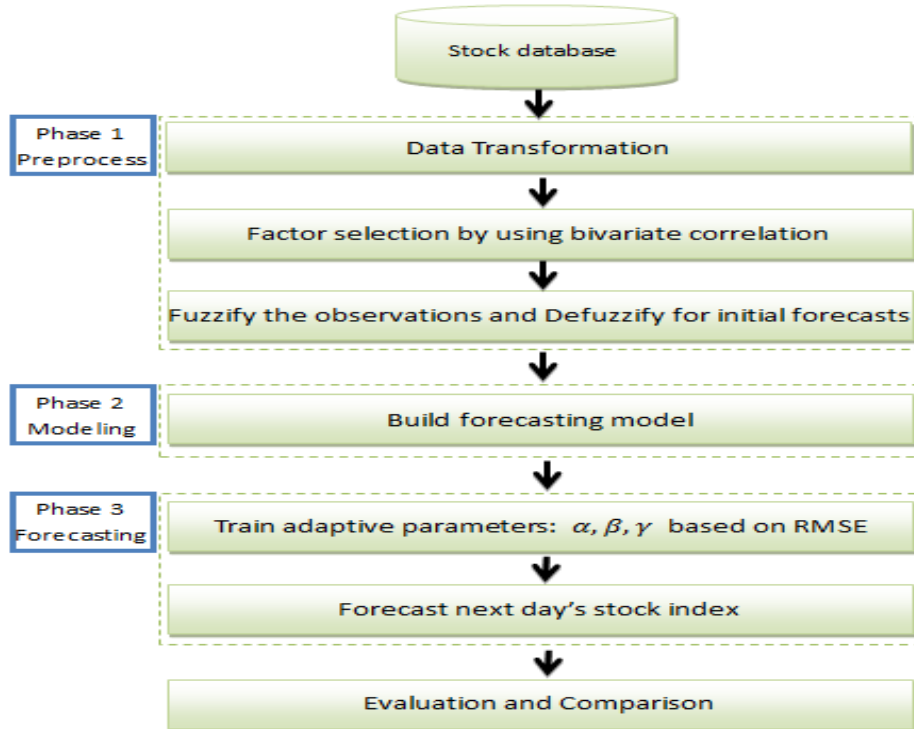
Figure 1. Algorithm of Determining Lower Bound and Bound Automatically

Step 2. Select technical indicators: After transforming data into technical indicators, this study calculates Pearson's correlation coefficient [20] of each technical indicator. The result stored in correlation matrix, and then this study selects the two important indicators from the correlation matrix.

Step 3. Fuzzify observations and defuzzify initial forecasts: This step contains six sub-steps:

Step 3.1. Define the universe of discourse and determine the length of intervals automatically: This step first defines the universe of discourse U, let U=[D_low,D_up], where D_low and D_up represent the lower bound and the upper bound of U, respectively. Then we use [1] to partition U into n equal intervals and the length is l of each interval as equation (6).

$$l = (\frac{(D_{max}-D_{min})}{n} + \frac{(D_{max}-D_{min})}{n-1})/2 \qquad \textbf{(6)}$$

where D_{min} and D_{max} are the minimum value and the maximum value of observation. According to the Miller's concept of limitation of humans on the capacity of processing information [21], this step partitions the universe of discourse into seven equal-length linguistic intervals. After determining the length of intervals, the lower bound (D_{low}) of universe of discourse U and upper bound (D_{up}) can be calculated.

Step 3.2. Spread partitioning: After determining upper bound, lower bound of universe of discourse, $U = [D_{low}, D_{up}]$ and interval length, partition U into seven equal length

intervals, u1, u2, …, and u7. Then this study uses Granular Spread Partition algorithm [1] to calculate the length of intervals under the given number of linguistic value.

Step 3.3. Establish fuzzy sets and fuzzify the observations:

Step 3.3.1: According to [3], each linguistic observation A_i can be defined by the intervals $u_1, u_2, u_3, …, u_b$. $A_i = f_{Ai}(u_1)/u_1 + f_{Ai}(u_2)/u_2 + ⋯ + f_{Ai}(u_b)/u_b$. Each A_i can be represented as $A_i = ⋯ + 0/u_{i-2} + 0.5/u_{i-1} + 1/u_i + 0.5/u_{i+1} + 0/u_{i+2} + ⋯$.

Step 3.3.2: Find out the degree of each stock index in A_i. Each A_i can be mapped to a fuzzy set. A A_i is fuzzified to A_j if the maximal degree of membership of that A_i is in A_j.

Step 3.4. Establish fuzzy logical relationship and groups: Establish fuzzy logical relationships (FLR) between two consecutive linguistic values, $A_i(t-1)$ and $A_j(t)$. Then, represent the relationship into a FLR such as $A_i → A_j$. Group the FLRs with the same LHSs into an ordered FLR group. For example, $A_i → A_j$, $A_i → A_k$, $A_i → A_m$ can be group as $A_i → A_j$, $A_k → A_m$. This group can be expressed by a fluctuation-type matrix which includes there trends: up trend, no change and down trend. And assume that the universe of discourse of stock index is divided into seven linguistic values. The FLRs are grouped into index fluctuation to which they belong to. For instance, $A_1 → A_2$, will be grouped into the "Up-trend", $A_1 → A_1$ into the "No-change" and $A_2 → A_1$ into the "Down-trend".

Step 3.5. Assign weights to all FLR groups: This step assigns weights to all FLR groups based on fluctuation-weighted method [22]. And weight matrix can be generated by normalizing weight matrix $W_n(t)$ as equation (7):

$$W_n(t) = [w_1', w_2', …, w_j'] = \left[\frac{W_1}{\sum_{k=1}^{j} W_k}, \frac{W_2}{\sum_{k=1}^{j} W_k}, …, \frac{W_k}{\sum_{k=1}^{j} W_k} \right] \qquad (7)$$

Step 3.6. Calculate initial forecasting value: After generating the normalized weight matrix, applies equation (8) to obtain the initial forecasting values based on factors of stock index. The whole process of "defuzzify" is defined:

$$\text{Forecast } (t+1) = L_{df}(t) × W_n(t) \qquad (8)$$

where $L_{df}(t) = [m_1, m_2, …, m_i]$ is deffuzified matrix.

Step 4. Build multi-factor forecasting model: In order to improve the performance of previous time series models, this study proposed a novel fuzzy time series model. The proposed model is defined as follows:

$M_A(t+1) = α × [deF(t-1) - A(t)] + β × F_1(t) + γ × F_2(t) + A(t)$

Where $deF(t-1)$ is the defuzzified forecast for the stock index at time $t-1$; $A(t)$ is the TAIEX index at time t; $F_1(t)$ is the first important technical indicator at time t; $F_2(t)$ is the second important technical indicator at time t. And

(1) $α$ denotes the degree of influential for the initial forecast based on the stock index. And the ranges of coefficient value are from -0.07 to 0.07, because the volatility limit of TAIEX is $± 7\%$.

(2) *β* denotes the degree of influential for the initial forecast based on the technical indicator. And the ranges of coefficient value are from -0.1 to 0.1 (-1 denotes perfect negative relation and + 1).

(3) *γ* denotes the degree of influential for the initial forecast based on the technical indicator. And the ranges of coefficient value are from -1 to 1 (-1 denotes perfect negative relation and + 1).

Step 5. Train the optimal fitting function based on minimal RMSE: In order to optimize fitting function, this step adjusts the optimal parameters (α, β and γ) under minimal RMSE for training data. And set 0.001 as the iterative step to obtain optimal parameter set (α, β and γ).

Step 6. Forecasting stock index by the optimal model: In the data training process, we obtain the best forecasting performance with the optimal parameters on minimal RMSE. Then use the optimal model to forecast M_i(t+1) for the testing datasets.

4. Experimental and Results

The experimental dataset is collected from 1998 to 2002 year TAIEX stock. For each year, the training period is the first ten months and the testing period is the last two months. Here, we choose the 2002-year TAIEX index which contains 244 transaction days as an example to verify the proposed model. Through proposed algorithm, the two important technical indicators (MA-5 and MA-10) are selected. Then, we feed the training data (2002/01~2002/10) of these factors into the proposed model, and the best model is obtained when RMSE = 95, α = -0.01 β = -0.01 and γ= 0.009. The parameters of the best model is utilized to forecast TAIEX index in 2002/11~2002/12. The result is RMSE=65 in testing period as the last row of Table 2. The result of TAIEX (2002) is showing in Figure 2.
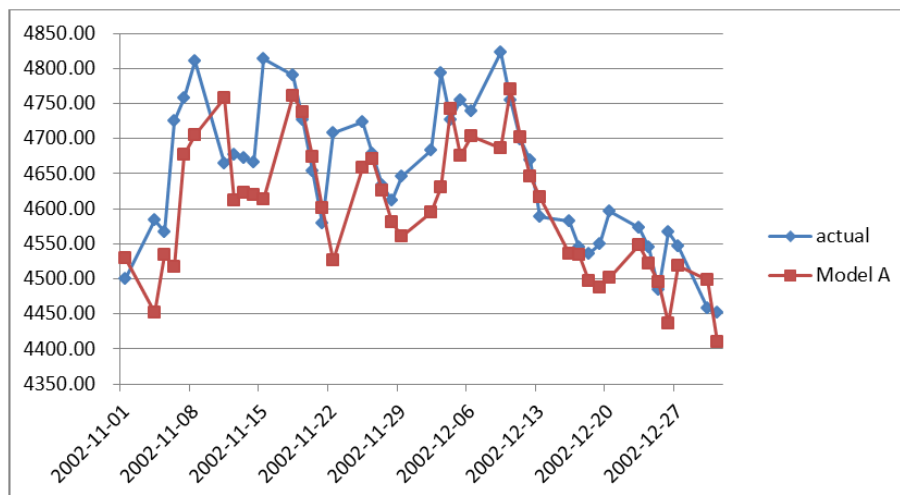

Figure 2. Forecasting Results for TAIEX from 2002/11/01 to 2002/12/31

Table 2. Performance Comparisons for the TAIEX

Testing	Chen's model (1996)	Yu's model (2005)	Proposed model
1998/11~1998/12	134	164	113[a]
1999/11~1999/12	120	145	102[a]
2000/11~2000/12	176	191	126[a]
2001/11~2001/12	148	167	114[a]
2002/11~2002/12	101	75	65[a]

[a]: The best performance among 3 models

In order to verify the proposed model, Chen's model [6], and Yu's model [3] are compared with the proposed model. The comparison results are shown in Table 2. From the performance comparison table, we can see that the proposed model outperforms the listed models in five testing period. Therefore, we can confirm that the proposed model is better than other methods in forecasting the TAIEX.

5. Conclusions

This study has proposed a novel fuzzy time series model based on fitting function. The proposed model utilized Pearson correlation to select the two most important factors, and utilized an objective algorithm to automatically determine the lower bound and upper bound of discourse of universe. Furthermore, this study used the spread-partition algorithm to determine linguistic intervals automatically, and then combined the transferred variables to build fuzzy time series model based on minimal RMSE. From the verified result, the proposed method has gotten a better performance than traditional methods in stock price forecasting. However, there are further experiments and improvements in the proposed model: (1) The proposed method was only compared with Chen's model, Huarng and Yu's model. In the future, we will compare proposed method with more methods. (2) To further evaluate proposed model, other stock databases such as HSI (Heng Song Index) would be implemented as experiment data. (3) To consider more evaluation criteria to measure forecasting performance such as mean absolute percentage error (MAPE) and directional accuracy (DA). (4) Calculate ROI of the proposed model which can be understand gain-loss situation easily for investors.

References

[1] G. Atsalakis and K. Valavanis, "Surveying Stock Market Forecasting Techniques – Part II: Soft Computing Methods", Journal of Expert Systems with Applications, vol. 36, **(2009)**, pp. 5932-5941.
[2] T. Bollerslev, "Generalized Autoregressive Conditional Heteroskedasticity", Journal of Econometrics, vol. 31, **(1986)**, pp. 307-327.
[3] H. K. Yu, "A type 2 fuzzy time-series model for stock index forecasting", Physica A, vol. 349, **(2005)**, pp. 609–624.
[4] J. I. Park, D. J. Lee, C. K. Song and M. G. Chun, "TAIFEX and KOSPI 200 forecasting based on two-factors high-order fuzzy time series and particle swarm optimization", Expert Systems with Applications, vol. 37, **(2010)**, pp. 959–967.
[5] K. H. Huarng and H. K. Yu, "A type 2 fuzzy time-series model for stock index forecasting", Physica A, vol. 353, **(2005)**, pp. 445–462.
[6] S. M. Chen, "Forecasting enrollments based on fuzzy time-series", Fuzzy Sets and Systems, vol. 81, **(1996)**, pp. 311–319.

[7] T. L. Chena, C. H. Cheng and H. J. Teoha, "High-order fuzzy time-series based on multi-period adaptation model for forecasting stock markets", Physica A, vol. 387, **(2008)**, pp. 876–888.

[8] Q. Song and B. S. Chissom, "Forecasting enrollments with fuzzy time series - part I", Fuzzy Sets and Systems, vol. 54, **(1993)**, pp. 19.

[9] Q. Song and B. S. Chissom, "Fuzzy time series and its models", Fuzzy Sets and Systems, vol. 54, **(1993)**, pp. 269-277.

[10] Q. Song and B. S. Chissom, "Forecasting enrollments with fuzzy time-series - Part II", Fuzzy Sets and Systems, vol. 62, **(1994)**, pp. 1-8.

[11] S. M. Chen, "Forecasting enrollments based on high-order fuzzy time series, Cybernetics and Systems", Cybernetics and Systems, vol. 33, **(2002)**, pp. 1–16.

[12] S. M. Chen and C. C. Hsu, "A new method to forecast enrollments using fuzzy time series", International Journal of Applied Science and Engineering, vol. 2, **(2004)**, pp. 234–244.

[13] S. M. Chen, N. Y. Wanga and J. S. Pan, "Forecasting enrollments using automatic clustering techniques and fuzzy logical relationships", Expert Systems with Applications, vol. 36, **(2009)**, pp. 11070–11076.

[14] C. F. Tsai, Y. C. Lin, D. C. Yen and Y. M. Chen, "Predicting stock returns by classifier ensembles", Applied Soft Computing, vol. 12, **(2011)**, pp. 2452-2459.

[15] J. W. Liu, "A Granular-Based Fuzzy Time Series Model for Stock Market Forecasting", National Yunlin Uninervisity of Science & Technology, Yunlin, Taiwan, **(2010)**.

[16] L. A. Zadeh, "Fuzzy sets", Information and Control, vol. 8, **(1965)**, pp. 338–353.

[17] A. Gorgulho, R. F. Neves and N. Horta, "Applying a GA kernel on optimizing technical analysis rules for stock picking and portfolio composition", Expert Systems with Applications, vol. 38, **(2011)**, pp. 14072-14085.

[18] P. C. Chang, T. W. Liao, J. J. Lin and C. Y. Fan, "A dynamic threshold decision system for stock trading signal detection", Applied Soft Computing, vol. 11, **(2011)**, pp. 3998-4010.

[19] A. W. Lo, H. Mamaysky and J. Wang, "Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation", Journal of Finance, vol. 55, **(2000)**, pp. 1705–1765.

[20] K. Pearson, "Notes on the history of correlation", Biometrika, vol. 13, **(1920)**, pp. 25–45.

[21] G. A. Miller, "The magical number seven, plus or minus two: Some limits on our capacity of processing information", The Psychological Review, vol. 101, **(1994)**, pp. 343–352.

[22] C. H. Cheng, T. L. Chen and C. H. Chiang, "Trend-weighted fuzzy time-series model for TAIEX forecasting", Lecture Note in Computer Science, vol. 4234, **(2006)**, pp. 469–477.

[23] J. J. Murphy, "Technical Analysis of the Futures Market", NYIF, New York **(1986)**, ISBN 0-13-898009-X, pp. 2-4.

[24] N. Clarence and W. Tan, "A Hybrid Financial Trading System Incorporating Chaos Theory, Statistical and Artificial Intelligence/Soft Computing Methods", School of Information Technology, Bond University, Queensland Finance Conference, **(1999)**.

[25] T. J. Ross, Fuzzy logic with engineering applications", New York: McGraw-Hill, **(1995)**.

[26] W. Shen, X. Guo, C. Wu and D. Wu, "Forecasting stock indices using radial basis function neural networks optimized by artificial fish swarm algorithm", Knowledge-Based Systems, vol. 24, **(2010)**, pp. 378-385.

[27] P. C. Chang, T. W. Liao, J. J. Lin and C.Y. Fan, "A dynamic threshold decision system for stock trading signal detection", Applied Soft Computing, vol. 11, **(2011)**, pp. 3998-4010.

[28] Y. M. Tanaka and S. Tokuoka, "Adaptive use of technical indicators for the prediction of intra-day stock prices", Physica A: Statistical Mechanics and its Applications, vol. 383, **(2007)**, pp. 125-133.