# Fuzzy Time Series Models for LNSZZS Forecasting

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## *Abstract*

*Fuzzy time series methods have been recently becoming very popular in forecasting, it has been applied to forecast various domain problems and have been shown to forecast better than other models. But there still some suspicion whether fuzzy time series models is assured to better than ARMA, which is the best defuzzifying method. The purpose of this paper is to answer these two questions. In this paper, we use traditional the fuzzy time series method purposed by Song and Chissom to forecast SSE Composite Index (LNSZZS). In order to compare the forecast results, we used Maximum degree of membership method and Degree of membership weighted average method for defuzzifying. After forecasting by fuzzy time series method, we also compared the result to that calculated by ARMA. The research found that fuzzy time series model is more accurate than ARMA. We also see that for fuzzy time series forecasting model in defuzzifying, maximum degree of membership method is better than Degree of membership weighted average method.*


**Keywords***: Fuzzy Time Series, LNSZZS, Forecasting, Linguistic Variable*

## 1. Introduction

Time series forecasting is a fundamental and important problem in many disciplines including finance, engineering, medicine, and science. Different time series approaches have been proposed, including statistic, neural network, and fuzzy methods. Traditional statistic forecasting models such as autoregressive (AR) and autoregressive integrated moving average (ARIMA) are the most popular ones, but the assumption of linearity and normal distribution may not hold in time series. The neural network approach, operating without the limitation of such an assumption, but neural network approach can only deal with established data, real-world historical data collected are neither compliant to normal distribution nor certain (i.e. complete, precise, and ambiguous), thus their applicability is limited.

Song and Chissom presented the concept of fuzzy time series [1] based on the fuzzy set theory which was first proposed by Zadeh [2]. They have developed the time-invariant fuzzy time series model [3] and the time-variant fuzzy time series model [4] to forecast the enrollments of the University of Alabama. The forecasting model that is mainly composed of five steps: (1) partitioning the universe of discourse into equal intervals, (2) defining fuzzy sets on the universe of discourse and fuzzifying the time series accordingly, (3) mining the fuzzy logical relationships that exists in the fuzzified time series, (4) forecasting and then (5) defuzzifying the forecasted output. Song and Chissom showed these steps to reduce the time complexity of FTS in comparison with the previous studies. Since the contribution of Song and Chissom, a number of other studies have been presented to develop the model. The model of Song and Chissom used the Max-Min operator, which made the calculation of model was very complex; Chen used Multiplication operators replace the Max-Min operator to reduce the Calculation [5]. Huarng proposed a new model which is based on heuristic methods [6]. The work was mainly based on heuristics and usually do not provide any proof or mathematical foundation for his models. Instead, he applies his model for different cases to show the validity of the model. In order to reduce the influence of the number of fuzzy relations and chronological, Yu proposed weighted fuzzy time series models [7], Leu and Chiu used Weighted Fuzzy Time Series to study effective stock portfolio trading strategy [8].

In recent years, the emergence of fuzzy time series has received more attention because of its capability of dealing with vagueness and incompleteness inherent in data. Some methods have been presented based on fuzzy time series to make predictions in many areas, such as forecasting stock price [9-11], temperature [12], Travel demand [13-14], enrollment [15], etc.

The rest of this paper is organized as follows. Section 2 reviews the related definitions of fuzzy time series models and then establish of fuzzy time series forecasting model. Section 3 is empirical analysis and Section 4 concludes the paper.

## 2. Fuzzy time series forecasting model

### 2.1 Basic concepts of fuzzy time series

The fuzzy time series model was first presented by Song and Chissom, here we list the definitions of fuzzy set firstly given by Zadeh (1965), and following with the framework of the models of Song and Chissom (1993a), Song and Chissom (1993b), Song and Chissom (1994).

Definition 1. A fuzzy set $A$ of the universe of discourse $U$ ,$U=\{u_1,u_2,...,u_n\}$ is defined as follows:

$$A = f_A(u_1)/u_1 + f_A(u_2)/u_2 + \cdots + f_A(u_n)/u_n \tag{1}$$

where $f_A$ is the membership function of the fuzzy set $A$ , $f_A: U \to [0,1]$ , $f_A(u_i)$ denotes the membership degree of $u_i$ in the fuzzy set $A$ ,and the symbol ‘‘+’’ means the operation of union instead of the operation of summation.

Definition 2. Let $Y(t)$ $(t=\cdots,0,1,2,\cdots)$ a subset of $R^1$, be the universe of discourse on which fuzzy sets $f_i(t)$ $(i=1,2,\cdots)$ are defined and let $F(t)$ be a collection of $f_1(t), f_2(t),\cdots$ Then, $F(t)$ is called a fuzzy time series defined on $Y(t)$ $(t=\cdots,0,1,2,\cdots)$ .

There are three common membership functions: Triangular membership function, Trapezoidal membership function, Bell-shaped membership function. This paper use Triangular membership function to convert Time series into fuzzy time series:

$Y(t)$ $(t=\cdots,0,1,2,\cdots)$ is time series, $m_i$ is the median of $u_i$ in $U$ ,if $Y(t)$ is between $m_i$ and $m_{i+1}$ ,then

$$F(t)=0/u_1+0/u_2+\cdots+\frac{m_{i+1}-Y(t)}{m_{i+1}-m_i}/u_i+\frac{Y(t)-m_i}{m_{i+1}-m_i}/u_{i+1}+\cdots+0/u_n \tag{2}$$

Example 1. $\{Y_t\}=\{0.8,1.7,2.9,4.1,3.5,3.2,4.3,3.6\}$ expressed a stock ups and downs prices of 8 days in a row. $U=\{(0,1],(1,2],(2,3],(3,4],(4,5]\}$ ,And the language variable is Very Low=$u_1 \to (0,1]$ , Low=$u_2 \to (1,2]$ , Medium=$u_3 \to (2,3]$ , High=$u_4 \to (3,4]$ , Very High=$u_5 \to (4,5]$ then, $m_1=0.5, m_2=1.5, m_3=2.5, m_4=3.5, m_5=4.5$ .Because $Y_1$ is between $m_1$ and $m_2$ ,so:

$$F(1)=\frac{1.5-0.8}{1.5-0.5}/u_1+\frac{0.8-0.5}{1.5-0.5}/u_2+0/u_3+0/u_4+0/u_5 .$$

All the $Y_t$ can be convert into $F(t)$ as follows:

**Table 1.** The result of Example 1

| | Very Low | Low | Medium | High | Very High |
|---|---|---|---|---|---|
| F(1) | 0.7 | 0.3 | 0 | 0 | 0 |
| F(2) | 0 | 0.8 | 0.2 | 0 | 0 |
| F(3) | 0 | 0 | 0.6 | 0.4 | 0 |
| F(4) | 0 | 0 | 0 | 0.4 | 0.6 |
| F(5) | 0 | 0 | 0 | 1 | 0 |
| F(6) | 0 | 0 | 0.3 | 0.7 | 0 |
| F(7) | 0 | 0 | 0 | 0.2 | 0.8 |
| F(8) | 0 | 0 | 0 | 0.9 | 0.1 |

Definition 3. Song and Chissom, 1993a. Current and the next state of the fuzzy logical relationship: let $F(t)$ be a fuzzy time series, where:

$$F(t) = F(t-1) \circ R(t, t-1) \tag{3}$$

and $R(t, t-1)$ is a fuzzy relation, and "$\circ$"is the Max–Min composi-tion operator. Then, $F(t)$ is caused by $F(t-1)$ and it is denoted by the fuzzy logical relationship $F(t-1) \to F(t)$.

## 2.2. Defuzzifying

In this paper we use the following two different methods to defuzzifying the output data

Maximum degree of membership method:

Let $w_1, w_2, \cdots, w_n$ are membership degree of the output element in $U$, if $w_0 = \max\{w_1, w_2, \cdots, w_n\}$, then its output value is the midpoint of the corresponding interval. If there is two or more maximum degree of membership, then its output value is the average midpoint of the corresponding interval.

Degree of membership weighted average method:

Let $w_1, w_2, \cdots, w_n$ are membership degree of the output element in $U$, then the output value $d$ is:

$$d = \sum_{i=1}^{n} w_i m_i / \sum_{i=1}^{n} w_i \tag{4}$$

Example2: $U = \{u_1, , u_2, u_3, u_4, u_5\} = \{(-2,-1), (-1,0), (0,1), (1,2), (2,3)\}$, $F = 0.2/u_1 + 0.3/u_2 + 0.6/u_3 + 0.1/u_4 + 0.4/u_5$, Then $\{m_i\} = \{-1.5, -0.5, 0.5, 1.5, 2.5\}$ .If use maximum degree of membership method, because $\max(0.2, 0.3, 0.6, 0.1, 0.4) = 0.6$ ,and its corresponding interval is $(0,1)$ ,so $d = m_3 = 0.5$ .If used Degree of membership weighted average method, then the output value is:

$$d = \frac{-1.5\times0.2 - 0.5\times0.3 + 0.5\times0.6 + 1.5\times0.1 + 2.5\times0.4}{0.2+0.3+0.6+0.1+0.4} = 1.1875$$

## 2.3. The steps of the fuzzy time series forecasting model

Our fuzzy time series forecasting model need five steps:

Step 1.Define the universe of discourse

Step 2.Observational data fuzzification

Step 3.Determine the fuzzy logical relationship

Step 4.Calculate the fuzzy correlation matrix

Step 5.Forcasting and defuzzifying

## 3. The application

We have applied this new technique to the time series data of SSE Composite Index (LNSZZS) for the period of 01/31/12 to 02/29/12 that is given in Table 2.

**Table 2.** SSE Composite Index (01/31/12 to 02/29/12)

| Date | Index |
|---|---|
| 2012/1/31 | 2292.61 |
| 2012/2/1 | 2268.08 |
| 2012/2/2 | 2312.56 |
| 2012/2/3 | 2330.41 |
| 2012/2/6 | 2331.14 |
| 2012/2/7 | 2291.9 |
| 2012/2/8 | 2347.53 |
| 2012/2/9 | 2349.59 |
| 2012/2/10 | 2351.98 |
| 2012/2/13 | 2351.86 |
| 2012/2/14 | 2344.77 |
| 2012/2/15 | 2366.7 |
| 2012/2/16 | 2356.86 |
| 2012/2/17 | 2357.18 |
| 2012/2/20 | 2363.6 |
| 2012/2/21 | 2381.43 |
| 2012/2/22 | 2403.59 |
| 2012/2/23 | 2409.55 |
| 2012/2/24 | 2439.63 |
| 2012/2/27 | 2447.06 |
| 2012/2/28 | 2451.86 |
| 2012/2/29 | 2428.49 |

According to the method of time series analysis, the trend is unstable, so we need to make a first difference for the original data. The result is in Table 3.

**Table 3**. First difference of SSE Composite Index (02/01/12 to 02/29/12)

| Date | First difference |
|---|---|
| 2012/2/1 | -24.53 |
| 2012/2/2 | 44.48 |
| 2012/2/3 | 17.85 |
| 2012/2/6 | 0.73 |
| 2012/2/7 | -39.24 |
| 2012/2/8 | 55.63 |
| 2012/2/9 | 2.06 |
| 2012/2/10 | 2.39 |
| 2012/2/13 | -0.12 |
| 2012/2/14 | -7.09 |
| 2012/2/15 | 21.93 |
| 2012/2/16 | -9.84 |
| 2012/2/17 | 0.32 |
| 2012/2/20 | 6.42 |
| 2012/2/21 | 17.83 |
| 2012/2/22 | 22.16 |
| 2012/2/23 | 5.96 |
| 2012/2/24 | 30.08 |
| 2012/2/27 | 7.43 |
| 2012/2/28 | 4.8 |
| 2012/2/29 | -23.37 |

Then the application is given step by step below.

Step 1.From the table we can see $U=(-39.24,\ 55.63)$ , To simplify the calculation, we let $U=(-40,\ 56)$ .Then we partition universe of discourse $U$ into five intervals of equal lengths $u_1=[-40,-21), u_2=[-21,-2), u_3=[-2,17), u_4=[17,36), u_5=[36,56]$ ,the median of them is $\{m_i\}=\{-30.5,-11.5,7.5,26.5,46\}$ , And the language variable is $\text{Crash}=u_1$ , $\text{Fall}=u_2$ , $\text{Flat}=u_3$ , $\text{Rise}=u_4$ , $\text{Rally}=u_5$ .

Step 2.Just like Example 1, we can convert the time series into fuzzy time series, the converted data are in Table 4.

**Table 4**. Fuzzy time series of SSE Composite Index (02/01/12 to 02/29/12)

| **Date** | **First difference** | $u_1$ | $u_2$ | $u_3$ | $u_4$ | $u_5$ |
|---|---|---|---|---|---|---|
| 2012/2/1 | -24.53 | 0.69 | 0.31 | 0.00 | 0.00 | 0.00 |
| 2012/2/2 | 44.48 | 0.00 | 0.00 | 0.00 | 0.07 | 0.93 |
| 2012/2/3 | 17.85 | 0.00 | 0.00 | 0.46 | 0.54 | 0.00 |
| 2012/2/6 | 0.73 | 0.00 | 0.36 | 0.64 | 0.00 | 0.00 |
| 2012/2/7 | -39.24 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2012/2/8 | 55.63 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| 2012/2/9 | 2.06 | 0.00 | 0.29 | 0.71 | 0.00 | 0.00 |
| 2012/2/10 | 2.39 | 0.00 | 0.27 | 0.73 | 0.00 | 0.00 |
| 2012/2/13 | -0.12 | 0.00 | 0.40 | 0.60 | 0.00 | 0.00 |
| 2012/2/14 | -7.09 | 0.00 | 0.77 | 0.23 | 0.00 | 0.00 |
| 2012/2/15 | 21.93 | 0.00 | 0.00 | 0.24 | 0.76 | 0.00 |
| 2012/2/16 | -9.84 | 0.00 | 0.91 | 0.09 | 0.00 | 0.00 |
| 2012/2/17 | 0.32 | 0.00 | 0.38 | 0.62 | 0.00 | 0.00 |
| 2012/2/20 | 6.42 | 0.00 | 0.06 | 0.94 | 0.00 | 0.00 |
| 2012/2/21 | 17.83 | 0.00 | 0.00 | 0.46 | 0.54 | 0.00 |
| 2012/2/22 | 22.16 | 0.00 | 0.00 | 0.23 | 0.77 | 0.00 |
| 2012/2/23 | 5.96 | 0.00 | 0.08 | 0.92 | 0.00 | 0.00 |
| 2012/2/24 | 30.08 | 0.00 | 0.00 | 0.00 | 0.78 | 0.22 |
| 2012/2/27 | 7.43 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 |
| 2012/2/28 | 4.8 | 0.00 | 0.14 | 0.86 | 0.00 | 0.00 |
| 2012/2/29 | -23.37 | 0.62 | 0.38 | 0.00 | 0.00 | 0.00 |

Step 3.Determine the fuzzy logical relationship

Based on the principle proposed by Song and Chissom (1993a), we defined:

$$\begin{aligned}
&\text{Crash } A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + 0/u_5 \\
&\text{Fall } \ A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + 0/u_5 \\
&\text{Flat } \ A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + 0/u_5 \\
&\text{Rise } \ A_4 = 0/u_1 + 0/u_2 + 0.5/u_3 + 1/u_4 + 0.5/u_5 \\
&\text{Rally } A_5 = 0/u_1 + 0/u_2 + 0/u_3 + 0.5/u_4 + 1/u_5
\end{aligned} \tag{5}$$

For simplify, it can also be expressed as:

$$\begin{aligned}
&A_1 = (1, 0.5, 0, 0, 0)^T, A_2 = (0.5, 1, 0.5, 0, 0)^T \\
&A_3 = (0, 0.5, 1, 0.5, 0)^T, A_4 = (0, 0, 0.5, 1, 0.5)^T \\
&A_5 = (0, 0, 0, 0.5, 1)^T
\end{aligned} \tag{6}$$

For every date in Table 3, if the biggest membership is belong to $u_i\,(i=1,2,\cdots,5)$ , let the standardized fuzzy value of that date is $A_i\,(i=1,2,\cdots,5)$ , the standardized fuzzy value is in Table 5

**Table 5**. Standardized fuzzy value

| Date | standardized fuzzy value |
|---|---|
| 2012/2/1 | $A_1$ |
| 2012/2/2 | $A_5$ |
| 2012/2/3 | $A_4$ |
| 2012/2/6 | $A_3$ |
| 2012/2/7 | $A_1$ |
| 2012/2/8 | $A_5$ |
| 2012/2/9 | $A_3$ |
| 2012/2/10 | $A_3$ |
| 2012/2/13 | $A_3$ |
| 2012/2/14 | $A_2$ |
| 2012/2/15 | $A_4$ |
| 2012/2/16 | $A_2$ |
| 2012/2/17 | $A_3$ |
| 2012/2/20 | $A_3$ |
| 2012/2/21 | $A_4$ |
| 2012/2/22 | $A_4$ |
| 2012/2/23 | $A_3$ |
| 2012/2/24 | $A_3$ |
| 2012/2/27 | $A_3$ |
| 2012/2/28 | $A_3$ |
| 2012/2/29 | $A_1$ |

Based on Table 4 and Definition 3, fuzzy logic relationship between the two consecutive days $F(t-1) \to F(t)$ can be concluded as follows:

$$\begin{aligned} &A_1 \to A_5,\ \ A_2 \to A_3, A_4,\ \ A_3 \to A_1, A_2, A_3, A_4, \\ &A_4 \to A_2, A_3, A_4,\ \ A_5 \to A_3, A_4 \end{aligned} \tag{7}$$

Step 4.Calculate the fuzzy correlation matrix

Through Definition 3 and Equation (7), we can calculate $R(t,t-1)$ by the following method:

$$\begin{aligned} &R_1 = A_1 \wedge A_5^T, R_2 = A_2 \wedge A_3^T, R_3 = A_2 \wedge A_4^T, \\ &R_4 = A_3 \wedge A_1^T, R_5 = A_3 \wedge A_2^T, R_6 = A_3 \wedge A_3^T, \\ &R_7 = A_3 \wedge A_4^T, R_8 = A_4 \wedge A_2^T, R_9 = A_4 \wedge A_3^T, \\ &R_{10} = A_4 \wedge A_4^T, R_{11} = A_5 \wedge A_3^T, R_{12} = A_5 \wedge A_4^T \end{aligned} \tag{8}$$

“ $\wedge$ ”is min operation, $T$ response for transpose operation.

$$R(t,t-1) = R = \bigvee_{i=1}^{12} R_i \tag{9}$$

“ $\bigvee$ ”is max operation. The final calculation result is:

$$R = \begin{bmatrix} 0 & 0.5 & 0.5 & 0.5 & 1 \\ 0.5 & 0.5 & 1 & 1 & 0.5 \\ 1 & 1 & 1 & 1 & 0.5 \\ 0.5 & 1 & 1 & 1 & 0.5 \\ 0.5 & 0.5 & 1 & 1 & 0.5 \end{bmatrix}$$

Step 5.Forcasting and defuzzifying

Based on the equation $F(t) = F(t-1) \circ R$, we can use the value of $t-1$ to forecasting the value of $t$, the result is in Table 6.

**Table 6**. Output data

| **Date** | $u_1$ | $u_2$ | $u_3$ | $u_4$ | $u_5$ |
|---|---|---|---|---|---|
| 2012/2/2 | 0.31 | 0.50 | 0.50 | 0.50 | 0.69 |
| 2012/2/3 | 0.50 | 0.50 | 0.93 | 0.93 | 0.50 |
| 2012/2/6 | 0.50 | 0.54 | 0.54 | 0.54 | 0.50 |
| 2012/2/7 | 0.64 | 0.64 | 0.64 | 0.64 | 0.50 |
| 2012/2/8 | 0.00 | 0.50 | 0.50 | 0.50 | 1.00 |
| 2012/2/9 | 0.50 | 0.50 | 1.00 | 1.00 | 0.50 |
| 2012/2/10 | 0.71 | 0.71 | 0.71 | 0.71 | 0.50 |
| 2012/2/13 | 0.73 | 0.73 | 0.73 | 0.73 | 0.50 |
| 2012/2/14 | 0.60 | 0.60 | 0.60 | 0.60 | 0.50 |
| 2012/2/15 | 0.50 | 0.50 | 0.77 | 0.77 | 0.50 |
| 2012/2/16 | 0.50 | 0.76 | 0.76 | 0.76 | 0.50 |
| 2012/2/17 | 0.50 | 0.50 | 0.91 | 0.91 | 0.50 |
| 2012/2/20 | 0.62 | 0.62 | 0.62 | 0.62 | 0.50 |
| 2012/2/21 | 0.94 | 0.94 | 0.94 | 0.94 | 0.50 |
| 2012/2/22 | 0.50 | 0.54 | 0.54 | 0.54 | 0.50 |
| 2012/2/23 | 0.50 | 0.77 | 0.77 | 0.77 | 0.50 |
| 2012/2/24 | 0.92 | 0.92 | 0.92 | 0.92 | 0.50 |
| 2012/2/27 | 0.50 | 0.78 | 0.78 | 0.78 | 0.50 |
| 2012/2/28 | 1.00 | 1.00 | 1.00 | 1.00 | 0.50 |
| 2012/2/29 | 0.86 | 0.86 | 0.86 | 0.86 | 0.50 |

After get the output data, we need to defuzzify the data. In Table 7, the second column is the forecasting value defuzzifying by Maximum degree of membership method, the third column is the forecasting value defuzzifying by Degree of membership weighted average method, the forth column is the forecasting value which is got by ARMA.

**Table 7**. Forecasting value

| **Date** | **MD** | **WA** | **ARMA** |
|---|---|---|---|
| 2012/2/2 | 46.00 | 13.29 | 34.65 |
| 2012/2/3 | 17.00 | 9.99 | -22.11 |
| 2012/2/6 | 7.50 | 7.59 | 24.54 |
| 2012/2/7 | -2.00 | 5.81 | -22.60 |
| 2012/2/8 | 46.00 | 22.90 | 12.11 |
| 2012/2/9 | 17.00 | 10.29 | 1.32 |
| 2012/2/10 | -2.00 | 5.15 | -0.76 |
| 2012/2/13 | -2.00 | 5.01 | 1.25 |
| 2012/2/14 | -2.00 | 6.29 | -1.18 |
| 2012/2/15 | 17.00 | 9.26 | -0.50 |
| 2012/2/16 | 7.50 | 7.58 | 5.42 |
| 2012/2/17 | 17.00 | 9.93 | -7.25 |
| 2012/2/20 | -2.00 | 6.03 | 6.79 |
| 2012/2/21 | -2.00 | 3.62 | -4.85 |
| 2012/2/22 | 7.50 | 7.60 | 8.53 |
| 2012/2/23 | 7.50 | 7.58 | -2.91 |
| 2012/2/24 | -2.00 | 3.75 | 4.04 |
| 2012/2/27 | 7.50 | 7.58 | 3.04 |
| 2012/2/28 | -2.00 | 3.35 | -1.14 |
| 2012/2/29 | -2.00 | 4.10 | 2.14 |

In order to compare the forecast results, we convert the Original data, forecasting value in Table 6 into standardized fuzzy value. See Table 8.

The last line of Table 7 is the total number of days whose standardized fuzzy value of forecasting value is equal to the Original Data.

From the last line of Table 8, $12 > 10 > 8$ ,so we can find that the forecasting value got by fuzzy time series forecasting model is more accurate than that got by ARMA. We can also see that for fuzzy time series forecasting model in defuzzifying, maximum degree of membership method is better than Degree of membership weighted average method.

**Table 8**. Standardized fuzzy value of forecasting value

| **Date** | **Original** | **MD** | | **ARMA** |
|---|---|---|---|---|
| 2012/2/2 | $A_5$ | $A_5$ | $A_3$ | $A_4$ |
| 2012/2/3 | $A_4$ | $A_4$ | $A_3$ | $A_1$ |
| 2012/2/6 | $A_3$ | $A_3$ | $A_3$ | $A_4$ |
| 2012/2/7 | $A_1$ | $A_3$ | $A_3$ | $A_1$ |
| 2012/2/8 | $A_5$ | $A_5$ | $A_4$ | $A_3$ |
| 2012/2/9 | $A_3$ | $A_4$ | $A_3$ | $A_3$ |
| 2012/2/10 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/13 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/14 | $A_2$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/15 | $A_4$ | $A_4$ | $A_3$ | $A_3$ |
| 2012/2/16 | $A_2$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/17 | $A_3$ | $A_4$ | $A_3$ | $A_2$ |
| 2012/2/20 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/21 | $A_4$ | $A_3$ | $A_3$ | $A_2$ |
| 2012/2/22 | $A_4$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/23 | $A_3$ | $A_3$ | $A_3$ | $A_2$ |
| 2012/2/24 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/27 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/28 | $A_3$ | $A_3$ | $A_3$ | $A_3$ |
| 2012/2/29 | $A_1$ | $A_3$ | $A_3$ | $A_3$ |
| Total | 20 | 12 | 10 | 8 |

## 4. Conclusions

Forecasting tasks are a crucial activity in all business types, and are necessary for planning and developing strategies even if the forecasting results are inferior. In business exercises, time series techniques are the most applied methodology for prediction objectives, but the assumption of linearity and normal distribution may not hold in time series, the purpose of fuzzy time series perfectly solved the limitation.

In order to know whether fuzzy time series models is better than ARMA and which be the best defuzzifying method. Our paper forecast SSE Composite Index (LNSZZS) by fuzzy time series model and ARMA, and we found the forecasting value got by fuzzy time series forecasting model is more accurate than that got by ARMA. We used two different methods, Maximum degree of membership method and Degree of membership weighted average method, to defuzzifying the output data, the result shows that Maximum degree of membership method is better than Degree of membership weighted average method.

However, there were several limitations in this study, such as the data and case of our research is not enough, which can Impact the correctness of the conclusions. Otherwise, there should more empirical research to text the ideal. The further research can be done to solve the limitations above.

## Acknowledgments

We should say thanks to the funding of Key Project of National Natural Science Foundation in China (No.91024028), Humanities and Social Sciences Foundation of Chinese Ministry of Education (No.10YJC860040), Social Science Foundation of Heilongjiang Province in China (No.11D080) and National Soft Science Foundation in China (No.2008GXS5D113).

## References

[1] Song, Q.; Chissom, B. S., Fuzzy time series and its models, Fuzzy sets and systems, vol. *54*, no. *3*, pp. 269-277, 1993.
[2] Zadeh, L. A., Fuzzy sets, Information and control, vol. 8, no. 3, pp. 338-353, 1965.
[3] Song, Q.; Chissom, B. S., Forecasting enrollments with fuzzy time series--Part I, Fuzzy sets and systems, vol. 54, no. *1*, pp. 1-9, 1993.
[4] Song, Q.; Chissom, B. S., Forecasting enrollments with fuzzy time series—part II, Fuzzy sets and systems, vol. 62, no. 1, pp. 1-8, 1994.
[5] Chen, S. M., Forecasting enrollments based on fuzzy time series, Fuzzy sets and systems, vol. 81, no. 3, pp. 311-319, 1996.
[6] Huarng, K., Heuristic models of fuzzy time series for forecasting, Fuzzy sets and systems, vol. 123, no. 3, pp. 369-386, 2001.
[7] Yu, H. K., Weighted fuzzy time series models for TAIEX forecasting, Physica A: Statistical Mechanics and its Applications, vol. 349, no. 3, pp. 609-624, 2005.
[8] Yungho Leu, Tzu-I Chiu, "An Effective Stock Portfolio Trading Strategy using Genetic Algorithms and Weighted Fuzzy Time Series", International Journal of Digital Content Technology and its Applications(JDCTA), Vol. 6, No. 6, pp. 333 ~ 344, 2012
[9] Hsu, Y. Y.; Tse, S. M.; Wu, B., A new approach of bivariate fuzzy time series analysis to the forecasting of a stock index, International Journal of Uncertainty Fuzziness and Knowledge-Based Systems, vol. 11, no. 6, pp. 671-690, 2003.
[10] Cheng, C. H.; Chen, T. L.; Chiang, C. H.: Trend-weighted fuzzy time-series model for TAIEX forecasting. Springer, pp 469-477, 2006.
[11] Huamg, K.; Yu, H. K., N-th order heuristic fuzzy time series model for TAIEX forecasting, International Journal of Fuzzy Systems, vol. 5, no. 4, pp. 247-253, 2003.
[12] Chen, S. M.; Hwang, J. R., Temperature prediction using fuzzy time series, Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, vol. 30, no. 2, pp. 263-275, 2000.
[13] Huarng, K. H.; Moutinho, L.; Yu, T. H. K., An advanced approach to forecasting tourism demand in Taiwan, Journal of Travel & Tourism Marketing, vol. 21, no. 4, pp. 15-24, 2007.
[14] Wang, C. H., Predicting tourism demand using fuzzy time series and hybrid grey theory, Tourism management, vol. 25, no. 3, pp. 367-374, 2004.
[15] Ming-Tao Chou, "The Logarithm Function with a Fuzzy Time Series", JCIT: Journal of Convergence Information Technology, Vol. 4, No. 1, pp. 47 ~ 51, 2009