iFUZZY 2013

National Taiwan University of Science and Technology,
Taipei, Tawian
December 6-8, 2013

2013 International Conference on Fuzzy Theory and Its Applications

CALL FOR PAPERS

Dec. 6 – 8, 2013

National Taiwan University of Science and Technology, Taipei, Taiwan

Technical Co-sponsors by IEEE Systems, Man and Cybernetics Society
International Fuzzy System Association (IFSA)

Theme

2013 International conference on Fuzzy Theory and Its Applications (*iFUZZY2013*) will be hosted by National Taiwan University of Science and Technology (NTUST), Taipei, Taiwan, on December 6-8, 2013. *iFUZZY* 2013 is soliciting novel research results on fuzzy theory and its applications and related topics. Jointly organized by Taiwan Fuzzy Systems Association and NTUST, this conference provides a very good opportunity for research scientists, investigators, industrial practitioners and government representatives to present their results and to exchange their ideas. For paper submissions and more information, please visit the conference website at http://isdlab.ie.ntnu.edu.tw/ifuzzy2013/. Topics of interests include but are not limited to:

- Business Intelligence
- Fuzzy Classification and Clustering
- Fuzzy Control and Robotics
- Fuzzy Image
- Speech and Signal Processing
- Fuzzy Integral
- Fuzzy Hardware and VLSI Chip
- Fuzzy Optimization
- Fuzzy Reasoning
- Fuzzy Applications in Bioinformatics
- Fuzzy Applications in Computer Vision
- Fuzzy Applications in Finance
- Fuzzy Applications in Insurance
- Fuzzy Applications in Risk Management
- Fuzzy Applications in Machine Design
- Hybrid Systems
- Intelligent Control
- Machine Learning
- Natural Language Processing
- Rough Set
- Computing with Words
- Evolutionary Computation and Optimization
- Fuzzy Data Analysis Fuzzy Decision Making and Support
- Fuzzy Identification and Estimation
- Fuzzy Information Processing
- Fuzzy Intelligent Database Systems
- Fuzzy Mathematics
- Fuzzy Pattern Recognition
- Fuzzy Applications in Biomedical
- Fuzzy Applications in Business Management
- Fuzzy Applications in Communications and Networking
- Fuzzy Applications in Engineering
- Fuzzy Applications in Logistic Management
- Fuzzy Applications in Diagnosis and Therapy
- Fuzzy Applications in Manufacture Process
- Fuzzy Applications in Statistical Process Control
- Intelligent Signal Processing
- Modeling and Simulation
- Neural Fuzzy Systems
- Soft Computing Applications
- Other

Important Dates

~~Sept. 1~~ Sept. 20, 2013: Deadline for submission of papers (full papers only)
~~Sept. 30~~ Oct. 6, 2013: Notification of acceptance
Oct. 20, 2013: Final camera-ready papers due

Submission Policies:

Papers submitted should be written in English. All submissions must be made electronically in PDF format via the conference website at http://isdlab.ie.ntnu.edu.tw/ifuzzy2013/. The official language of the conference is English. ***All the accepted papers are EI-indexed and included in the IEEE Xplore database.*** *Some high-quality papers can be directly published in the special issue of International Journal of Fuzzy Systems with Impact Factor of 1.362;for details, please see* ***Call for paper for Special Issue on International Journal of Fuzzy Systems.***

Contributed Papers:

Submit full paper manuscripts of no more than 6 pages in total length. Download ***Paper Template.***

Organized/ Invited Sessions:

iFUZZY2013 welcomes proposals for organized/ invited sessions within conference scope. Please put the proposal and the extended abstracts of all constituent papers in ONE electronic file when submitting. Please see ***Guidelines for Proposals of Organized/Invited Sessions*** *for details.*

Best Conference Paper Award Contest:

Identify your submission as the contest entry when you upload your manuscript electronically. Please see ***Guidelines for the Best Conference Paper Award Contest*** *for details.*

Commitiees

Honorary General Chair

Tsu-Tian Lee,Chair Professor,Chung-Yuan Christian Univ.

Ching-Jong Liao, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

International Advisory Committee

Oscar Castillo, President, IFSA, Tijuana Inst. Technology, Mexico

Philip C. L. Chen, University of Macao, Macao

Qijun Chen, Tongji Univ., China

Shyi-Ming Chen, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

Sungshin Kim,Pusan Natl Univ.,Korea

Vladik Kreinovich, Univ. of Texas at El Paso, USA

Hak-Keung Lam, King's Coll. London, UK

Han-Xiong Li, City Univ. of Hong Kong, Hong Kong

Ching-Ting Lin, Natl Chiao Tung Univ.,Taiwan

Chun-Liang Lin, Natl Chung Hsing Univ.,Taiwan

Mao-Kang Luo, Sichuan Univ.,China

Patricia Melin, Tijuana Institute of Tech., Mexico

Javier Montero, Complutense Univ., Spain

Hajime Nobuhara, University of Tsukuba, Japan

Gyei-Kark Park, Mokpo Natl Maritime Univ., Korea

Witold Pedrycz,University of Alberta, Canada

Imre. J. Rudas, President of Obuda Univ., Hungary

Eugene Santos Jr., Dartmouth College, USA

Peng Shi, The Univ.of Adelaide, Australia

Kazuo Tanaka, Univ. of Electro-Communications, Japan

Ricardo Tanscheit, PUC-RJ, Brazil

Jun Wang, Chinese Univ. of Hong Kong, Hong Kong

Koichi Yamada, Nagaoka Univ. of Tech., Japan

Advisory Committee

Bor-Sen Chen, Natl Tsing Hua Univ., Taiwan

Jyh-Horng Chou, Natl Kaohsiung First Univ. of Sci. and Tech., Taiwan

Tzung-Pei Hong, Natl. Univ. of Kaohsiung, Taiwan

Yo-Ping Huang , Natl Taipei Univ. of Tech., Taiwan

Jin-Tsong Jeng, Natl Formosa Univ., Taiwan

Chia-Feng Juang, Natl Chung Hsing Univ., Taiwan

Tsu-Tian Lee, Chung Yuan Christian Univ., Taiwan

Tzuu-Hseng S. Li, Natl Cheng Kung Univ., Taiwan

Cheng-Jian Lin, Natl Chin-Yi Univ. of Tech., Taiwan

Chih-Min Lin, Yuan Ze Univ., Taiwan

Chin-Teng Lin, Natl Chiao Tung Univ., Taiwan

Kuo-Kai Shyu, Natl Central Univ., Taiwan

Shun-Feng Su, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

Tsung-Ying Sun, Natl Dong Hwa Univ., Taiwan

Chin-Wang Tao, Natl Ilan Univ., Taiwan

Ching-Chih Tsai, Natl Chung Hsing Univ., Taiwan

Kuo-Yang Tu, Natl Kaohsiung First Univ. of Sci. and Tech., Taiwan

Gwo-Hshiung Tzeng, Kainan Univ., Taiwan

Wen-June Wang, Natl Central Univ., Taiwan

Wei-Yen Wang, Natl Taiwan Nornal Univ., Taiwan

Leeh-Ter Yao, Natl Taipei Univ. of Tech., Taiwan

General Chair

Shun-Feng Su, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

General Co-Chairs

Wei-Yen Wang, Natl Taiwan Nornal Univ.,Taiwan

Ching-Chih Tsai, Natl Chung Hsing Univ.,Taiwan

Yo-Ping Huang, Natl Taipei Univ. of Tech., Taiwan

Faa-Jeng Lin, Natl Central Univ., Taiwan

Program Chair

Chin-Wang Tao, Natl Ilan Univ. ,Taiwan

Program Co-Chair

Chia-Feng Juang, Natl Chung Hsing Univ. ,Taiwan

Invited Session Chairs

Jyh-Horng Chou, Natl Kaohsiung First Univ. of Sci. and Tech., Taiwan

Ching-Chang Wong, TamKang Univ., Taiwan

Award Committee Chair

Tzuu-Hseng S. Li, Natl Cheng Kung Univ.,Taiwan

Publicity Chair

Kao-Shing Hwang, Natl Sun Yat-Sen Univ., Taiwan

Publications Chair

Chen-Chien James Hsu, Natl Taiwan Nornal Univ.,Taiwan

Registration Chair

I-Hsum Lee, Lee-Ming Institute of Tech., Taiwan

Finance Chairs

Jiann-Jone Chen, Natl Taiwan Univ. of Sci. and Tech., Taiwan

Hsiao-Chin Chen , Natl Taiwan Univ. of Sci. and Tech.,Taiwan

Local Arrangements Chair

Jing-Ming Guo, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

Local Arrangements Co-Chair

Chih-Hsien Hsia, Chinese Culture Univ. , Taiwan

Exhibition Chair

Chung-Hsien Kuo, Natl Taiwan Univ. of Sci. and Tech. ,Taiwan

Webmaster

Ming-Chang Chen, Natl Taiwan Univ. of Sci. and Tech.,Taiwan

iFUZZY 2013 - 2013 International Conference on Fuzzy Theory and Its Applications

Proceedings of 2013 International Conference on Fuzzy Theory and Its Application
National Taiwan University of Science and Technology, Taipei, Taiwan, Dec. 6-8, 2013

Accuracy Enhancement for Fuzzy Time Series using Modified Fuzzy Relationship

Kraimon Maneesilp
Department of Information Technology,
Science and Technology Faculty
Rajamangala University of Technology Thanyaburi
e-mail: kraimon@hotmail.com

Abstract— **Traditional fuzzy time series have more forecasting errors when clustering the universe of discourse is too low. This paper presents a new method using Cartesian product of a matrix to define the fuzzy relationship on the first order fuzzy time series. This technique can improve the accuracy and reduces a number of not-found relationships in historical time series compared to traditional method. In the experiment, it has two scenarios to consider; the forecasting enrollments of the University of Alabama and the forecasting foreign exchange rate from Euro to US$. The results represent the errors behaviors when changing values of various parameters and prove that proposed method yields better accuracy than the traditional method, especially in the low clustering of the universe of discourse and short historical time series.**

Keywords:-forecasting; time series; fuzzy time series; time series forecasting.

I. INTRODUCTION

Fuzzy time series (FTS) are popular methods in time series forecasting, because it is simply practical technique. FTS was presented by Q. Song and B.S. Chissom [1] in 1993. In 1996, S.M. Chen proposed the Chen's method [4] to reduce the complexity of processes which leads to the simpler forecasting method and forecasting results were similar to an original one [1]. After that, C.C. Tsai and S.J. Wu studied the high order FTS in [5, 6] and S.M. Chen proposed and applied to enrollments of the University of Alabama on [7]. The high order FTS can increase the forecasting accuracy with high complexity time series, but it requires the continuous historical time series longer than the first order FTS.

Fuzzy time series have been applied to any application. For examples, the social information [8], meteorology [9], commodity prices [10], exchange rates [11], stock index [12] financial prediction [13] and trading systems [14,15] In addition, the practice has developed in conjunction with other methods to make predictions more accurate [16,17].

The prediction accuracy of fuzzy time series is de-pended on time series pattern, number of clustering the universe of discourse [18] and length of historical time series for recovered state relationships [3]. For solves this problem, K. Huarung presented the Heuristic models of FTS [19] after at, he and H.T. Yu proposed Ratio-based lengths of intervals technique [20]. Moreover, N.Y.Wang and S.M. Chen proposed the automatic clustering technique for solve this problem [21]. In this problem, the number of clustering the universe of discourse have very affected to the error rate of prediction. If it is too low, the found relationship will be rough thus the chance of forecasting results have been rough too. In the other hand, if it is high, it increases a probability of the not-found relationship on a current state. This paper proposes the new method to define the fuzzy relationship in historical time series, applied to the first order FTS. This method can reduce the effect of a small partitions number on universe of discourse.

In this work, two scenarios are considered as shown in Section IV. The first case is to forecast the enrollments of the University of Alabama problem; it presents fore-casting errors from the new method and compares to the traditional one. The second one is to forecast the foreign exchange rate from Euro to US$ using proposed method and traditional method when the number of partitions on universe of discourse and length of historical time series haves be changed. The objective of this experiment is to ob-serve forecasting error behaviors when various parameters of systems are changed on proposed method com-pared to traditional method.

The rest of this paper is organized as follows: Section II introduces the modified fuzzy relationship definition. Section III explains the proposed forecasting process. Experimental results in both scenarios have been discussed in Section IV. Finally, Section V concludes the paper.

II. MODIFIED FUZZY RELATIONSHIP DEFINITION

The traditional fuzzy time series are normally defined fuzzy relationships in term of max-min composition. In [1], its definition may have more than one model to define the fuzzy relationship, however it will employ only one model that defined by a max-min composition. This paper proposes another model using matrix's Cartesian product to define fuzzy time series and uses center of the area to defuzzification. For the proposed method, the fuzzy time series definition will be changed on definition from traditional model. This paper scope on first order FTS. So, it will discuss only definition 1 to 5 of [1], as follows:

$$A=f_A(u_1)/u_1+f_A(u_2)/u_2+\ldots+f_A(u_n)/u_n$$

where f_A is the membership function of the fuzzy set A, f_A:U→[0, 1], $f_A(u_1)$ denotes the grade of membership of u_i in the fuzzy set A, and $1\leq i\leq n$.

978-1-4799-0386-3/13/$31.00 ©2013 IEEE

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

The definition 1 is defined the fuzzy time series, it is constant from traditional paper [1]. Definition 2 and 3 are modified for covers matrix's Cartesian product fuzzy relationship, as follows.

Definition 2: If for any $f_j(t) \in F(t)$ where $j \in J$, there exists an $f_j(t-1) \in F(t-1)$ where $i \in I$ such that there exists a fuzzy relation $R_{ij}(t,t-1)$ and, $f_j(t)=f_i(t-1) \times R_{ij}(t,t-1)$ then $F(t)$ is said to be caused in $F(t-1)$ by Cartesian product. Denote this as

$$f_i(t-1) \rightarrow f_j(t) \qquad (1)$$

and

$$F(t-1) \rightarrow F(t). \qquad (1a)$$

Definition 3: If for any $f_j(t) \in F(t)$ where $j \in J$, there exists an $f_j(t-1) \in F(t-1)$ where $i \in I$ such that there exists a fuzzy relation $R_{ij}(t,t-1)$ and, $f_j(t)=f_i(t-1) \times R_{ij}(t,t-1)$ let $R(t,t-1) = \bar{X}_{i,j}(R_{ij}(t,t-1))$ where '$\bar{X}_{i,j}$' is the arithmetic mean of all fuzzy relation i to j. Then $R(t,t-1)$ is called the fuzzy relation between $F(t)$ and $F(t-1)$ and define this as the following fuzzy relational equation:

$$F(t) = F(t-1)) \times R(t,t-1) \qquad (2)$$

Definition 4: Suppose $F(t)$ is a fuzzy time series $(t= \ldots, 1, 2, \ldots)$ and $t_1 \neq t_2$. If for any $f_i(t_1) \in F(t_1)$ there exists an $f_j(t_2) \in F(t_2)$ such $f_i(t_1)=f_j(t_2)$ that and vice versa, then define $F(t_1)= F(t_2)$.

Definition 4 is constant from traditional paper [1]. However definition 5 has been modified follows.

Definition 5: Suppose $R_1(t,t-1) = \bar{X}_{i,j}(R^1_{i,j}(t,t-1))$ and $R_2(t,t-1) = \bar{X}_{i,j}(R^2_{ij}(t,t-1))$ are two fuzzy relations between $F(t)$ and $F(t-1)$. If for any $f_j(t) \in F(t)$ where $j \in J$ there exists as $f_i(t-1) \in F(t-1)$ where $i \in I$ and fuzzy relations $R^1_{ij}(t,t-1)$ and $R^2_{ij}(t,t-1)$ such that $f_i(t) = f_i(t-1) \times R^1_{ij}(t,t-1)$ and $f_i(t) = f_i(t-1) \times R^2_{ij}(t,t-1)$, Then define

$$R_1(t,t-1) = R_2(t,t-1) \qquad (3)$$

III. Forecasting Process

The forecasting processes have 6 steps. It consists of 3 steps in design processes and 3 steps for learning and forecasting. Procedures are as follows.

Step 1: Define universe of discourse U as $[D_{min} - D_1, D_{max} + D_2]$ when D_{min} and D_{max} are minimum and maximum of values in historical data, respectively. D_1 and D_2 are two proper positive values which D_1 is round down value of D_{min} and D_2 is round up value of D_{max}. We use data from Song and B.S. Chissom [2]. The minimum and maximum values of enrollments historical data are 13,055 and 19,328, defined D_1 = 55 and D_2 = 672. Thus, the universe of discourse values are assigned from 13,000 to 20,000.

Step 2: Partition the universe U into n equal length steps. In this case, we partition U to 8 steps, as follows s_1=13,000, s_2 =14,000, s_3=15,000, s_4=16,000, s_5=17,000, s_6=18,000, s_7=19,000 and s_8 =20,000.

Step 3: Define Fuzzy memberships function into triangle membership form using $U_i \in \{U_1, U_2, U_3, \ldots, U_n\}$ when U_i has the apex at S_i and slope down to base of triangle at S_{i-1} and S_{i+1}. For boundary step (S_0 and S_n), the membership values are saturated to 1 at all enrollments, because they are exceeding the range of universe of discourse. This fuzzy membership function is shown in Fig.1.

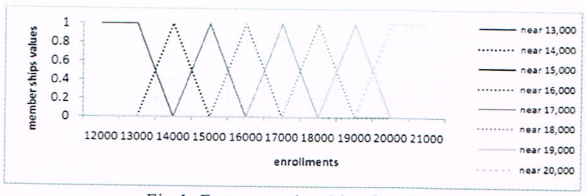

Fig.1. Fuzzy memberships function

Step 4: Fuzzified the historical data by the fuzzy membership function in step 3 in form of horizontal vector matrices. Fuzzified historical data at time i is

$$A_i = \left[\mu_{U_{1_i}} \ \mu_{U_{2_i}} \ \mu_{U_{3_i}} \cdots \ \mu_{U_{n_i}}\right]^T. \qquad (4)$$

Using step 1 - 3 to Fuzzified enrollments data in original papers [2, 3, 4], the result is illustrated in Table1.

Table1. Fuzzified enrollments data

A_i	Year	Enrollments	μ_{u_1}	μ_{u_2}	μ_{u_3}	μ_{u_4}	μ_{u_5}	μ_{u_6}	μ_{u_7}	μ_{u_8}
A_1	1971	13055	0.945	0.055	0	0	0	0	0	0
A_2	1972	13563	0.437	0.563	0	0	0	0	0	0
A_3	1973	13867	0.133	0.867	0	0	0	0	0	0
A_4	1974	14696	0	0.304	0.696	0	0	0	0	0
A_5	1975	15460	0	0	0.54	0.46	0	0	0	0
A_6	1976	15311	0	0	0.689	0.311	0	0	0	0
A_7	1977	15603	0	0	0.397	0.603	0	0	0	0
A_8	1978	15861	0	0	0.139	0.861	0	0	0	0
A_9	1979	16807	0	0	0	0.193	0.807	0	0	0
A_{10}	1980	16919	0	0	0	0.081	0.919	0	0	0
A_{11}	1981	16388	0	0	0	0.612	0.388	0	0	0
A_{12}	1982	15433	0	0	0.567	0.433	0	0	0	0
A_{13}	1983	15497	0	0	0.503	0.497	0	0	0	0
A_{14}	1984	15145	0	0	0.855	0.145	0	0	0	0
A_{15}	1985	15163	0	0	0.837	0.163	0	0	0	0
A_{16}	1986	15984	0	0	0.016	0.984	0	0	0	0
A_{17}	1987	16859	0	0	0	0.141	0.859	0	0	0
A_{18}	1988	18150	0	0	0	0	0	0.85	0.15	0
A_{19}	1989	18970	0	0	0	0	0	0.03	0.97	0
A_{20}	1990	19328	0	0	0	0	0	0	0.672	0.328
A_{21}	1991	19337	0	0	0	0	0	0	0.663	0.337
A_{22}	1992	18876	0	0	0	0	0	0.124	0.876	0

Step 5: Define the length of historical time series w and find the fuzzy relation matrix $R^w(t,t-1)$ from $R(t,t-1)$ by

$$R(t,t-1) = A_{t-1} \times A_t^T \tag{5}$$

and

$$r_{i,j}^{w} = \frac{1}{w}\sum_{k=0}^{W-1} r_{i,j}^{k} \tag{6}$$

when

$$R^w(t,t-1) = \begin{bmatrix} r_{1,1}^w & r_{1,2}^w & \cdots & r_{1,n}^w \\ r_{2,1}^w & r_{2,2}^w & & r_{2,n}^w \\ \vdots & & \ddots & \vdots \\ r_{m,1}^w & r_{m,2}^w & \cdots & r_{m,n}^w \end{bmatrix} \tag{7}$$

and

$$R(t-i,t-i-1) = \begin{bmatrix} r_{1,1}^i & r_{1,2}^i & \cdots & r_{1,n}^i \\ r_{2,1}^i & r_{2,2}^i & & r_{i\,2,n} \\ \vdots & & \ddots & \vdots \\ r_{m,1}^i & r_{m,2}^i & \cdots & r_{m,n}^i \end{bmatrix}. \tag{8}$$

Step 6: Forecast next data from

$$A_{t+1} = R^w(t,t-1) \times A_t \tag{9}$$

And

$$F(t+1) = \begin{cases} COA(A_{t+1}), & |A_{t+1}| \neq 0 \\ F(t), & |A_{t+1}| = 0 \end{cases} \tag{10}$$

When $F(t)$ and $F(t+1)$ is current state data and next state data from time series, respectively. $COA(A_{t+1})$ is center of area of A_{t+1} and $|A_{t+1}|$ is scalar value of vector A_{t+1} and

$$COA(A) = \frac{\sum_{i=1}^{n} \mu_{u_i}(A) s_i}{\sum_{i=1}^{n} \mu_{u_i}(A)} \tag{11}$$

where n is clustering the universe of discourse, $\mu_{u_i}(A)$ is membership value of A on s_i

In practical, the system has been constructed by step 1-3 of forecasting process. Thereafter, we will know the number of the universes of discourse partitions, the membership functions and maximum values of all membership functions. Then, we define a length of historical time series for training (w) and design the structure of system as follows.

- Create 2 of one dimensional arrays, names are $A[i]$ and $B[i]$ for a fuzzification process. Their lengths are equivalent to the number of the universes of discourse partitions.
- Create a three-dimensional array, namely $R[i,j,k]$, to store R-matrices. Dimensions i and j are equivalents to number of the universes of discourse partitions. The dimension k is equivalent to the length of historical time series for training (w).
- Construct the Relationship matrix calculation part as shown in Fig.2.

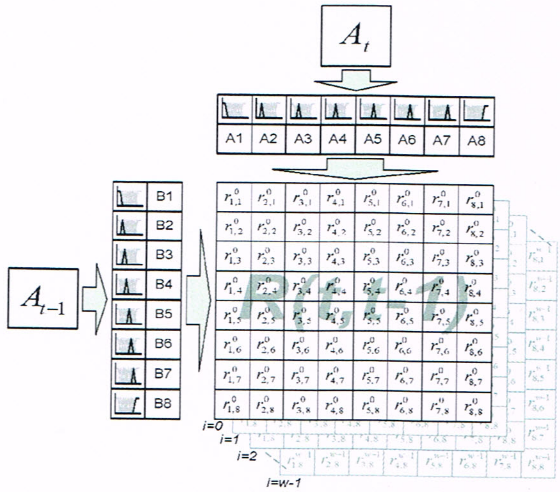

Fig.2. Relationship matrix calculation part

After relationship matrix calculation part has been constructed, the system must be prepared values before using it. It can do follows:

- Fuzzified A_t and A_{t-1} with membership functions, store in $A[i]$ and $B[i]$, respectively.
- Calculating $r_{i,j}^0$ by $r_{i,j}^0 = Ai \times Bj$.
- Fuzzified A_{t-1} and A_{t-2} by membership functions, store in $A[i]$ and $B[i]$, respectively.
- Calculating $r_{i,j}^1$ using $A[i]$ and $B[i]$ similar $r_{i,j}^0$
- Repeated above steps for all elements of $R[i,j,k]$.
- Create a two-dimensional array, named $RW[i,j]$ for $R^w(t,t-1)$ matrix. The dimensions i and j are equivalents to the number of the universes of discourse partitions.
- Uses the equation (6) for calculating all elements of $RW[i,j]$.

For forecasting, we must construct the forecasting part which is composed by $RW[i,j]$ and two of one- dimensional array., as shoyvn in Fig.3. It is constructed by:

- Create two of one-dimensional array; namely $N[i]$ and $F[i]$, for defuzzification process. Their lengths are equivalent to the number of the universes of discourse partitions.
- Construct the forecast part as illustrated in Fig.3.

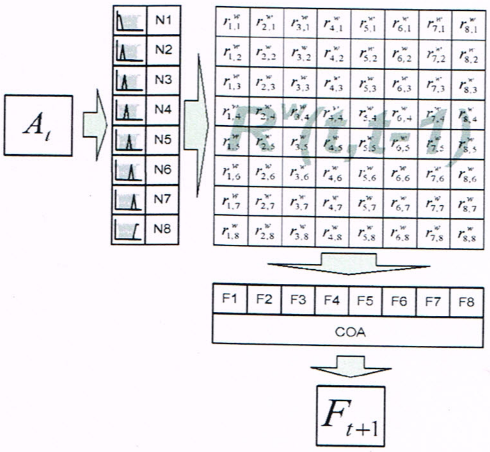

Fig.3. Forecasting part

The forecasting process starts by, Fuzzified A_t by membership functions and stores it in $N[i]$ and then calculates the forecasting vector by equation (9) and stores it into $F[i]$. Finally, we use equation (11) for calculating the forecasting output of this state.

IV. EXPERIMENTAL

Our experiment focus on two scenarios; the first one is test forecasting performance on forecasts enrollments of the University of Alabama [4] with our proposed method, compared to the traditional method and Chen's method, respectively. The second one is forecasting EURO to US$ exchange rate, when using any clustering the universe of discourse and length of historical time series to observe the clustering the universe of discourse affected of traditional method compare to proposed method.

Table2. Forecasting results of proposed method and original methods

Year	Actual	Proposed method		Song and Chissom[2]		Chen's method	
		Forecast	Error (%)	Forecast	Error (%)	Forecast	Error (%)
1971	13055	-	-	-	-	-	-
1972	13563	13800	1.747	14000	3.222	14000	3.222
1973	13867	14221	2.553	14000	0.959	14000	0.959
1974	14696	14440	1.742	14000	4.736	14000	4.736
1975	15460	15411	0.317	15500	0.259	15500	0.259
1976	15311	15794	3.155	16000	4.5	16000	4.5
1977	15603	15714	0.711	16000	2.544	16000	2.544
1978	15861	15870	0.057	16000	0.876	16000	0.876
1979	16807	16004	4.778	16000	4.802	16000	4.802
1980	16919	16659	1.537	16813	0.627	16833	0.508
1981	16388	16799	2.508	16813	2.593	16833	2.715
1982	15433	16291	5.56	16709	8.268	16833	9.071
1983	15497	15779	1.82	16000	3.246	16000	3.246
1984	15145	15814	4.417	16000	5.645	16000	5.645
1985	15163	15623	3.034	16000	5.52	16000	5.52
1986	15984	15633	2.196	16000	0.1	16000	0.1
1987	16859	16067	4.698	16000	5.095	16000	5.095
1988	18150	16721	7.873	16813	7.366	16833	7.256
1989	18970	19050	0.422	19000	0.158	19000	0.158
1990	19328	19184	0.745	19100	1.18	19000	1.697
1991	19337	19177	0.827	19000	1.743	19000	1.743
Average errors (%)			2.535		3.172		3.233
Minimum error (%)			0.057		0.1		0.1
Maximum error (%)			7.873		8.268		9.071

The results of the first scenario are shown in Table2. The average error percentage of proposed method is only 2.535 compared to 3.172 for Q. Song and BS. Chissom's method and 3.233 for Chen's method. In the same way, minimum error percentage and maximum error percentage of proposed method are lower than the two traditional methods. The forecasting out of each method compare to actual values are shown by Fig.4.

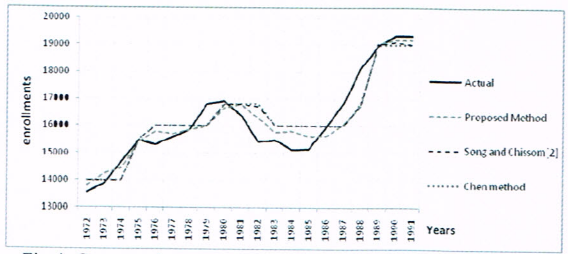

Fig.4. Compared results of proposed method with original method

The second scenario experiments the errors behaviors, when the number of partitions on the universes of discourse and length of historical time series (w) are changed. In this case, we compare the result between proposed method and Chen's method. The experiments use time series of daily exchange rate of EURO to US$ from Jan 2, 2013 to Jun 28, 2013. The exchange rate is come from Web site of Federal Reserve System [22]. They are tested on 4 lengths of historical time series at $w=3$, $w=5$, $w=8$, $w=10$. The observations are the root mean square error (RMSE) and count of not-found fuzzy relationship in historical time series (NFR) of forecasting process.

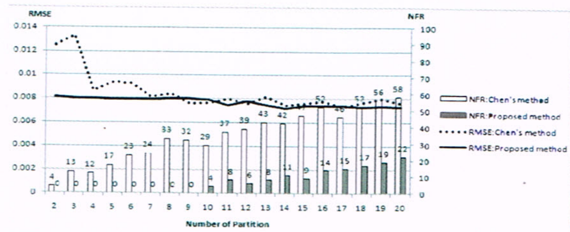

Fig.5. Result of section 2 when setting w at 3

The result of scenario two when setting w =3 is shown in Fig.5. We can see; the RMSE of proposed method has little changed from 0.008. The train of changed is slow down. In the other hand, the RMSE of Chen's method is very high when the number of partitions is lower 5 and it comes to near the RMSE of proposed method at number of partitions is 7. After that, its RMSE is nearly proposed method.

The proposed method do not has the NFR when the number of partitions is lower than 10. In the other hand, when the number of partitions is more than 10, the NFR growth rate is lower than Chen's method.

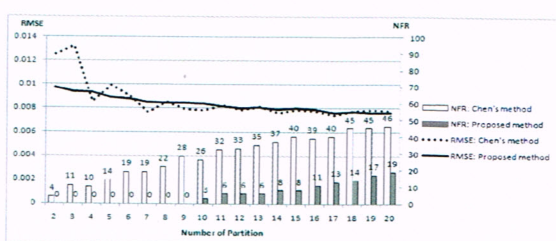

Fig.6. Result of section 2 when setting w at 5

At $w=5$, the results have a trend similar to $w=3$ but slope of proposed method is higher than earlier one. However, the minimum error is equivalent to $w=3$ which is around 0.008.

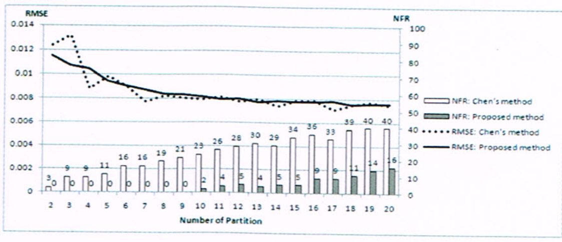

Fig.7. Result of section 2 when setting w at 8

At w=8 and 10, the results of all methods are closely related. The minimum error is around 0.008 and maxi-mum is around 0.012. However, the RMSE of proposed method is smoothly changed but the RMSE of Chen's method swings near the RMSE of proposed me-thod.

The results of proposed method have more efficiency than traditional when applied at low number of partitions and short lengths of historical time series. However, at the high number of partitions and short lengths of historical time series, the efficiency of proposed method is similar to the traditional method.

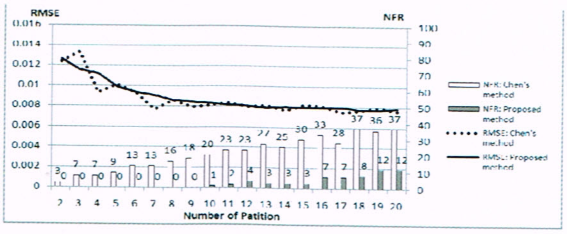

Fig.8. Result of section 2 when setting w at 10

V. Conclusion

First section of the experiment proves that the pro-posed method has average error, minimum error and maximum error less than the traditional method and Chen's method. The second one shows that the proposed method can reduce the occurrence of not-found fuzzy relationship in historical time series. The relationship between the number of partitions and forecasting error, in the case of the traditional method, RMSE is higher at the low number of partitions and decreases when it is higher, while the proposed method has little changed when number of partitions is changed. This effect has also been confirmed by the results of all parameters, which show that it also has features like this, even if a time series is changed.

All experiments demonstrate that the proposed system can reduce forecasting errors, especially the case of the divided universe of discourse that is too small. The proposed method can also reduce the event not-found fuzzy relationship in historical time series which makes forecasting method is practical especially in low clus-tering the universe of discourse and short historical time series.

References

[1] Q. Song and B.S. Chissom, "Fuzzy time series and its models," *Fuzzy Set and Systems*, Vol.54, pp269-277, 1993.

[2] Q. Song and B.S. Chissom, "Forecasting enrollments with Fuzzy time series: Part I," *Fuzzy Set and Systems*, Vol.54, pp1-9, 1993.

[3] Q. Song and B.S. Chissom, "Forecasting enrollments with Fuzzy time series: Part II," *Fuzzy Set and Systems*, Vol.62, pp.1-8, 1994.

[4] S.M. Chen, "Forecasting enrollments base on fuzzy time series," *Fuzzy Set and Systems*, Vol.81, pp.311-319, 1996.

[5] C.C. Tsai and S.J. Wu, "A study for second-order modeling of fuzzy time series," *Proceedings of IEEE International Fuzzy Systems Conference* ,Vol.2, pp.22-25, 22-25 Aug 1999.

[6] C.C. Tsai and S.J. Wu, "Forecasting enrollments with high-order fuzzy time series," *Proceedings of 19th International Conference of the North American Fuzzy Information Processing Society*, pp.196-200, 13-15 Jul 2000.

[7] S.M. Chen, "Forecasting enrolments based on high-order fuzzy time series," *Cybernetics and Systems*, Vol.33, pp.1-16, 2002.

[8] R.C. Tsaur and T.C. Kuo, "The adaptive fuzzy time series model with an application to Taiwan's tourism demand," *Expert Systems with Applications*, Vol.38, pp.9164–9171, 2011.

[9] S.F.Huang and C.H. Cheng, "Predicting Daily Ozone Concentration Maxima Using Fuzzy Time Series Based on Two-stage Partition Method," *Proceedings of 2008 International Workshop on Education Technology and Training & 2008 International Workshop on Geosciences and Remote Sensing*, pp.569-573, 21-22 Dec 2008.

[10] X.Zhang, Q. Wu, and J. Zhang, "Crude Oil Price Forecasting Using Fuzzy Time Series," *Proceedings of 3rd International Symposium on Knowledge Acquisition and Modeling*, pp.213-216, 20-21 Oct 2010.

[11] L. Abdullah and I. Taib, "High Order Fuzzy Time Series for Exchange Rates Forecasting," *Proceedings of 3rd Conference on Data Mining and Optimization*, pp.1-5, 28-29 June 2011.

[12] C.H. Cheng, T.L. Chen and H.J. Teoh, "Multiple-period Modified Fuzzy Time-series for Forecasting TAIEX," proceeding of Fourth International Conference on Fuzzy Systems and Knowledge Discovery, pp.2-6, 24-27 Aug 2007.

[13] C.H.L. Lee, A. Liu and W.S. Chen, "Pattern Discovery of Fuzzy Time Series for Financial Prediction," *IEEE Trans on knowledge and data engineering*, Vol. 18, No. 5, pp.613-625, MAY 2006.

[14] Y. Leu and T.I Chiu, "An Effective Stock Portfolio trading Strategy using Genetic Algorithms and Weighted Fuzzy Time Series," *Proceeding of The 16th North-East Asia Symposium on Nano, Information Technology and Reliability*, pp70-75,24-26 Oct 2011.

[15] K. Maneesilp, B. Kruatrachue and P. Sooraksa, "Adaptive parameter forecasting for FOREX Automatic trading system using fuzzy time series," *Proceeding of International Conference on Machine Learning and Cybernetics*, pp.189-194, July 2011.

[16] Q. Song, R.P. Leland and B.S. Chissom, "Fuzzy stochastic fuzzy time series and its models," *Fuzzy Sets and Systems*, vol.88 pp.333-341, 1997.

[17] E. Egrioglu, C.H. Aladag, U. Yolcu, M.A. Basaran and V.R. Uslu, "A new hybrid approach based on SARIMA and partial high order bivariate fuzzy time series forecasting model," *Expert Systems with Applications*, vol.36, pp.7424–7434, 2009.

[18] K. Huarng, "Effective lengths of intervals to improve forecasting in fuzzy time series," *Fuzzy sets and systems*, vol.123, pp. 387–394, 2001.

[19] K. Huarng, "Heuristic models of fuzzy time series for forecasting." *Fuzzy set and system*, vol.123, pp.369-386, 2001.

[20] K. Huarng and T.H. Yu, "Ratio-based lengths of intervals to improve fuzzy time series forecasting." *IEEE transaction on Systems, Man, Cybernetics*, vol.36, pp.328-340, 2006.

[21] Y.N.Wang and S.M.Chen, "Handling forecasting problem base on automatic clustering techniques and two-factor high-order fuzzy time series." Proceedings of the 2007 *8th international symposium on advanced intelligent systems*, pp432-437, Sep 2007.

[22] Board of Governors of the Federal Reserve System. (2013, Aug 26). *Release--Foreign Exchange Rates-Country Data* [Online]. Available: http://www.federalreserve.gov/releases/h10/hist/