# 行政院國家科學委員會專題研究計畫 成果報告

## 情境調整因子之模糊時間序列方法
## 研究成果報告(精簡版)

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行政院國家科學委員會補助專題研究計畫 ■ 成 果 報 告 □期中進度報告

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# 行政院國家科學委員會專題研究計畫成果報告

計畫編號： NSC 97-2221-E-343-004

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計畫主持人：王佳文　計畫參與人員：劉經緯、黃俊翔、張茜柔

**中文摘要**

本計畫提出一個多期多屬性模糊時間序列架構，其中結合分群方法與循序權重平均方法。本計畫改良 Cheng 等人(2008) 所提模糊叢集時間序列的概念，結合指數平滑預測法之概念，加入誤差修正因子，其利用(1) 指數平滑預測法與(2) 最大熵循序加權運算子(ME-OWA operator)來調整誤差。 本計畫所提出的架構可解決以下三個問題 (1)主觀決定宇集分布與語意區間長，(2) 單一屬性預測而非多屬性。再者，我們可以根據不同情境 α 去調整多期的預測值。為了驗證我們所提出的架構，我們使用阿拉巴馬新生人數、台灣期貨交易所、與台灣股票交易所之資料集當作實驗資料。最後計畫結果與 Huang 和 Cheng 學者比較，所得預測正確率優於所比較的方法。

**關鍵字:** 模糊時間序列，循序權重平均運算子，模糊分群，模糊邏輯關係

## FUZZY TIME SERIES METHOD BASED ON SITUATION ADJUSTMENT FACTOR

**Abstract**

This project proposes a high-order multiple attribute fuzzy time series model, which incorporates a clustering method and order weighted averaging (OWA) operator. This research improved fuzzy clustering time series concept by Cheng et al.'s [2], further, this project combine the Exponential Smoothing method and adjust error method. We use exponential Smoothing forecasting and ME-OWA operator to adjust error. The proposed model can deal with the fact that there is: (1) a persuasiveness lacking in determining the universe of discourse and the linguistic length of intervals, and (2) only one attribute that is usually considered in forecasting, not multiple attributes. Furthermore, we can accord a different situation α to adjust high order forecasting values. To verify the proposed model, we use the yearly data on enrollments at the University of Alabama, TAIFEX (Taiwan Futures Exchange), and TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) as experimental datasets. Finally, this project compares forecasting performances of the proposed methods with Huang et al.'s [1] and Cheng et al.'s [2] models; the results of empirical analysis conclude that the proposed model surpasses the listing models in accuracy.

**Keywords:** Fuzzy time series, Order Weighted Averaging (OWA) operator, Fuzzy clustering, Fuzzy logic relationship (FLR)

# 1. Introduction

In recent years, time series models have utilized the fuzzy theory to solve various forecasting problems, such as university enrolment forecasting [3], financial forecasting [1, 4], and temperature forecasting [5]. Many researchers have proposed different methods to predict stock price based on fuzzy time series. In 1993, Song and Chissom [6] proposed the first fuzzy time series method, where the definitions, the time-invariant model [4], and the time-variant model [1] of fuzzy time series were presented. The following research proposed simple calculation methods to get a higher forecasting accuracy [3]. Huang and Yu utilized two methods, distribution-based and average-based length, to set the linguistic intervals of the universe of discourse to improve forecasting accuracy [7]. From the literature above, there are drawbacks: (1) Many factors in stock markets, such as financial report, macroeconomic data, and the fluctuations of foreign stock markets, influence the decisions of stock investors practically, and therefore, multiple attributes should be considered in forecasting models. (2) In stock market forecasting, it is not reasonable to partition the universe of the discourse for the dataset, because the distribution of stock prices is not uniform.

Therefore, this project proposes a multiple attribute fuzzy time series model, which incorporates a clustering method and ordered weighted averaging (OWA) operator. The proposed model can deal with (1) lack of persuasiveness in determining the universe of discourse and the linguistic length of intervals, and (2) the fact that only one attribute is usually considered in forecasting, not multiple attributes. Additionally, we use the owa operator to adjust error values and utilize previous periods to forecast the next period. Hence, not only does this project forecast one order but we can also deal with forecasting of high-order problems. Furthermore, we can, according to a different situation α, adjust forecasting values.

The rest of this project is organized as follows: section 2 introduces the related literature of the fuzzy time series model and Order Weighted Averaging (OWA) operator; in section 3, we demonstrate the proposed model and algorithm; section 4 evaluates the performance of the proposed model; and finally, conclusions are presented in section 5.

# 2. Related work

In this section, several related literatures, including fuzzy time series, order weighted averaging (OWA), and evaluation criteria, are briefly reviewed.

### 2.1Fuzzy Time Series

Song and Chissom [6] proposed a fuzzy time series model to deal with the problems involving human linguistic terms [8-10]. In the following research, they continued to discuss the difference between time-invariant and time-variant models [6, 11]. Besides the above researchers, Chen presented a method to forecast the enrollment at the University of Alabama based on fuzzy time series [3].Over the past 14 years, many fuzzy time series models have been proposed by following Song and Chissom's definitions [6, 11, 12]. Among these models, Chen's model is a very conventional one due to easy calculations and good forecasting performance [3, 5].

### 2.2 Information Fusion Technique: Ordered Weighted Averaging (OWA)

Yager proposed an ordered weighted averaging (OWA) operator that had the ability to get optimal weights of the attributes based on the rank of these weighting vectors after an aggregation process [13]. An OWA operator of dimension $n$ is a mapping $f$: $R^n \rightarrow R$, which has an associated weighting vector $W = [w_1, w_2, \ldots\ldots, w_n]^T$ with the following properties:

$W_i \in [0,1]$ for $i \in I = \{1,2,\ldots,n\}$ and $\sum_{i \in I} W_i = 1$, such that

$$f(a_1, a_2, \ldots, a_n) = \sum_{i \in I} W_i b_i \qquad \textbf{(1)}$$

where $b_i$ is the *i*th largest element in the collection. Thus, it satisfies the relation $Min_i[a_i] \le f(a_1, a_2, \ldots, a_n) \le Max_i[a_i]$.

Fuller and Majlender [14] transformed Yager's OWA equation to a polynomial equation by using Lagrange multipliers. According to their approach, the associated weighting vector can be obtained by (2) ~ (4)

$$\ln w_j = \frac{j-1}{n-1} \ln w_n + \frac{n-j}{n-1} \ln w_1 \Rightarrow w_j = \sqrt[n-1]{w_1^{n-j} w_n^{j-1}} \qquad \textbf{(2)}$$

and $w_1[(n-1)\alpha + 1 - n w_1]^n =$ **(3)**

$$[(n-1)\alpha]^{n-1} [((n-1)\alpha - n) w_1 + 1]$$

if $w_1 = w_2 = \ldots\ldots = w_n = \frac{1}{n} \Rightarrow$ disp($W$) = $\ln n$ ($\alpha = 0.5$) then

$$w_n = \frac{((n-1)\alpha - n) w_1 + 1}{(n-1)\alpha + 1 - n w_1} \qquad \textbf{(4)}$$

where $W_i$ is weight vector, N is number of attributes, and $\alpha$ is the situation parameter.

### 2.3 Evaluation criteria

MSE (Mean Squared Error) is used to measure performance. MSE is defined as eq (5).

$$MSE = \frac{\sum_{i=1}^{n} (Actual(t) - Forecast(t))^2}{n} \qquad \textbf{(5)}$$

where actual(t) is the actual observations on time t, forecast(t) is the forecasting value, and n is the number of periods for forecasts.

## 3. The Proposed model

In order to deal with multiple attribute prediction and improve forecasting accuracy, this project hence proposes a hybrid model: (1) a clustering method (fuzzy c-mean [15]) for the partitioning process and (2) the OWA operator for high order adjusting.

### 3.1 Information Fusion Technique

In this section, we utilized an algorithm in order to calculate the OWA weights [16]. The main idea is from equation (2) ~ (4)[16]. The main procedure of the program is simply presented as follows (as Fig. 1).

For example, we compute the OWA weight under n=3 and situation α=0.5~1.0 in Table 1

### 3.2 Algorithm of the proposed method

In this section, we utilize the yearly data on enrollments at the University of Alabama to present the proposed algorithm.

**Step 1: Select attributes**

According to research problem, select attributes by domain experts. From Table 2, the yearly enrollments of the University of Alabama only have one attribute; hence, we use enrollments as the main attribute.

**Step 2: Computing the difference of each period**

In this step, we calculate the difference of each period.

**Step 3: Cluster multi-attribute time series S(t)**

Supposed a time series S(t) with *n* observations of *m* attributes, an appropriate fuzzy clustering procedure, is selected to cluster time series S(t) into *c* ($2 \le c \le n$) clusters in this step. In this study, FCM is chosen because it is one of the fuzzy clustering methods.

According to (Miller, 1956), seven (linguistic value) is utilized as the number of clusters for demonstration to correspond with the limitation of human cognition in shortened memory. Hence, we use the difference from each period into FCM by equation (3).

**Step 4: Rank each cluster and fuzzify the time series S(t) as fuzzy time series F(t)**

In Table 2, we ranked each cluster center value and got the linguistic value.

**Step 5: Fuzzify the historical data**

Firstly, define the fuzzy set $L_1$ $L_2$... $L_7$, on the universe of discourse.

Secondly, find out the degree of each observation value belonging to each $L_i$ ($i=1,\ldots,7$). If the maximum membership of the observation value is under $L_7$, then the fuzzified observation value is labeled as $L_7$. Lastly, convert each stock price in the training dataset to corresponding linguistic values, $L_7$. From Table 2, the maximum membership of the difference from 1971 and 1972 is 0.999773 in the fifth cluster.

**Step 6: Establish fuzzy logic relationships and the fuzzy logic relationships groups**

Construct a fuzzy logical relationship between two consecutive linguistic values, such as $A_i \to A_j$, where $A_i$ is called the LHS (left-hand side) and $A_j$ is the RHS (right-hand side) of the FLR. Then, we establish fuzzy logical relationship groups. For instance, $A_i$ includes the fuzzy logical relationship $A_i \to A_j$, $A_i \to A_k$, and $A_i \to A_l$; hence, the fuzzy logical relationship group is $A_i \to A_j, A_k, A_l$.

**Step 7: Defuzzify and compute forecast value**

Suppose $F(t) = L_i$; the forecasting of $F(t+1)$ is conducted using the following rules.

Rule 1: According to the Naïve Forecasting Principle, if the fuzzy relationship group of Li is empty, such as $L_i$→empty, the forecasting of F(t+1) is $L_i$.

Rule 2: If the fuzzy relationship group of Li is one-to-one, such as $L_i$→Lx, then the forecasting of F(t+1) is Lx.

Rule 3: If the fuzzy relationship group of $L_i$ is one-to-many, such as $L_i$→$L_2$,…,Lk, then the forecasting of F(t+1) supposes that each linguistic value is of equal weight. Therefore, the arithmetic mean is used as the forecasted value. The equation is as follows:

$$\frac{\mathrm{Def}(L_1)+\mathrm{Def}(L2)+\ldots+\mathrm{Def}(L_k)}{k} \qquad \textbf{(6)}$$

where Def( ) is denoted as the defuzzified value of that linguistic value and k is the number of linguistic values.

**Step 8: Calculate adjusted forecasting values based on the OWA operator**

From 3.1, the attributes ordering and number are known. For computing the aggregated values, we multiply the values of the attributes ordering by corresponding to the weights of OWA. Hence, the adjusted forecasting value is defined:

$$\text{The adjusted forecasting value} = \text{actual\_value} + \sum_{i=1}^{i} W_i x_{ik}. \qquad \textbf{(7)}$$

where $W_i$ is the OWA operator of the *i*th input variable, and $x_{ik}$ is the *i*th difference of forecasting. *n* is the number of rows in the database.

## 4. Verifications and comparisons

In this section, to illustrate how the proposed model performs fuzzy time series forecasting, practically collected TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) futures and TAIEX data are employed as experiment datasets. Finally, we use MSE as a performance indicator to compare the proposed model with Hang et al.'s [1] and Cheng et al.'s [2] models.

**Forecasting TAIEX Futures**

In this case, we practically collected TAIEX futures (2004/1/1~2004/12/15) as experiment datasets. From this dataset have 208 records, which are utilized 248 records (2004/1/1~2004/11/19) as training datasets; others are testing datasets (18 records, 2004/11/22~2004/12/15). To examine the improvement in performance, three fuzzy time series models, Hang et al.'s [1], and Cheng et al.'s [2]] models are employed as comparison models. The comparison result is shown in Table 3 and Table 4. We utilize an order from 3 to 7, and each order has an α value (0.5~1.0). Hence, we compute the average MSE (α value:0.5~1.0) as the performance of every order. Clearly, the performance of the proposed model surpasses the listing models.

**Forecasting TAIEX**

In this case, we practically collected TAIEX (2000/1/4~2001/12/31) data as experiment datasets. We utilized 10 months as training datasets, and 2 months are testing datasets. The comparison result is shown in Table 5 ~ Table 8. Clearly, the performance of the proposed model surpasses the listing models.

## 5. Conclusions

In this project, a high-order multiple attribute fuzzy time series method is proposed, which employs a fuzzy c-mean clustering method and OWA operator. From the experiment results, the performance of the proposed model surpasses the listing models. In order to enhance the forecasting accuracy, this project proposed an error adjust method to improve forecasting accuracy, and further utilized the OWA operator to decrease the data dimension. Moreover, the proposed model can overcome (1) a lack of persuasiveness in determining the universe of discourse and the linguistic length of intervals, and (2) that fact that only one attribute is usually considered in forecasting, not multiple attributes. Besides, we utilized a different situation α to adjust high order forecasting values. Finally, from the compared result, we can see that the proposed model outperforms the listing models. Based on the verification results, we conclude that the research goal has been reached.

## 6. 計畫成果自評

本研究內容與計畫內容大致相符，其目的均已達成。

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For different $\alpha$ and *n*, we can get different OWA weights. /* n is the number of attributes; $\alpha$ is the situation parameter */

OWA (n, $\alpha$ )

If $\alpha < 0.5$

Then $\alpha = 1 - \alpha$

If $\alpha > 0.5$

Then $w_1[(n-1)\alpha + 1 - nw_1]^n = [(n-1)\alpha]^{n-1}[((n-1)\alpha - n)w_1 + 1]$ //Calculate $W_1$

$w_n = [((n-1)\alpha - n)w_1 + 1]/[(n-1)\alpha + 1 - nw_1]$ //Calculate $W_n$

For *i* = 2 to *n*-1 do

$w_i = \sqrt[n-1]{w_1^{n-i} w_n^{i-1}}$ //Calculate $W_i$

**Figure 1.** Algorithm of OWA [16]

**Table 1**. The $w_1$ *~ $w_3$* values for different situation values α

| | α=0.5 | α=0.6 | α=0.7 | α=0.8 | α=0.9 | α=1 |
|---|---|---|---|---|---|---|
| $w_1^*$ | 0.333333 | 0.438355 | 0.553955 | 0.681854 | 0.826294 | 1 |
| $w_2^*$ | 0.333333 | 0.323242 | 0.291992 | 0.23584 | 0.146973 | 0 |
| $w_3^*$ | 0.333333 | 0.238392 | 0.153999 | 0.081892 | 0.026306 | 0 |

**Table 2** Results of forecasting difference

| Year | Enrollments | difference | Linguistic value | Forecasted | Year | Enrollments | difference | Linguistic value | Forecasted |
|---|---|---|---|---|---|---|---|---|---|
| 1971 | 13055 | | | | … | … | … | … | … |
| 1972 | 13563 | 508 | 5 | 297 | 1990 | 19328 | 358 | 4 | 387 |
| 1973 | 13867 | 304 | 4 | 387 | 1991 | 19337 | 9 | 3 | 230 |
| 1974 | 14696 | 829 | 6 | 612 | 1992 | 18876 | -461 | 2 | -465 |

**Table** 3 Results and comparisons for TAIFEX forecasting (training)

| Huarng's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 21950 | 20431 | 3 | 4 | 5 | 6 | 7 |
| | | 11768 | 11712 | 11689 | 11706 | 11629 |

**Table** 4 Results and comparisons for TAIFEX forecasting (testing)

| Haung's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 32252 | 8298 | 3 | 4 | 5 | 6 | 7 |
| | | 3683 | 2755 | 2331 | 2309 | 2377 |

**Table** 5 Results and comparisons for TAIEX forecasting (training) in 2000

| Huarng's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 115426 | 87696 | 3 | 4 | 5 | 6 | 7 |
| | | 31664 | 31488 | 31074 | 31363 | 31377 |

**Table** 6 Results and comparisons for TAIEX forecasting (testing) in 2000

| Huarng's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 129007 | 373176 | 3 | 4 | 5 | 6 | 7 |
| | | 19260 | 19431 | 20128 | 20236 | 20617 |

**Table 7** Results and comparisons for TAIEX forecasting (training) in 2001

| Huarng's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 32882 | 19312 | 3 | 4 | 5 | 6 | 7 |
| | | 8368 | 8330 | 8276 | 8268 | 8263 |

**Table 8** Results and comparisons for TAIEX forecasting (testing) in 2001

| Huarng's [1] | Cheng et al.'s [2] | The proposed model | | | | |
|---|---|---|---|---|---|---|
| | | order | | | | |
| 66615 | 15815 | 3 | 4 | 5 | 6 | 7 |
| | | 13047 | 13245 | 13355 | 13517 | 13505 |

# 國科會補助教師出席國際學術會議報告書

2009 年 7 月 22 日

| | | | |
|---|---|---|---|
| 報告人姓名 | 王佳文 | 服務單位<br>及職稱 | 電子商務管理學系<br>助理教授 |
| 會議時間 | July 10-12, 2009 | 會議地點 | 澳洲、柏斯 |
| 會議名稱 | (中文)2009 國際 IACSIT 機器學習與計算研討會<br>(英文) 2009 International IACSIT Conference on Machine Learning and Computing (IACSIT ICMLC 2009) | | |
| 論文名稱 | (中文)資訊融合技術於模糊時間序列<br>(英文) Information Fusion Technique for Fuzzy Time Series Model | | |

一、參加會議經過

本會議的主題是有關機器學習與電腦計算，恰巧與本人的這次資訊融合技術與模糊時間序列的研究方向相關，發表地點於澳洲柏斯。與會中本人與多位學者相互交流各國文化，彼此了解各國的人文風情，會議中主辦單位安排了一連串正式發表與學術研討的議程，內容十分充實。本次會議期間是從澳洲當地時間七月十日到七月十二日，環顧整個會場，各國研究精英齊聚一堂，相互交頭接耳、聚精會神地討論起各式新型演算法的貢獻與緣由，讓本人受益良多，無形之中我也感染了這種氛圍，了解許多各項新式演算法的使用，而且在不知不覺當中，我竟然慢慢地放鬆了身心，自然地與與會人事交流。研討會結束之後，並經由墨爾本、雪梨轉機回台，結束這難忘的研討會之旅。

二、與會心得

此次研討會最大的收穫，就是多了些機會與他國研究精英們共同討論研究，以改善了解我研究方面的不足，另一方面也開拓了我國際化研究的視野。我個人認為，本次研討會對於我日後赴他國，不論是發表演說，或從事共同研究性質方面的工作等等，是個難得的經驗；此外，由於這次的研討會，使得本人能夠更進一步地與各國演算法領域的專家相互交流研究心得，並且也深切地瞭解到他們的努力，與其優異性和其研究之重要性。

三、建議

希望日後能繼續推動國內研究學者出席國際研討會發表，讓更多台灣本土的研究學者，都能夠有更多的機會與國際接軌，讓我們的研究無時差。

四、攜回資料名稱及內容

此次會議主要攜回有 IACSIT ICMLC 2009 論文集、與會證明書與照片，內容主要是此次與會

的所有論文，與參與的證明，附件為本次投稿之論文。



六、其他

最後必須感謝國科會與南華大學給予以本人此次出國的補助款，讓本人能夠順利成行這次的研討會。

# Information Fusion Technique for Fuzzy Time Series Model

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**Abstract.** This paper proposes a high order multiple attribute fuzzy time series model, which corporate a clustering method and order weighted averaging (OWA) operator. The proposed model can deal with (1) lacking persuasiveness in determining the universe of discourse and the linguistic length of intervals, and (2) only one attribute is usually considered in forecasting not multiple attributes. Furthermore, we can accord different situation α to adjust high order forecasting value. To verify the proposed model, we use the yearly data on enrollments at the University of Alabama and TAIFEX (Taiwan Futures Exchange) as experimental datasets. Finally, this paper compares forecasting performances of proposed methods with Hang et al.'s [1] and Cheng et al.'s [2] models, the results of empirical analysis conclude that the proposed model surpasses in accuracy the listing models.

**Keywords:** Fuzzy time series, Order Weighted Averaging (OWA), Fuzzy clustering, Fuzzy logic relationship (FLR)

## 1. Introduction

In recent years, time-series models have utilized the fuzzy theory to solve various forecasting problems, such as university enrolment forecasting [3], financial forecasting [1, 4] and temperature forecasting [5]. Many researchers have proposed different methods to predict stock price based on fuzzy time series. In 1993, Song and Chissom[6] proposed the first fuzzy time series method, where the definitions, the time-invariant model[4] and the time-variant model[1] of fuzzy time series were presented. The following research proposed simple calculation methods to get a higher forecasting accuracy [3]. Huang and Yu utilized two methods, distribution-based and average-based length, to set the linguistic intervals of the universe of discourse to improve forecasting accuracy [1]. From the literature above, there are drawbacks: (1) Many factors in stock markets, such as financial report, macro economical data, and the fluctuations of foreign stock markets, influence practically the decisions of stock investors, and, therefore, multiple attributes should be considered in forecasting model. (2) In stock market forecasting, it is not reasonable to partition the universe of the discourse for dataset because the distribution of stock price is not uniform.

Therefore, this paper proposes a multiple attribute fuzzy time series model, which corporate a clustering method and order weighted averaging (OWA) operator. The proposed model can deal with (1) lacking persuasiveness in determining the universe of discourse and the linguistic length of intervals, and (2) only one attribute is usually considered in forecasting not multiple attributes. Furthermore, we can according to different situation α to adjust forecasting value.

The rest of this paper is organized as follows: section 2 introduces the related literature of fuzzy time-series model, Order Weighted Averaging (OWA) operator; in section 3, demonstrates the proposed model and algorithm; section 4 evaluates the performance of the proposed model; and, finally, conclusions are presented in section 5.

## 2. Related work

In this section, several related literatures including Fuzzy time-series, order weighted averaging (OWA), and Evaluation criteria are briefly reviewed.

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## 2.1Fuzzy Time-series

Song and Chissom [6] proposed a Fuzzy Time Series model to deal with the problems involving human linguistic terms [8-10]. In the following research, they continued to discuss the difference between time-invariant and time-variant models[6, 11]. Besides the above researchers, Chen presented a method to forecast the enrollments of the University of Alabama based on fuzzy time series [3].

Over the past fourteen years, many fuzzy time-series models have been proposed by following Song and Chissom's definitions [6, 11, 12]. Among these models, Chen's model is very conventional one because of easy calculations and good forecasting performance [3, 5]. Therefore, Song and Chissom's definitions and Chen's algorithm are used for illustrations as follows:

Definition 1: fuzzy time-series

Let $Y(t)(t=\ldots,0,1,2,\ldots)$, a subset of real numbers, be the universe of discourse by which fuzzy sets $f_j(t)$ are defined. If $F(t)$ is a collection of $f_1(t), f_2(t)\ldots$ then $F(t)$ is called a fuzzy time-series defined on $y(t)$.

Definition 2: fuzzy time-series relationships

Assuming that $F(t)$ is caused only by $F(t-1)$ , then the relationship can be expressed as: $F(t)=F(t-1)*R(t,t-1)$ , which is the fuzzy relationship between $F(t)$ and $F(t-1)$, where * represents as an operator. To sum up, let $F(t-1)=A_i$ 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 $A_i$ refers to the left-hand side and $A_j$ refers to the right-hand side of the fuzzy logical relationship. Furthermore, these fuzzy logical relationships can be grouped to establish different fuzzy relationships.

## 2.2 Information Fusion Techniques: Order Weighted Averaging (OWA)

Yager proposed an order weighted averaging (OWA) operator which had the ability to get optimal weights of the attributes based on the rank of these weighting vectors after aggregation process [13]. An OWA operator of dimension $n$ is a mapping $f$ : $R^n \rightarrow R$ , that has an associated weighting vector $W=[w_1, w_2, \ldots\ldots, w_n]^T$ with the following properties: $W_i \in [0,1]$ for $i \in I = \{1,2,\ldots,n\}$ and $\sum_{i\in I} W_i = 1$, Such that

$$f(a_1,a_2,\ldots,a_n)=\sum_{i\in I} W_i b_i \qquad \textbf{(1)}$$

where $b_i$ is the $i$th largest element in the collection. Thus, it satisfies the relation $Min_i[a_i] \le f(a_1,a_2,\ldots,a_n) \le Max_i[a_i]$.

Fuller and Majlender [14] transform Yager's OWA equation to a polynomial equation by using Lagrange multipliers. According to their approach, the associated weighting vector can be obtained by (2) ~ (4)

$$\ln w_j = \frac{j-1}{n-1}\ln w_n + \frac{n-j}{n-1}\ln w_1 \Rightarrow w_j = \sqrt[n-1]{w_1^{n-j} w_n^{j-1}} \qquad \textbf{(2)}$$

and

$$w_1[(n-1)\alpha+1-n w_1]^n = [(n-1)\alpha]^{n-1}\,[((n-1)\alpha-n)w_1+1] \qquad \textbf{(3)}$$

if $w_1 = w_2 = \ldots\ldots = w_n = \frac{1}{n} \Rightarrow$ disp($W$) = $\ln n$ ( $\alpha$ = 0.5) then

$$w_n = \frac{((n-1)\alpha-n)w_1+1}{(n-1)\alpha+1-n w_1} \qquad \textbf{(4)}$$

where $W_i$ is weight vector, N is number of attributes, and $\alpha$ is the situation parameter.

## 2.3 Evaluation criteria

MSE (Mean Squared Error) is used to measure performance. MSE is defined as eq(5).

$$MSE = \frac{\sum_{i=1}^{n}(Actual(t) - Forecast(t))^2}{n} \qquad \textbf{(5)}$$

where actual(t) is the actual observations on time t; forecast(t) is the forecasting value; and n is the number of periods for forecasts.

## 3. The Proposed model

In order to deal with multiple attribute prediction and improve forecasting accuracy, hence, this paper proposes a hybrid model: (1) clustering method (fuzzy c-mean [15]) for partitioning process, and (2) OWA operator for high order adjusting.

### 3.1 OWA weight

In this section, we utilized an algorithm in order to calculate the OWA weights [16]. The main idea is from equation (2) ~ (4)[16]. The main procedure of the program is simply presented as following (as fig. 1):

For different $\alpha$ and *n*, we can get different OWA weight. /* n is the number of attributes; $\alpha$ is the situation parameter */

OWA (n, $\alpha$ )

If $\alpha < 0.5$

Then $\alpha = 1-\alpha$

If $\alpha > 0.5$

Then $w_1\left[(n-1)\alpha+1-nw_1\right]^n = \left[(n-1)\alpha\right]^{n-1}\left[\left((n-1)\alpha-n\right)w_1+1\right]$ //Calculate $W_1$

$w_n = [((n-1)\alpha-n)w_1+1]/[(n-1)\alpha+1-nw_1]$ //Calculate $W_n$

For *i* = 2 to *n*-1 do

$w_i = \sqrt[n-1]{w_1^{n-i}w_n^{i-1}}$ //Calculate $W_i$

Figure 1. Algorithm of OWA [16]

For example, we compute OWA weight under n=3 and situation α=0.5~1.0 in table1

**Table 1**. The $w_1$ *~ $w_3$* values for different situation values α

| | α=0.5 | α=0.6 | α=0.7 | α=0.8 | α=0.9 | α=1 |
|---|---|---|---|---|---|---|
| $w_1^*$ | 0.333333 | 0.438355 | 0.553955 | 0.681854 | 0.826294 | 1 |
| $w_2^*$ | 0.333333 | 0.323242 | 0.291992 | 0.23584 | 0.146973 | 0 |
| $w_3^*$ | 0.333333 | 0.238392 | 0.153999 | 0.081892 | 0.026306 | 0 |

### 3.2 Algorithm of the proposed method

In this section, we utilize the yearly data on enrollments at the University of Alabama to present the proposed algorithm.

Step 1: Select attributes

According to research problem, select attributes by domain experts. From table 2, the yearly enrollments of the University of Alabama only have one attribute; hence, we use enrollments as main attribute.

Step 2: Computing difference of each period

In this step, we calculate difference of each period. From table 1, difference of 1971 and 1972 is 508(=13563-13055). Therefore, we can get difference of each period in table 2.

Step 3: Cluster multi-attributes time series S(t)

Supposed a time series S(t) with *n* observations of *m* attributes, an appropriate fuzzy clustering procedure is selected to cluster time series S(t) into *c* ($2 \le c \le n$) clusters in this step. In this study, FCM is chosen because it is one of the fuzzy clustering methods.

According to (Miller, 1956), seven (linguistic value) is utilized as the number of clusters for demonstration to correspond with the limitation of human cognition in shorten memory. Hence, we use difference of each period into FCM by equation (3).

Step 4: Rank each cluster and fuzzify the time series S(t) as fuzzy time series F(t)

In table 2, we ranked each of cluster center value and got linguistic value.

Step 5: Fuzzify the historical data

Firstly, define the fuzzy set, $L_1$ $L_2$... $L_7$, on the universe of discourse.

Secondly, find out the degree of each observation value belonging to each $L_i$ ($i=1,...,7$). If the maximum membership of the observation value is under $L_7$, then the fuzzified observation value is labeled as $L_7$. Lastly, convert each stock price in training dataset to corresponding linguistic values, $L_7$. From table 2, the maximum membership of the difference of 1971 and 1972 is 0.999773 in fifth cluster.

Step 6: Establish fuzzy logic relationships and the fuzzy logic relationships groups

Construct fuzzy logical relationship between two consecutive linguistic values such as $A_i \rightarrow A_j$, where $A_i$ is called the LHS (left-hand side) and $A_j$ the RHS (right-hand side) of the FLR. Then, we establish fuzzy logical relationship groups. For instance, $A_i$ include fuzzy logical relationship $A_i \rightarrow A_j$, $A_i \rightarrow A_k$, and $A_i \rightarrow A_l$, hence, the fuzzy logical relationship group is $A_i \rightarrow A_j, A_k, A_l$.

Step 7: Defuzzify and compute forecast value

Suppose $F(t) = L_i$, the forecasting of $F(t+1)$ is conducted using the following rules.

Rule 1: According to the Naïve Forecasting Principle, if the fuzzy relationship group of Li is empty, such as $L_i$→empty, the forecasting of F(t+1) is $L_i$.

Rule 2: If the fuzzy relationship group of Li is one-to-one, such as $L_i$→Lx, then the forecasting of F(t+1) is Lx.

Rule 3: If the fuzzy relationship group of $L_i$ is one-to-many, such as $L_i$→$L_2$,…,Lk, then the forecasting of F(t+1) is supposed that each linguistic values is of the equal weight. Therefore, arithmetic mean is used as the forecasted value. The equation is as following:

$$\frac{\mathrm{Def}(L_1)+\mathrm{Def}(L2)+\ldots+\mathrm{Def}(L_k)}{k} \quad \textbf{(6)}$$

where Def( ) is denoted as the defuzzified value of that linguistic values and k is number of linguistic values.

From table 2, if we want to forecast the enrollments in 1973, fuzzy relation group $L_4 \rightarrow L_3$, $L_4$, $L_6$ is inferred. The forecasted value = *(center of $L_3$ + center of $L_4$+ center of $L_6$)/3*=(297+24+840)/3=387

**Table 2** Results of forecasting difference(part)

| Year | Enrollments | difference | Linguistic value | Forecasted | Year | Enrollments | difference | Linguistic value | Forecasted |
|---|---|---|---|---|---|---|---|---|---|
| 1971 | 13055 | | | | … | … | … | … | … |
| 1972 | 13563 | 508 | 5 | 297 | 1990 | 19328 | 358 | 4 | 387 |
| 1973 | 13867 | 304 | 4 | 387 | 1991 | 19337 | 9 | 3 | 230 |
| 1974 | 14696 | 829 | 6 | 612 | 1992 | 18876 | -461 | 2 | -465 |

Step 8: Calculate adjusted forecasting values based on OWA operator

From 3.1, the attributes ordering and number are known. For computing the aggregated values, we multiply the values of attributes ordering by corresponding to the weights of OWA. For example, we calculate forecasting value in 1975 under α=0.5 and n=3. $\text{Forecasting_value}_{1975=}$15460+612*0.333333+387*0.333333+297*0.333333= 15892

## 4. Verifications and comparisons

In this section, to illustrate how the proposed model performs fuzzy time series forecasting, practically collected TAIEX (Taiwan Stock Exchange Capitalization Weighted Stock Index) futures are employed as experiment datasets. Finally, we use MSE as performance indicator to compare proposed model with Hang et al.'s [1], and Cheng et al.'s [2] models.

### Forecasting TAIEX Futures

In this case, we practically collect TAIEX futures (2004/1/1~2004/12/15) as experiment datasets. From this datasets have 208 records, which are utilized 248 records (2004/1/1~2004/11/19) as training datasets, others are testing datasets (18 records, 2004/11/22~2004/12/15). To examine the improvement in performance, three fuzzy time-series models, Hang et al.'s [1], and Cheng et al.'s [2]] models, are employed as comparison models. The comparison result is shown in Table 3, MSE of the proposed model are 496.87. Clearly, the performance of the proposed model surpasses the listing models.

**Table** 3 Results and comparisons for TAIFEX forecasting

| | | Type 2 method [1] | Cheng et al.'s[2] | The proposed model |
|---|---|---|---|---|
| MSE | Training data | 21950.16 | 20431.44 | 488.81 |
| | Testing data | 32252.22 | 8297.627 | 496.87 |

## 5. Conclusions

In this paper, a high order multiple attribute fuzzy time series method is proposed which employs fuzzy c-mean clustering method and OWA operator. The proposed model can overcome (1) lacking persuasiveness in determining the universe of discourse and the linguistic length of intervals, and (2) only one attribute is usually considered in forecasting not multiple attributes. Besides, we utilize different situation α to adjust high order forecasting values. Finally, from the compare result, we can see that the proposed model outperforms the listing models. Based on the verification results, we conclude that the research goal has been reached.


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