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An efficient forecasting model based on an improved fuzzy time series and a modified group search optimizer

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Abstract This paper presents a prediction model based on an improved fuzzy time series (IFTS) and a modified group search optimizer to effectively solve forecasting problems. IFTS can accurately predict whether subsequent predicted data will increase or decrease according to ratio value in the fuzzy logical relationship. In addition, the modified group search optimizer is used to adjust the length of an interval. The proposed prediction model is also used to forecast the enrollments of the University of Alabama the enrollments of a university of technology in central Taiwan, and the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) Experimental results show that the proposed model obtains the smallest prediction error than those of other methods.

Keywords Fuzzy time series · Forecast · Group search optimizer · Interval range stock index

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1 Introduction

The fuzzy time series model is widely used. It has been applied to temperature prediction [1] forecasting of tourism demand [2], and prediction of shipping index [3]. The fuzzy time series model was first proposed by Song and Chissom [4, 5]. Although, it has since received much attention from researchers, it has a complex and time-consuming calculation process. Hence, Chen [6] presented a simplified model to overcome this disadvantage, but it still has some defects for precision. Yu [7] combined fuzzy time series and weights to adequately distribute variant weights to different fuzzy relations and time series, and added a weight matrix to compute prediction values with higher accuracy. Huarng [8] found that the length of interval has a significant effect on prediction results and thus suggested averaging the lengths instead of randomly assigning the intervals.

The above-mentioned forecasting models use fixed interval and degrade the forecasting accuracy. Some researchers have applied evolutionary computation to adjust the intervals. For example, Huarng [8] presented a high-order fuzzy time series for forecasting the enrollments of the University of Alabama, in which the length of each interval in the universe of discourse is tuned by genetic algorithms to enhance the prediction rate. Kuo et al. [10] presented a hybrid forecasting model called HPSO based on fuzzy time series and particle swarm optimization, which is used to determine the fuzzy intervals to improve accuracy. Huang et al. [11, 12] proposed a hybrid of fuzzy time series and particle swarm optimization to improve the forecasting accuracy of fuzzy time series, where the global information of fuzzy logical relationships is aggregated with the local information of the latest fuzzy fluctuation to find the forecasting value in fuzzy time series.

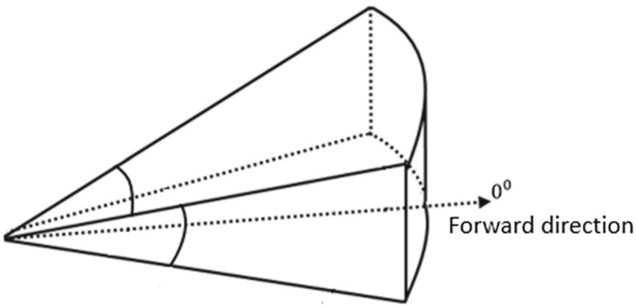

Fig. 1 Scanning field in three-dimensional space

However, existing fuzzy time series methods have the drawbacks of the fixed intervals and the forecasting accuracy. In this study, an efficient forecasting model based on improved fuzzy time series (IFTS) and modified group search optimizer (GSO) is proposed for determining the intervals and increasing forecasting accuracy. IFTS can efficiently forecast an increase or decrease in subsequent predicted data from the ratio value in the fuzzy logical relationship. The modified GSO can effectively determine the lengths of intervals. Eventually, the enrollments of the University of Alabama the enrollments of a university of technology in central Taiwan, and the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) are used to verify the effectiveness of the proposed model in terms of forecasting accuracy.

The major contributions of this study comprise the following aspects:

(1) An effective improved fuzzy time series model is proposed. The adjacent data in time series is calculated to obtain the ratio value. Every fuzzy logical relationship has a corresponding ratio value. Since the fuzzy logical relationship group consists of the same left-hand side of the fuzzy logical relationship, the ratio values are accumulated and then the average ratio (AR) value is obtained. Therefore, the forecasting value is received by means of the current actual data and the AR.

(2) A modified group search optimizer (GSO) is proposed for determining the intervals and increasing forecasting accuracy. In a traditional GSO, except for a producer, the remaining members are selected as scroungers or rangers by a fixed ratio (i.e., 80:20). In contrast, the proposed method adopts a dynamic ratio to determine the incoming member to be the scroungers or the rangers.

The rest of this paper is organized as follows. Section 2 introduces the concept of fuzzy time series. Section 3 describes the proposed model and shows the forecasting results in the enrollments of universities. Section 4 presents the forecasting results for TAIEX. Section 5 gives the conclusions.

2 Review of fuzzy time series

Fuzzy time series (FTS) model was proposed by Song and Chissom [4] based on Zadeh's [13] fuzzy logic theory. It is defined as follows.

Let U be the universe of discourse, $\mathbf{U} = \{\mathbf{u_1 u_2}, \cdots, \mathbf{u_n}\}$ and let A be a fuzzy set in the universe of discourse U; then $\mathbf{A_i}$ ($\mathbf{i}= \mathbf{1}, \mathbf{2}, \cdots, \mathbf{n}$) is defined as follows

$$\mathrm{A}_i = \frac{f_{A_i}(u_1)}{u_1} + \frac{f_{A_i}(u_2)}{u_2} + \cdots + \frac{f_{A_i}(u_n)}{u_n} \tag{1}$$

Table 1 Pseudo code of the traditional GSO algorithm

```
Set k = 0;
Randomly initialize positions x_i and head angles φ_i of all members;
Calculate the fitness values of initial members: f(x_i)
WHILE (the termination conditions are not satisfied)
  FOR (each members i)
    Choose producer: Find the producer x_p with the best fitness value
    Update a producer: 1) The producer scans at zero degrees and then scans laterally by randomly sampling three points in
                         the scanning field using Eqs. (7), (8), and (9).
                       2) Find the best point with the best resource (fitness value). If a producer scans a point that is better
                         than the previous best point, it will move to the better one; if not, it will turn its head to a new
                         randomly generated angle via Eq. (5).
                       3) If it does not search a better angle after α iterations, it will come back to the original head angle
                         via Eq. (6);
    Update scroungers: Randomly select 80% of the rest members to perform scrounging by Eq. (10);
    Update rangers: Except for the producer and scroungers, the rest members perform dispersion by Eq. (11);
    Calculate fitness: Calculate the fitness value of current member: f(x_i)
  END FOR
  Set k = k + 1;
END WHILE
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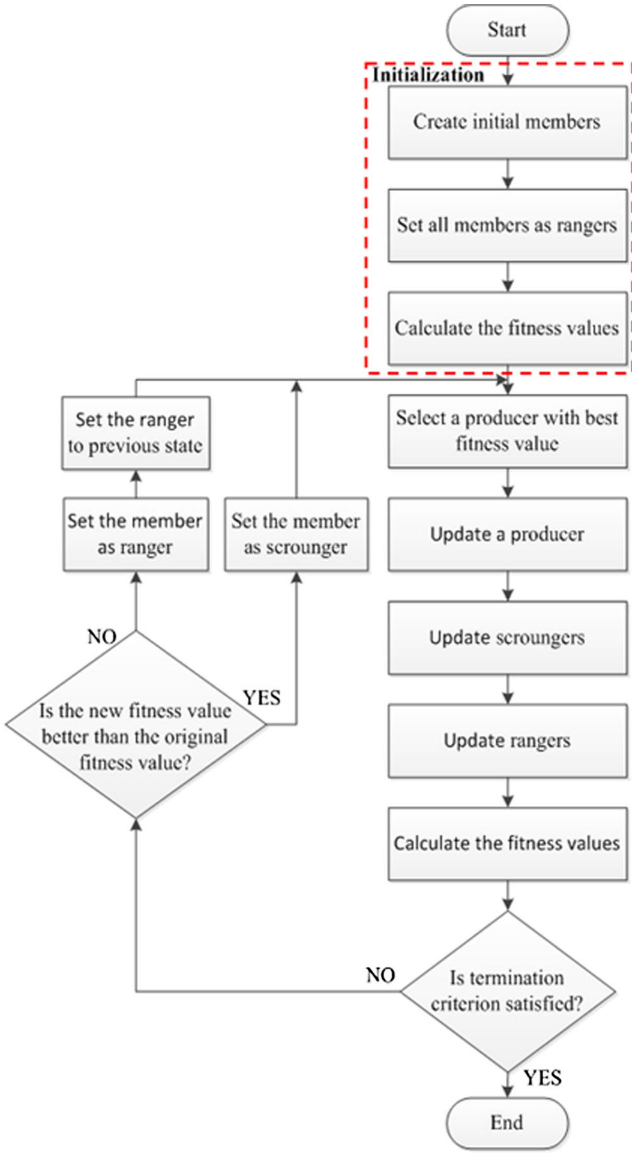

Fig. 2 Flowchart of the modified group search optimizer

where f_{A_i} is the membership function of A_i and $f_{A_i}(u_1)$ indicates the degree of membership of u_1 in the fuzzy set A_i

Let universe of discourse $Z(t)$ $(t = \cdots, 0, 1, 2\cdots)$ be a subset of R, and let fuzzy set $f_i(t)$ (i $= 1, 2, \cdots$) be defined in $Z(t)$ I fF(t) is a collection of f_i $(i = 1, 2, \cdots)$ then F(t) is called a fuzzy time series of $Z(t)$ $(t = \cdots, 0, 1, 2\cdots)$.

If $R(t,t-1)$ is a first-order model of $F(t)$, let $F(t) = F(t-1) \circ R(tt-1)$, which indicates that F(t) is caused by F(t $-$ 1), where the symbol "$\circ$" denotes the Max-Min composition operator. $R(t,t-1)$ is called the fuzzy logical relationship (FLR), and $R(tt-1)$ is a fuzzy relation between F (t) and $F(t-1)$.

Table 2 Enrollments of the University of Alabama

Years	Historical Data
1971	13055
1972	13563
1973	13867
1974	14696
1975	15460
1976	15311
1977	15603
1978	15861
1979	16807
1980	16919
1981	16388
1982	15433
1983	15498
1984	15145
1985	15163
1986	15984
1987	16859
1988	18150
1989	18970
1990	19328
1991	19337
1992	18876

If F(t $-$ 1) $= A_i$ and F(t) $= A_j$, where F(t) is caused by F(t $-$ 1), then $A_i \rightarrow A_j$ denotes the FLR.

3 Proposed forecasting model

This section presents the proposed hybrid forecasting model that consists of IFTS and the modified GSO as a modified forecasting model to upgrade the accuracy rates of the prediction. The modified GSO avoids the drawback of a traditional GSO [14] in which the scroungers and rangers are randomly selected, and the members cannot be ensured to become the rangers for breaking away local optimum.

3.1 Modified group search optimizer

GSOs are widely applied in various fields [15–18] because they used fewer fixed parameters and their best members do not converge to a local optimum. In an n-dimensional search space, the ith member at the kth iteration has a current position $X_i^k \in R^n$ a head angle $\varphi_i^k = (\varphi_{i1}^k, \cdots \varphi_{i(z-1)}^k) \in R^{n-1}$ and a head direction $D_i^k(\varphi_i^k) = \left(d_{i_1}^k, \cdots d_{i_y}^k\right) \in R^n$, which

Fig. 3 The coding of members

g1	g2	g3	g4	g5	g6

can be calculated from φ_i^k via a polar to Cartesian coordinate transformation.

$$d_{i_1}^k = \prod_{q=1}^{n-1} \cos(\varphi_{i_q}^k) \tag{2}$$

$$d_{i_1}^k = \sin(\varphi_{i_{(y-1)}}^k) \cdot \prod_{q=1}^{n-1} \cos\left(\varphi_{i_q}^k\right) (j = 2, \cdots, n-1) \tag{3}$$

$$d_{i_1}^k = \sin\left(\varphi_{i_{(y-1)}}^k\right) \tag{4}$$

The GSO consists of three different members including producers, scroungers, and rangers, in which producers execute production, scroungers involve scrounging or following, and rangers conduct random search. These three members are described in detail as below.

(1) Producer: The producer represents the member with the best fitness value for finding the best point with the best resource. Its search behavior imitates those of animals. The search in three-dimensional space of the producer is shown in Fig. 1. If a producer scans a point that is better than the previous best point, it will move to the better one; if not, it will turn its head to a new randomly generated angle via Eq. (5) If it does not search a better angle after α iterations, it will come back to the original head angle via Eq. (6)

$$\varphi^{k+1} = \varphi^k + r_2 \alpha_{\max} \tag{5}$$

$$\varphi^{k+a} = \varphi^k \tag{6}$$

where r_2 is a normally distributed random number in the range (0, 1), $\alpha_{\max} = \frac{\theta_{\max}}{2}$, where $\theta_{\max}$ is the maximum pursuit angle and $\alpha_{\max}$ is the maximum turning angle; $\theta_{\max} = \frac{\pi}{a^2}$, $\alpha = round\sqrt{n+1}$.

The producer scans at zero degrees and then scans laterally by randomly sampling three points in the scanning field using Eqs. (7), (8) and (9), and randomly select three points. The equations are

Zero degrees:

$$x_z = x_p^k + r_1 l_{\max} D_p^k \left(\varphi^k\right) \tag{7}$$

Righthand side:

$$x_r = x_p^k + r_1 l_{max} D_p^k \left(\varphi^k + \frac{r_2 \theta_{\max}}{2}\right) \tag{8}$$

Lefthand side:

$$x_l = x_p^k + r_1 l_{max} D_p^k \left(\varphi^k - \frac{r_2 \theta_{max}}{2}\right) \tag{9}$$

where x_p is the produce, r_1 is the normally distributed random sequence in the range (-1, 1), and r_2 is a uniformly distributed random sequence in the range (0, 1). $\theta_{\max}$ denotes the maximum pursuit angle

(2) Scroungers: The scroungers move around in the search space taking into consideration the location of the producer and the center of the group. The movement equation is

$$x_i^{k+1} = x_i^k + r_3 \circ \left(x_p^k - x_i^k\right) \tag{10}$$

Table 3 The length of each interval

Number of interval	interval range
$u-1$	[13000, 14000]
$u-2$	[14000, 15000]
$u-3$	[15000, 16000]
$u-4$	[16000, 17000]
$u-5$	[17000, 18000]
$u-6$	[18000, 19000]
$u-7$	[19000, 20000]

Table 4 The results of fuzzification

years	Historical Data	Fuzzification
1971	13055	A_1
1972	13563	A_1
1973	13867	A_1
1974	14696	A_2
1975	15460	A_3
1976	15311	A_3
1977	15603	A_3
1978	15861	A_3
1979	16807	A_4
1980	16919	A_4
1981	16388	A_4
1982	15433	A_3
1983	15497	A_3
1984	15145	A_3
1985	15163	A_3
1986	15984	A_3
1987	16859	A_4
1988	18150	A_6
1989	18970	A_6
1990	19328	A_7
1991	19337	A_7
1992	18876	A_6

Table 5 Corresponding to fuzzy logical relationship and ratio values

The number of FLR	Fuzzy Logical Relationship(FLR)	Ratio value
1	$A_1 \to A_1$	1.038912
2	$A_1 \to A_1$	1.022414
3	$A_1 \to A_2$	1.059782
4	$A_2 \to A_3$	1.051987
5	$A_3 \to A_3$	0.990362
	...	
21	$A_7 \to A_6$	0.976160

In Eq. (10) x_i is the scroungers, r_3 is a uniform random sequence in the range (0, 1), and the symbol "$\circ$" represents the entrywise product

(3) Rangers

The rangers mainly execute random search action. As soon as the rangers randomly select an angle "φ", the new points are replaced according to the following equation:

$$x_i^{k+1}=x_i^k+l_i D_i^k\left(\varphi^{k+1}\right) \tag{11}$$

where x_i is the rangers, and $l_i = a \cdot r1 \cdot l_{\max}$ is a random distance. $l_{\max}=\|UL - DL\|$, where UL and DL are the lower and upper bounds, respectively. The pseudo code of the traditional GSO algorithm is shown in Table 1.

In a traditional GSO, members rarely leave the local optimum when trapped. For example, if a member is the ranger and its value of each dimension is almost the same as that of the producer, it may become trapped at a local optimum point. This situation occurs because scroungers and rangers are randomly selected, which cannot ensure that the incoming member will become the ranger in order to escape the local optimum.

An optimal solution to this problem is to make all members initially rangers. After random search, if the updated fitness of the member is better than or equal to the previous one, the member will become the ranger; otherwise, the member will become the scrounger. That is if the updated fitness of the member is better than the previous fitness of the member this situation indicates the member will not fall into local optimum and turns out to be the ranger pursuing the producer. If the updated fitness of the member is not better, which will make the member easily become trapped, the member will continue to be the ranger to leave the local optimum and move back to the previous point. The proposed modified GSO provides many more chances for the members to leave the local optimum when trapped and obtains more resources than the traditional GSO does.

In a traditional GSO, a producer is selected and then incoming members are randomly selected scroungers in a ratio of 80:20. In contrast, the proposed method adopts a dynamic ratio to determine the incoming member to be the scroungers or the rangers; that is to say, in each generation, the selection result could be 60 percent are the scroungers while 40 percent are the rangers, or 70 percent are the scroungers and 30 percent are the rangers. A flowchart of the modified GSO is shown in Fig. 2.

3.2 Proposed hybrid of IFTS and modified GSO

In this subsection, the detailed procedures of the proposed forecasting model are described. The modified GSO is used to effectively determine the interval range, and IFTS is used to increase prediction accuracy. The historical enrollments of the University of Alabama are used to verify the forecasting result of the proposed method. The procedures are described as follows:

Step 1: Define the universe of discourse U, $U = [D_{\min}-D_1, D_{\max}+D_2]$, where $D_{\min}$ and $D_{\max}$ indicating the minimum and maximum value of historical data respectively and D_1 and D_2 are two appropriate values. Then, make the number of intervals n and assume that the universe of discourse U is partitioned into n intervals, with each interval denoted as $u_1 u_2 \cdots u_n$.

Table 2 shows the historical data of enrollments of the University of Alabama. According to the table, $D_{\min}$= 13055 and $D_{\max}$= 19337. The two appropriate values are set as D_1= 55 and D_2= 663. Since the GSO is integrated into

Table 6 Unduplicated fuzzy logical relationships

Fuzzy logical relationship(FLR)
$A_1 \to A_1, A_1 \to A_2$
$A_2 \to A_3$
$A_3 \to A_3, A_3 \to A_4$
$A_4 \to A_3, A_4 \to A_4, A_4 \to A_6$
$A_6 \to A_6, A_6 \to A_7$
$A_7 \to A_7, A_7 \to A_6$

Table 7 Fuzzy logical relationship group (FLRG)

The number of FLRG	Fuzzy Logical relationship group(FLRG)
1	$A_1 \to A_1, A_2$
2	$A_2 \to A_3$
3	$A_3 \to A_3, A_4$
4	$A_4 \to A_3, A_4, A_6$
5	$A_6 \to A_6, A_7$
6	$A_7 \to A_7, A_6$

Table 8 Forecasting rules

Number of rule	Corresponding fuzzy set A_i	Corresponding FLRG number	corresponding condition	Corresponding AR
1	1	1	–	1.04369
2	2	2	–	1.051987
3	3	3	x (t) $< mid_3$	1.0077
			x (t) $> mid_3$	1.043640
4	4	4	x (t) $< mid_4$	0.941726
			x (t) $> mid_4$	1.017285
5	6	5	–	1.032025
6	7	6	x (t) $< mid_4$	0.988313
			x (t) $> mid_4$	–

the forecasting model, the minimum and maximum of U are set as $g_0 = (D_{\min} - D_1)$ and $g_n = (D_{\max} + D_2)$ The initial interval of each member is [13000 20000] and initial angle φ is $\frac{\pi}{4}$.

Step 2: The universe of discourse U is the actual enrollments of the University of Alabama. In this step, we define the length of each interval as $u_1 = (g_0g_1], u_2 = (g_1g_2] \cdots u_7 = (g_{n-1}g_n]$ The number of adjustable intervals, except for the upper and lower boundaries of U is $n-1$. The number of intervals in the enrollment forecasting is set to $n = 7$; therefore, the dimension of each member is set to 6. All members are randomly selected, in which each dimension is restricted within [13000, 20000]. In the GSO, the members are coded as shown in Fig. 3. For example, if the members [14000 15000, 16000, 17000, 18000, 19000] are randomly selected, their codes are [g_1 , g_2 , g_3 , g_4 , g_5 , g_6]= [14000 15000, 16000, 17000, 18000,19000]. According to the dimension of each member and the upper and lower boundaries of the universe of discourse, the length of each interval is obtained, as shown in Table 3.

Step 3: Let all members be rangers.

Step 4: The fitness value of each member is calculated, which is defined as follows:

$$Fit = \frac{1}{1 + MSE} \tag{12}$$

where MSE is the mean square error. The definition of the fitness value is subject to the forecasting accuracy. A smaller MSE value indicates less forecasting error; that is, the higher the fitness value indicates the higher forecasting accuracy. The definition of MSE is as follows:

$$MSE = \sum_{i=1}^{dn} (A_i - F_i)^2 / dn \tag{13}$$

where A_i and F_i represent the actual value and the predicted value, respectively, and dn is the number of data points.

Step 5: In order to present the meaning of each range, let fuzzy set sA_i $1 \le i \le 7$, be linguistic values of the linguistic variable "enrollments" i.e., $A_1 =$

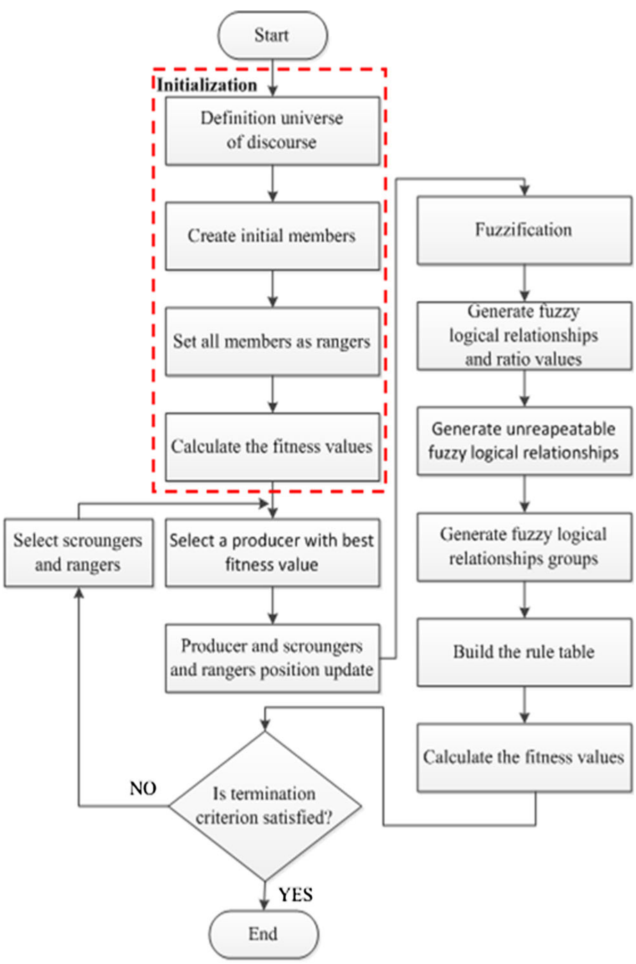

Fig. 4 Flowchart of the proposed forecasting model

Table 9 Comparison results of traditional and modified GSO

Model \ MSE \ Number of Interval	7	8	9	10	11	12	13	14
IFTS + Tradition GSO	45036	42691	33414	38432	25930	21012	26835	23511
The proposed method	43513	38058	31832	25273	22861	20466	18241	13360

(not many), A_2 = (not too many) $\cdots$ A_7 = (too many) as follows:

$$A_1 = \frac{1}{u_1}+\frac{0.5}{u_2}+\frac{0}{u_3}+\frac{0}{u_4}+\cdots+\frac{0}{u_7}$$
$$A_2 = \frac{0.5}{u_1}+\frac{1}{u_2}+\frac{0.5}{u_3}+\frac{0}{u_4}+\cdots+\frac{0}{u_7}$$
$$A_3 = \frac{0}{u_1}+\frac{0.5}{u_2}+\frac{1}{u_3}+\frac{0.5}{u_4}+\cdots+\frac{0}{u_7}$$
$$\vdots$$
$$A_7 = \frac{0}{u_1}+\frac{0}{u_2}+\cdots+\frac{0}{u_{7-2}}+\frac{0.5}{u_{7-1}}+\frac{1}{u_7} \quad (14)$$

Step 6: Fuzzify the historical data and find out the membership degree of each year's enrollments belonging to each $A_i (i = 1, 2, \cdots, m)$. In this study, m is set to 7. If the maximum membership degree of one year's enrollment is under A_k, then the fuzzified enrollment for this year is treated as A_k The fuzzified historical data in the second column of Table 2 are shown in the third column of Table 4. The fuzzy logical relationship from the fuzzified historical enrollments in Table 4 is shown in the second column of Table 5.

Step7: According to the results in Step 6, a ratio value corresponding to each fuzzy logical membership will be recorded. Every fuzzy logical relationship has a corresponding ratio value. These ratio values are listed in the third column of Table 5. The ratio values are calculated as follows:

$$R=\left(\frac{x(t)}{x(t-1)}\right) \quad (15)$$

where $x(t)$ and $x(t\text{-}1)$ represent the current state of the enrollment and the next state of the enrollment, respectively.

Step 8: Integrate all fuzzy logical relationships to find out if any does not repeat. Then, sort out the result of unduplicated fuzzy logical relationships from the second column of Table 5, as shown in Table 6.

Step 9: Based on those fuzzy logical relationships in Table 6, sort out those whose left side of A_i are the same as a group and assign a code for each group. Then there are 6 fuzzy logical relationship groups (FLRGs) are shown in Table 7.

Step 10: Create a table of forecasting rules based on the obtained corresponding fuzzy sets, FLRGs, determined conditions, and average ratio values as shown in Table 8. The average ratio value is obtained as follows:

$$AR=\frac{\sum_{k=0}^{r} R_k}{r} \quad (16)$$

where r is the number of FLRs and R_k represents the kth ratio value of FLR.

Step 11: Conduct forecasting using

$$F(t)=Y(t-1)*AR \quad (17)$$

where $F(t)$ is the forecasting value and $Y(t-1)$ presents the actual historical data. Then, the MSE of forecasting is obtained using Eq. (3).

Step 12: After obtaining MSE, assign the member whose fitness value is the largest (i.e., the smallest MSE) to be the producer. Then, Eqs. (2)–(4) are utilized to process the producer via a polar to Cartesian coordinate transformation. The producer will scan three points in the scanning field. If one of the points is better than the previous best point, the producer approaches this point;

Table 10 Comparison results of enrollment forecasting of the University of Alabama using various methods

Model	Mean Square Error(MSE)
Song and Chissom 1993 [4]	775687
Song and Chissom 1994 [5]	412499
Chen [6]	407507
Sullivan and Woodall [19]	386055
Huarng [20]	226611
Qiu et al. [21]	261473
Gangwar and Kumar [22]	62976
Egrioglu et al. [23]	85089
Wang and Chen [24]	193373
Qiu et al. [25]	71250
Proposed method	43513

Table 11 Comparison results of enrollment forecasting of the University of Alabama using various evolutionary methods and interval numbers

Model \ MSE \ Number of Interval	8	9	10	11	12	13	14
CC06F [9]	132963	96244	85486	55742	54248	42497	35324
HPSO [10]	119962	90527	60722	49257	34709	24687	22965
FMPSO [11]	30426	24672	23929	22888	22666	22616	22655
AFPSO [12]	27435	24860	19698	19040	16995	11589	8224
The proposed method	23861	17219	11492	8045	6235	5086	1519

otherwise, the producer turns toward a random angle using Eq. (5). If the producer cannot obtain a better angle after α iterations, it will head back to its original angle using Eq. (6).

Step 13: The scrounger cadges the producer via Eq. (10).

Step 14: The scrounger conducts a random search using Eqs. (2)–(4) to perform a polar to Cartesian coordinate transformation and obtains a new angle via Eq. (5) It then updates its own position through Eq. (11).

Step 15: Based on Step 4 to Step 11, calculate the fitness values of all members.

Step 16: This step is used to decide whether the termination condition is satisfied. If so, the procedure is finished; if not, the procedure goes to Step 17.

Step 17: It is judged whether or not the updated fitness values of all members are better than before. If so, these members will become scroungers; if not, these members will become rangers and reverse their position back to the previous one. Then, the process goes back to Step 12.

These steps describe the proposed forecasting model based on IFTS and the modified GSO. Figure 4 shows a flowchart of the proposed forecasting model.

3.3 Forecasting results of university enrollments

To verify the robustness of the proposed model, the forecasting results of university enrollments are presented through two experimental tests. One is the University of Alabama, the other is a university of technology in central Taiwan.

Example 1 Forecasting Enrollments of the University of Alabama

In the experiments, the members of GSO were set to 30, the number of iterations was 100, and the number of intervals was from 7 to 14. For each interval 100 experiments were run. The average forecasting results of these 100 experiments was used. Table 9 shows a comparison of experimental results for the traditional GSO and the proposed modified GSO.

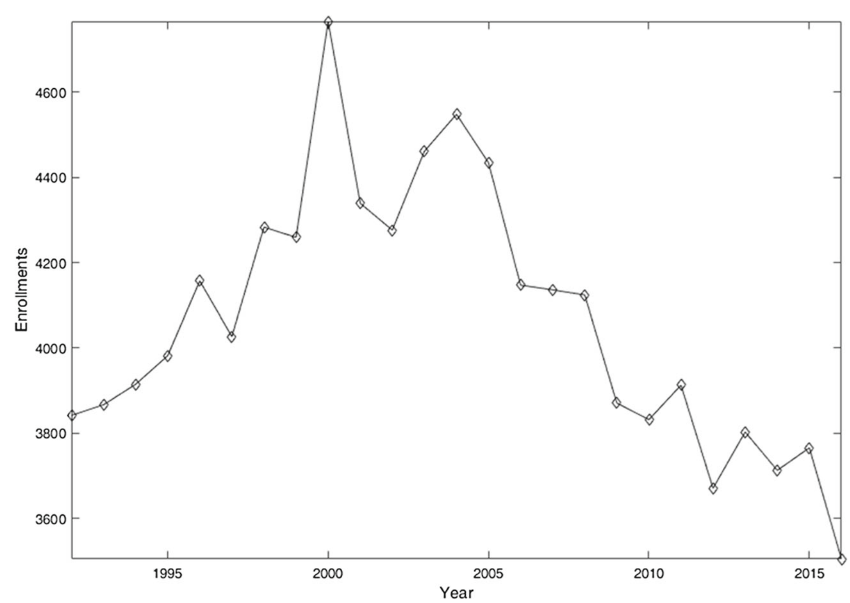

Fig. 5 Enrollments of a university of technology in central Taiwan

Table 12 Comparison results of enrollment forecasting of a university of technology in central Taiwan using various methods

Model	Mean Square Error (MSE)
Chen [6]	20742
Sullivan and Woodall [19]	18561
Huarng [20]	16195
Qiu et al. [21]	17867
Gangwar and Kumar [22]	12753
Egrioglu et al. [23]	14249
Wang and Chen [24]	15724
Qiu et al. [25]	13138
IFTS	11529
IFTS+Traditional GSO	5012
Proposed method	3767

Recently, several researchers [20–25] proposed different fuzzy time series models for solving forecast problems. Huarng [20] used heuristic models by integrating problem-specific heuristic knowledge with Chen's model [6] to improve forecasting. Qiu et al. [21] applied ensemble technique to fuzzy time series and proved that some forecasting models [4–6] can be approximated by the limitation of the fuzzy weights. Gangwar and Kumar [22] proposed a forecasting method based on the nested partition in universe of discourse and the difference parameters as relations for forecasting. This algorithm minimizes the time of generating relational equations by using complex min-max composition operations and various defuzzification processes. Egrioglu et al. [23] presented a new first-order fuzzy time series model which includes both autoregressive and moving average structures. The proposed model in [23] is a time invariant model and bases on particle swarm optimization heuristic. Wang and Chen [24] proposed a frequency-weighted fuzzy time series model which considers not only the variation of the dataset but also the frequency of trend patterns. The model lacked persuasiveness in determining the universe of discourse and the linguistic length of intervals. In [24], it can deal with multiple attribute prediction and improve forecasting accuracy. Qiu et al. [25] presented a novel forecast model based on particle swarm optimization and generalized fuzzy logical relationships. They adopted particle swarm optimization to optimize the given intervals in the universe of discourse for increasing the forecasting accuracy.

In this study, to demonstrate the effectiveness of various forecast models, the forecasting performance of the proposed model was compared with that of other state-of-the-art techniques [20–25]. The comparison results are shown in Table 10. In this table, the number of intervals used by each method is 7. The results show that the proposed model has the smallest forecasting error. The results of the proposed model were compared to those of other methods based on various evolutionary models. Table 11 shows the smallest mean square error for 100 experiments. This table presents the forecasting results for various numbers of intervals. That is, a larger interval number will obtain a smaller forecasting error. In Table 11, the proposed method has the smallest MSE.

Example 2 Forecasting Enrollments of a University of Technology in Central Taiwan

In order to verify the performance of the proposed forecasting model, the historical enrollments of a university of technology in central Taiwan are adopted. Figure 5 shows that a total of 25 historical enrollments from 1992 to 2016 are used. The forecasting performance of the proposed model is also compared with that of other state-of-the-art techniques [20–25]. In the experiments, the number of

Fig. 6 The forecasting curve of TAIEX

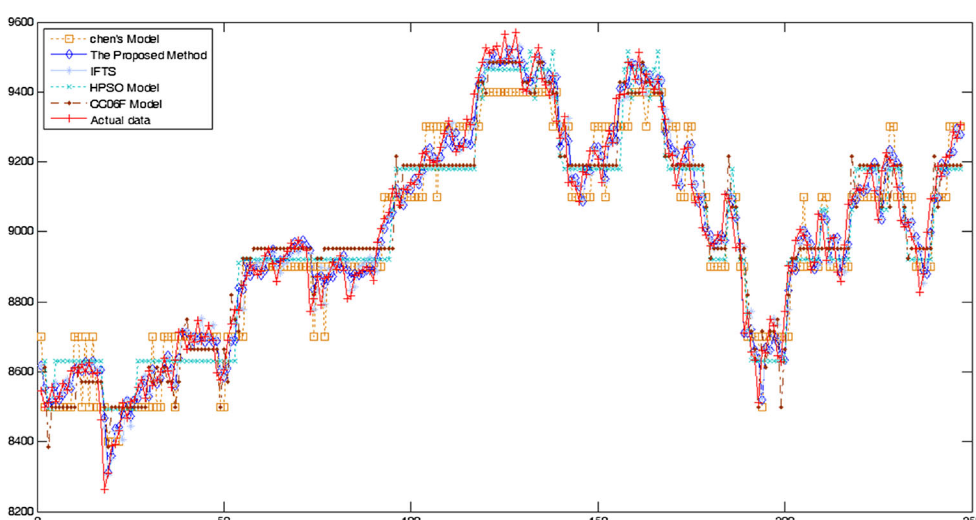

Table 13 Comparison results of TAIEX forecasting using various methods

Model	MSE
Chen [6]	7130
CC06F[9]	5767
HPSO[10]	5538
Huarng [20]	6023
Qiu et al. [21]	5981
Gangwar and Kumar [22]	5419
Egrioglu et al. [23]	5578
Wang and Chen [24]	5864
Qiu et al. [25]	5593
IFTS	3630
Proposed method	3051

intervals used by each method is set as 7. The set parameters are the same as the previous example–the enrollments of the University of Alabama. The comparison results are shown in Table 12. Experimental results show that the proposed model also has the smallest forecasting error in the enrollments of the university of technology in central Taiwan.

4 Application of model to forecasting of TAIEX

In the section, the proposed forecasting model is utilized to predict Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX). A total of 248 historical data from 2014/1/02 to 2014/12/31 were used. Several forecasting models, namely Chen's [6], IFTS, CC06F model [9], HPSO model [10], Huarng [20], Qiu et al. [21] Gangwar and Kumar [22], Egrioglu et al. [23] Wang and Chen [24], Qiu et al. [25], and the proposed model were used to forecast TAIEX. The number of intervals was 7. The results are shown in Fig. 6 The MSE values for the forecasting models are presented in Table 13. In this table, the proposed method also has the smallest RMS.

5 Conclusion

This study proposed a forecasting model based on IFTS and a modified GSO to effectively predict the enrollments of Alabama University, the enrollments of a university of technology in central Taiwan, and TAIEX. IFTS can efficiently forecast an increase or decrease in subsequent predicted data from the ratio value in the fuzzy logical relationship. The modified GSO can effectively determine the lengths of intervals. A dynamic ratio method is proposed to determine the incoming member to be the scroungers or the rangers. The proposed modified GSO provides more chances for the members to leave the local optimum when trapped and obtains more resources than the traditional GSO does. Experimental results verify that the proposed model has better prediction ability (i.e., smaller prediction error) than those of other forecasting models.

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