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Temperature Prediction based on Fuzzy Time Series and MTPSO with Automatic Clustering Algorithm

Yashvardhan Sharma, Sheetal Sisodia
Department of Computer Science and Information Systems
BITS-Pilani, Rajasthan, 333031, India
Email: yashvardhan.sharma@gmail.com , sheetal.sisodia@pilani.bits-pilani.ac.in

***Abstract*—Weather prediction is an essential activity in today's world economy with its detrimental effects on various fields like Agriculture, Utility companies, Marine etc. Many methods have been presented based on fuzzy time series to make predictions in areas such as stock price, university enrolments, weather, etc. When using fuzzy time series for forecasting, the length of intervals in the universe of discourse is important due to the fact that it can affect the forecasting accuracy rate. This paper proposes a better approach to forecasting temperature by applying automatic clustering algorithm to partition the universe of discourse. Improvement in results is observed as compared to existing techniques that involve partitioning the universe of discourse in static intervals. The proposed method is tested on temperature prediction and improvements in results are compared to some of already existing techniques.**

Keywords: Temperature prediction modified turbulent particle swarm optimization (PSO), clustering algorithm, fuzzy time series.

I. Introduction

Accurate weather predictions are important for making our day to day decisions. Sectors like agriculture that are heavily dependent on weather conditions need better forecasting techniques for better production. Airlines and Marines need weather forecasts to schedule their operations. Weather forecasting helps us to make informed decisions and may even help keep us out of danger. Many researchers have worked in this field and proposed various techniques to predict weather accurately. Song and Chissom [1, 2] presented the concept of fuzzy time series based on the fuzzy set theory. They developed the time-invariant fuzzy time series model and the time variant fuzzy time series model to forecast the enrolments of the University of Alabama. This method is mainly composed of four steps: (1) determining and partitioning the universe of discourse, (2) defining fuzzy sets on the universe of discourse and fuzzifying the time series, (3) deriving fuzzy logical relationships existing in the fuzzified time series, and (4) forecasting and defuzzifying the forecasting outputs. Many researches followed these basic definitions to do forecasting in different areas and proposed many enhancements of this method.

Zadeh[3] proposed the fuzzy set theory first which opened door to solve many problems in various fields. Li et al. [4] proposed a method for the weather forecast by using fuzziness between the demarcation lines of fuzzy grades and the membership functions of fuzzy grade. Song and Chissom[1. 2] introduced a new forecast model based on the concept of fuzzy time series. They use the time variant fuzzy time series model and the time-invariant fuzzy time series model based on the fuzzy set theory for forecasting the enrolments of the University of Alabama. Chen [5] later improved this fuzzy time series model by max–min composition. Chen [6] also proposed a method for forecasting based on fuzzy time series. Huarng[7, 8] proposed a method to improve forecasting results in forecasting the enrolments of the University of Alabama and the Taiwan Futures Exchange (TAIFEX). Lee et al. [9, 10]. presented methods for forecasting the temperature and the TAIFEX based on two-factor high-order fuzzy time series. They used the genetic algorithm and genetic simulated annealing with fuzzy time series. Kuo et al. [11] presented an improved method for forecasting enrolments based on the fuzzy time series and particle swarm optimization. They propose an effective and accuracy method to forecasting enrolments considering lengths of intervals and the content of forecast rules. Hsu et al. [12] proposed a method based on fuzzy time series and modified turbulent particle swarm optimization to predict temperature and TAIFEX. Liu et al. [13] presented a method to forecasting TAIEX using multi-attribute Fuzzy time series model. Chen et al. [14] proposed forecasting model based on fuzzy time series and automatic clustering techniques.

Two main factors have been crucial in the forecasting methods used in the above mentioned works, (1) length of the intervals of the universe of discourse and (2) content of the forecast rules. This paper proposes the use of automatic clustering algorithm for partitioning the universe of discourse thereby removing the disadvantage of using static length intervals. This method is based on two-factor high-order fuzzy relationships with automatic clustering of intervals and turbulent particle swarm optimization. The proposed method uses particle swarm optimization techniques to optimize the accuracy of temperature prediction by changing the size of intervals and generating rules which will give more accurate forecast.

II. The Proposed Method

We have taken two-factor fuzzy time series to predict temperature as described by Hsu et al. [12]. The procedure has two phases: Training phase and testing phase.

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A. fuzzy time series and clustering algorithm details:

Step 1: Define two universes of discourse $Y_A(t)$ and $Y_B(t)$

Let $Y_A(t)$ and $Y_B(t)$ be two historical data for some period. For defining the universe, first find the minimum data D_{min} and the maximum data D_{max} of known historical data. Based on D_{min} and D_{max}, define the universe $Y_A(t)$ as $[D_{min} - D_1, D_{max} + D_2]$ where D_1 and D_2 denote the buffers to adjust the lower bound and the upper bound of the universe of discourse, $Y_A(t)$ (or $Y_B(t)$), respectively.

Step 2: Partition the universes $Y_A(t)$ and $Y_B(t)$ into several intervals.

In our approach we are using Automatic clustering algorithm as described in section III which partitions the universe of discourse in some number of intervals. $Y_A(t)$ is divided in intervals $u_1, u_2, u_3, \ldots, u_n$ and $Y_B(t)$ into $v_1, v_2, \ldots, v_n$. The automatic clustering algorithm produces average difference and standard deviation difference of $Y_A(t)$ and $Y_B(t)$ as follows:

avg_diff($Y_A(t)$):0.06859504132231406
dev_diff($Y_A(t)$): 0.01600550964187325

avg_diff($Y_B(t)$):0.8016528925619835
dev_diff($Y_B(t)$):1.5769972451790624

Step 3: Define fuzzy set linguistic terms

According to the number of intervals as mentioned above, let historical data be the linguistic variable. First, define the main factor represented by fuzzy sets A_i. Each A_i($1 \le i \le n$) denotes a fuzzy set. Similarly define the second-factor represented by fuzzy sets B_i.

Step 4: Fuzzify all historical data

To fuzzify a historical data find an interval to which it belongs and assign the corresponding linguistic value to it.

Step 5: Construct all two-factor kth-order fuzzy relationship groups

After two fuzzy time series $F_A(t)$ and $F_B(t)$ have been created, we can find out all fuzzy relationships under different orders. The way to construct all two-factor first-order fuzzy relationship is to find any relationship consisting of the type $(F_A(t-1), F_B(t-1)) \Rightarrow FA(t)$, where $F_A(t-1), F_B(t-1)$, and $F_A(t)$ are called the current state and the next state, respectively. Then a fuzzy relationship can be obtained by replacing $F_A(t-1), F_B(t-1)$, and $F_A(t)$ with the corresponding fuzzy set.

Step 6: Calculate the forecasting value and create all fuzzy forecast rules based on all fuzzy relationship groups

In this step, calculate the forecasting value and create all fuzzy forecast rules based on all two-factor kth-order fuzzy relationship groups, respectively, and then find out the matched forecast rule to get the forecast value. Suppose the two-factor kth-order fuzzified historical data before day i are $(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2})$ and (A_{i1}, B_{i1}), where $A_{ik}, \ldots, A_{i2}$ and A_{i1} are fuzzified values of the main-factor of day i-k, . . ., i-2, and i-1, respectively, $B_{ik}, \ldots, B_{i2}$ and B_{i1} are fuzzified values of the second- factor of day i-k, . . . , i-2, and i-1, respectively, and $\lambda >= 2$.

First, we calculate the forecasting value using the two-factor kth-order fuzzy relationship groups based on the following cases.

Case 1: one member only

Suppose there is a group which has a member having the two factor kth-order fuzzy relationship shown as follows:

$(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2}), (A_{i1}, B_{i1}) \Rightarrow A_j$;

where the maximum membership value of A_j occurs at interval u_j, and the midpoint of interval u_j is m_j, then the forecasting value of day i is $0.5 * (A_{(i-1)} + m_j)$

Case 2: multiple members

Suppose there is a group which has multiple members and each member has a two-factor kth-order fuzzy relationship shown as follows:

$$(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2}), (A_{i1}, B_{i1}) \Rightarrow A_{j1};$$
$$(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2}), (A_{i1}, B_{i1}) \Rightarrow A_{j2};$$
$$\ldots$$
$$(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2}), (A_{i1}, B_{i1}) \Rightarrow A_{jp}$$

where the maximum membership values of $A_{j1}, A_{j2}, \ldots$ and A_{jp} occur at intervals $u_{j1}, u_{j2}, \ldots$, and u_{jp}, respectively, and the midpoints of $u_{j1}, u_{j2}, \ldots$ and u_{jp} are $m_{j1}, m_{j2}, \ldots$ and m_{jp}, respectively, then the forecasting value of day i is

$$0.5 * \left(A_{(i-1)} + \frac{\sum_{n=1}^{p} mjn}{p}\right).$$

Here repeated rules are considered as many number of times they occur, this gives them more weight on other rule as per there number of occurrence.

Case 3: a member with an unknown value

Suppose there is a group which has a member having the two factor kth-order fuzzy relationship with an unknown value shown as follows:

$$(A_{ik}, B_{ik}), \ldots, (A_{i2}, B_{i2}), (A_{i1}, B_{i1}) \Rightarrow \#;$$

where the symbol ‘‘#” denotes an unknown value, the maximum membership values of $A_{ik}, A_{i(k-1)}, \ldots$ and A_{i1} occur at intervals u_{ik}, $u_{i(k-1)}, \ldots$ and u_{i1}, respectively, and the midpoints of $u_{ik}, u_{i(k-1)}, \ldots$ and u_{i1} are $m_{ik}, m_{i(k-1)}, \ldots$ and m_{i1}, respectively, then the forecasting value of day i is

$$m_{i1} + \sum_{j=2}^{\lambda} \frac{m_{i(j-1)} - m_{ij}}{2^{(j-1)}}.$$

B. Training Phase is described as follows:

1. Define the universe of discourse as per step 1 in previous section.

2. Partition the universe into several intervals as per step2 in previous section.

3. Define fuzzy set linguistic terms(Step-3).

4. Apply PSO to generate rules as follows.

Particle swarm optimization is applied which repeatedly work on training data by modifying the interval size with an objective to reduce Average Forecast Error Rate(AFER) which is calculated as

$$\text{AFER}=\frac{\sum_{i=1}^{n}\frac{|Forecast\ value\ of\ day\ i-Actual\ value\ of\ day\ i|}{Actual\ value\ of\ day\ i}}{n}$$

Where n is the number of forecasted values.

PSO model can be used to forecast the new testing data. It works as follows: Let the number of the intervals of the main-factor be x, the lower bound and the upper bound of the universe of discourse on historical data $Y_A(t)$ of the main-factor be b_0 and b_x, respectively. Let the number of the intervals of the second-factor be y, the lower bound and the upper bound of the universe of discourse on historical data $Y_B(t)$ of the second-factor be d_0 and d_y, respectively. A particle is a vector consisting of $x + y - 2$ elements (i.e. $b_1,b_2, \ldots ,b_{j-1},b_j, \ldots , b_{x-2},b_{x-1}$, and $d_1,d_2,\ldots ,d_{k-1},d_k, \ldots ,d_{y-2},d_{y-1}$ where $1 \prec j \le x-1$, $b_{j-1} \le b_j$ and $1 \prec k \le y-1$, $d_{k-1} \le d_k$), based on these $x + y-2$ elements, define the $x + y$ intervals as $u_1 =[b_0,b_1)$, $u_2= [b_1,b_2), \ldots ,u_j = [b_{j-1},b_j), \ldots ,u_x = [b_{x-1},b_x]$, and $v_1 = [d_0,d_1),v_2= [d_1,d_2), \ldots ,v_k = [d_{k-1},d_k), \ldots ,v_y = [d_{y-1},d_y]$, respectively. If a particle moves to another position, the elements of the corresponding new vector need to be sorted to ensure that each element b_j ($1 \prec j \le x-1$) and d_k ($1 \prec k \le y-1$) arrange in non-decreasing order, respectively.

The PSO model exploits the intervals denoted by each particle to create an independent group of fuzzy forecast rules to forecast all main-factor historical training data and get the forecasted accuracy for each particle.

For the training phase, the PSO algorithm moves all particles to another position according to PSO equations of velocity and position, and the intervals of the main-factor and the second-factor of all particles are sorted in an ascending order, respectively. Then repeat the steps mentioned above to evaluate the forecasted accuracy of all particles until the pre-defined stop condition (the optimal solution is found or the maximal moving steps are reached) is satisfied. If the stop condition is satisfied, then all two-factor k^{th}-other fuzzy forecast rules trained by the best one of all personal best positions of all particles are chosen to be the final result.

C. Testing phase is described as follows:

For the testing phase, the PSO algorithm uses all well trained two-factor k^{th}-other fuzzy forecast rules to forecast the new testing data. The testing phase of the PSO algorithm is to perform a two-factor k^{th}-other fuzzy forecast rules table searching problem for matching parts of the forecast rules, then we can get a forecasted value from the forecasting part of the matched forecast rule as per forecast methods given in previous steps. The algorithm is given in detail as follows:

III. CASE STUDY

In this paper we applied the given method on data taken from the case study considered in paper by Hsu et al. on temperature prediction [12]. The steps for the method go as follows:

Step1: Define two universes of discourse $Y_A(t)$ and $Y_B(t)$

Here $Y_A(t)$ is average temperature per day and $Y_B(t)$ is average cloud density for 4 months of time. Now minimum data D_{min} and the maximum data D_{max} is calculated. Universe here is $Y_A(t)$ as [23.0,32.0] and $Y_B(t)$ as [0.0,100.0]

Step 2: Partition the universes $Y_A(t)$ and $Y_B(t)$ into several intervals.

In our approach we are using Automatic clustering algorithm as described in section III which cut the universe of discourse in some number of intervals. In this example $Y_A(t)$ is divided in 51 intervals and $Y_B(t)$ into 51 intervals as shown in Table III and Table IV.

Step 3: Define fuzzy set linguistic terms

According to the number of intervals fuzzy sets are defined. Main factor represented by fuzzy sets A_i. Each A_i($1 \le i \le 51$) and Secondary factor represented by fuzzy sets B_i. Each B_i($1 \le i \le 51$). These are shown in Table III.

Step 4: Fuzzify all historical data.

Fuzzification of historical data means to find out the interval in which the data point belongs and assign the corresponding linguistic variable to it. For example, the historical data on 23rd June, 1996, the actual daily average temperature and cloud density are 27.8°C and 63%, respectively. They belong to the intervals u_{21}=[27.75,27.85) and v_{37}=[61.5,64.5) respectively. Hence, we assign the fuzzy set A_{21} corresponding to interval u_{21} of the main-factor and assign the fuzzy set B_{37} corresponding to intervalv_{37} of the second-factor, respectively. The results of fuzzification are listed in Table IV.

Step 5: Construct all two-factor 2^{nd} order fuzzy relationships.

The way to construct all two-factor first-order fuzzy relationship is to find any relationship consisting of the type($F_A(t-1)$,$F_B(t-1)$)→$F_A(t)$, where $F_A(t-1)$,$F_B(t-1)$ and $F_A(t)$ are called the current state and the next state, respectively. Then a fuzzy relationship can be obtained by replacing, ($F_A(t-1)$,$F_B(t-1)$) and $F_A(t)$ with the corresponding fuzzy set. For example, (FA(August-1-1996), FB(August-1-

1996))→F_A(August-2-1996) is a relationship, and a fuzzy relationship (A_9,B_{21})→A_{19} is obtained by replacing (F_A(August-1-1996), F_B(August-1-1996)) and F_A(August-2-1996) to (A_9,B_{21}) and A_{19}, respectively.

Step 6: Calculate the fuzzy forecast values using the fuzzy linguistic rules.

When we are going to forecast the data $Y_A(t)$ based on the forecast rules, it is necessary to find out the matched forecast rule to get the forecasted value. If we use the two-factor second-order forecast rules in Table V to forecast the data $Y_A(t)$, we need to find out the corresponding linguistic values of ($F_A(t-2)$, $F_B(t-2)$) and ($F_A(t-1)$, $F_B(t-1)$) with respect to the data ($Y_A(t-2)$, $Y_B(t-2)$) and ($Y_A(t-2)$, $Y_B(t-2)$), and compare with all matching parts of the forecast rules, then we can get a forecasted value from the forecasting part of the matched forecast rule.

The advantages of using automatic clustering algorithm can be observed by the decrease in the Average Forecasting Error Rate in the training phase. The various error rates of training phases have been compared by Hsu et al. [12]. The minimum average error rate is 0.36%. The automatic clustering algorithm improves the results to 0.30% error in the training phase.

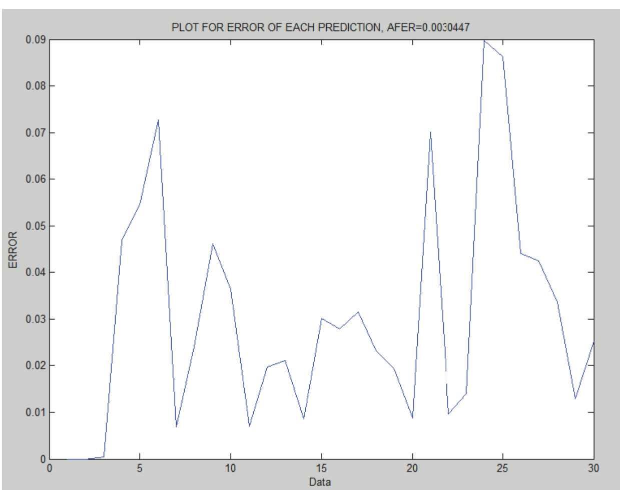

Figure I Fuzzy Training Phase error

Step 7: Modified Particle Swarm Optimization.

On training data PSO algorithm is applied as specified in Algorithm 2. The parameters of PSO model for the temperature prediction are set as follows. We simulated 10 runs in each order taking number of iterations to be 500, the number of particles be 40, the value of inertial weight as 0.3, c1 and c2 both as 2, the velocity of the main-factor, average temperature, limited to [-5, 5], the minimum velocity threshold of the main-factor V_{s1} as 0.001, the velocity of the second-factor, the daily cloud density be limited to [-50, 50], the minimum velocity threshold of the second-factor V_{s2} be 0.005.

In each iteration of PSO the intervals are modified such that AFER is reduced and new rules are generated corresponding to training data. At the end of 500 iterations the intervals and rules corresponding to global best are considered for forecasting. AFER for 10 iterations is shown in Fig II. To improve results for each forecast this procedure is run for 10 times and then average value is considered.

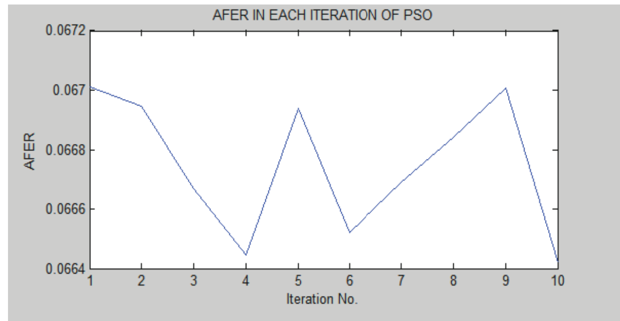

Figure II AFER in each iteration of PSO

Using these rules and intervals temperature is forecasted for month of September and AFER is calculated which comes to be less compared to already existing technique proposed bu Hsu et al.[12].

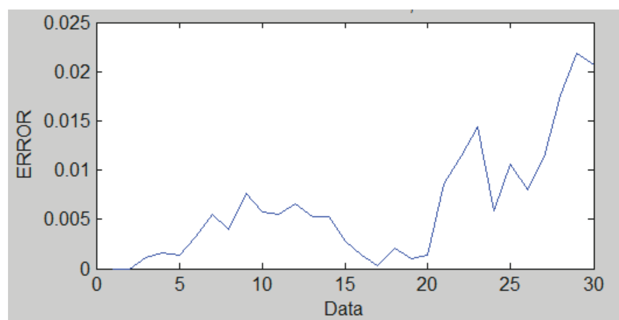

Figure III AFER of Hsu et al. prediction method(0.6852%)

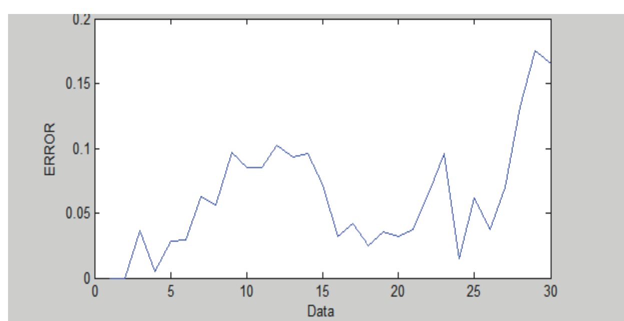

Figure IV AFER of proposed method(0.62359%)

The results are shown in graphs of Fig III and Fig IV. It can be seen that in this example AFER for this 30 day forecast AFER reduced from 0.68% to 0.62359 %.

IV. CONCLUSION

In this paper, we tried to improve the accuracy of forecast based on two-factor high-order fuzzy relationships and particle swarm optimization. The proposed method uses the MTPSO technique to adjust the length of each interval in the universe of discourse for the temperature prediction after the intervals are decide by Automatic clustering algorithm. The experimental results show that this method is an improvement to the existing method proposed by Hsu et al.[12]. The use of Automatic clustering algorithm improved the results in both the training phase and the testing phase.

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