Middle-East Journal of Scientific Research 22 (3): 458-463, 2014
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2014.22.03.21910

Improving Performance of Electricity Demand Forecasting using Variants of Particle Swarm Optimization

[1]S. Sridevi and [2]S. Rajaram

[1]Department of Computer Science and Engineering,
Thiagarajar College of Engineering, Madurai- 15, Tamilnadu, India
[2]Department of Electronics and Communications Engineering,
Thiagarajar College of Engineering, Madurai- 15, Tamilnadu, India

Abstract: In recent years, Fuzzy Time Series (FTS) is popularly used in forecasting since it handles nonlinear data. Fuzzy time series forecasting provides a powerful framework to handle hazy problems, so it is widely used in real time applications. Most of the fuzzy time series forecasting methods depend on universe of discourse and the length of intervals. In many existing works, number of intervals and length of intervals is fixed without assigning any reasons results in poor accuracy. To overcome these problems, the proposed work uses fuzzy C means (FCM) clustering algorithm along with variants of particle swarm optimization (PSO) to forecast the future values of time series data. In this work, Variants of PSO: standard PSO and weighted improved PSO are used to improve the forecasting accuracy. To show the effectiveness of the proposed algorithm, the method is tested with Australian electricity dataset. The results provide better forecasting accuracy than previous methods.

Key words: Prediction · Weighted Improved Particle Swarm Optimization (WIPSO) · Fuzzy C means (FCM) clustering algorithm · Fuzzy Time Series (FTS)

INTRODUCTION

Data mining is the process of extracting or "mining" knowledge from large amount of data. It allows users to analyze data from many different perspective or angles, categorize it and summarize the relationships identified. Basically data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. Data mining can be classified into temporal data mining, spatial mining, web mining, text mining and spatio- temporal mining. This work concentrates on temporal mining. Many fascinating and novel techniques of temporal data mining were proposed by Ale and Rossi [1] and shown to be useful in real applications. Temporal Data Mining is a rapidly evolving area of research. It is the intersection of several disciplines including statistics, time series analysis, temporal pattern recognition, optimization, visualization, high-performance computing and parallel computing. It can be used in variety of fields like weather prediction, stock market prediction, banking, fraud detection, targeted marketing and scientific data analysis. Temporal data mining uses time series or temporal databases. Now a days, most of the researchers use stationary time series data to verify the forecasting performance of their approaches or models. Time series can be viewed as a set of observations from a stochastic process. Both time series and temporal database contains attributes along with the time. The proposed work uses time series database to perform the forecasting. Forecasting can be divided into short term, medium term and long term forecasting. Short term forecasting involves the period between 1 day and 3 months. Medium term forecasting involves the period between 3 months and 3 years. Long term forecasting involves the period beyond 3 years.

In recent years, Fuzzy Time Series (FTS) is frequently used for forecasting since it handles nonlinear data. FTS method was introduced by Song and Chissom [2]. FTS can be divided into two subclasses: time variant and time invariant. Time invariant FTS makes the assumption

Corresponding Author: S. Sridevi, Department of Computer Science and Engineering, Thiagarajar College of Engineering, Madurai- 15, Tamilnadu, India.

that auto correlations do not change with respect to time. In the analysis of time invariant FTS, the determination of fuzzy logic relationships has immense impact on forecasting performance. However, when fuzzy logic group relationships tables are used, membership values of fuzzy sets are ignored. This situation causes information loss and decrease in the explanation power of the model. Huarng [3] introduced heuristic models to improve forecasting accuracy of fuzzy time series. Chen [4] proposed a forecasting model which is based on high-order fuzzy time series. This method is used to forecast the enrollments of University of Alabama. This model predicts the value based on fuzzy relationships of the historical data. In this model, fuzzification is done based on universe of discourse. In the earlier works, they used seven number of intervals in the fuzzification phase. No evidences are provided to fix this number of intervals.

From the above work, it is noted that adapting lengths of intervals and creating forecasting rules are two important issues considered to be critical. These issues are influencing the forecasting accuracy. Later, it is found that effective length of intervals can improve forecasting accuracy in FTS model. To resolve this issue, Huarng introduced two methods to adjust the interval lengths on Chen's FTS model. They are the average-based length and the distribution- based length, respectively.

The drawback of these FTS models is that they need high computation time when the fuzzy rule matrix is big. In this paper we present a new method for medium term electricity demand and weather forecasting. The method is based on Fuzzy C Means clustering (FCM) algorithm and variants of PSO (Particle Swarm Optimization). The proposed method constructs membership values based on the historical data and uses variants of PSO (Standard PSO and weighted improved PSO) to improve the forecasting accuracy rate.

The rest of the paper is organized as follows. Section 2 briefs the design methodology based on FCM and variants of PSO. Section 3 presents experimental results on the proposed work. Conclusion and future work is given in section 4.

MATERIALS AND METHODS

Existing Fuzzy Time Series (FTS) has three fundamental issues: determination of the number of intervals, selecting interval length and membership degrees. To fix the values of these parameters had a great impact in forecasting. In order to deal these problems, Cheng *et al*. [5]and Li *et al*. [6] used Fuzzy C-Means (FCM) clustering method for fuzzification. In the proposed work, FCM is used along with Particle Swarm Optimization (PSO) method to predict the future values of non-linear time series data. FCM algorithm is used in fuzzification phase to minimize the least squared errors within the groups. PSO is used to calculate membership values in the fuzzy relationship matrix. Design methodology for the proposed work is shown in Figure 1.

Based on the historical values, FCM algorithm calculates centroid cluster values. These cluster values are arranged in ascending order to generate the membership values. Based on membership values and parameters of PSO, defuzzified forecasts values are generated. In the proposed work Root Mean Squared Error (RMSE) is used as an objective function. The working principles of FCM and PSO are explained as follows:

Fuzzy C Means Clustering (FCM) Algorithm: FCM algorithm is an extension of K –Means algorithm. In FCM algorithm data can be assigned into more than one cluster. Fuzzy clustering is an approach operating towards fuzzy logic and it provides the flexible method of assigning the data points to the cluster. In clustering, deciding the number of clusters play a vital role. Correct number of clusters can be decided by using indices like silhouette index, Dunn index and Davies index. In the proposed work, FCM algorithm is used in fuzzification phase.

FCM Algorithm Consists of Following Steps:

- Generate c number of clusters randomly (Based on historical values) and arrange them in ascending order.
- Initialize $U= [u_{ij}]$ matrix, $U^{(0)}$. (1)
- For each iteration, calculate the center of the cluster and update the membership values using the following formula,

$$V_i = \frac{\sum_{j=1}^{n} x_j u_{ij}^{\beta}}{\sum_{j=1}^{n} u_{ij}^{\beta}} \quad (2)$$

$$U_{ij} = \frac{1}{\sum_{k=1(d(xj,vi)|d(xj,vk))}^{c} {}^{2/(\beta-1)}} \quad (3)$$

- If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then STOP; otherwise return to step 3. ε is a termination criterion between 0 and 1.

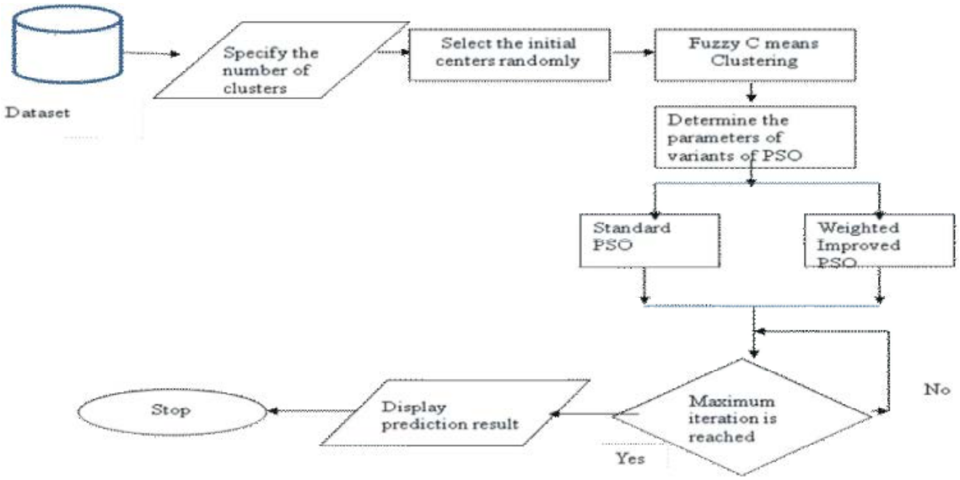

Fig. 1: Design Methodology

In the above equations, U_{ij} is the membership values, v_i is the center of cluster, n is the number of variables, c is the number of clusters. k is the number of iterations, β is a constant (β > 1) and called as fuzzy index. d (x_j, v_i) is a similarity measure between an observation and the center of corresponding fuzzy cluster. X_i and C_j be the historical data point and the centroid cluster value. Using the above algorithm, membership values are generated at each step until the termination criterion is satisfied. The output of FCM is given to the input of PSO.

Variants of Particle Swarm Optimization: Particle Swarm Optimization (PSO) method is a swarm intelligence and population based method for solving optimization problems. Since the PSO is based on a simple concept, it has been applied for complex real world problems. Each particle in PSO flies through the search space with its own velocity that is dynamically modified according to its own flying experience. Further, each particle has a memory and hence it is talented of remembering the best position in the search space ever visited by it. In the PSO, pbest and gbest plays an important role. Pbest is the best position for each particle. Each particle remembers the best position from its own flying experience. Gbest is the overall best out of all the particles in the population. Initial positions of pbest are different. Using the different direction of pbest and gbest, all particles progressively get close to the global optimum. PSO is an approach to problems whose solutions can be represented as a point in an n-dimensional solution space. To compare the performance of forecasting accuracy the proposed work uses: standard PSO and weighted improved PSO.

The two equations used in PSO are position update and velocity update equations. These equations are modified in an each iteration of the algorithm until it converges to the optimal. In general for an n-dimensional search space, the i^{th} particle of the swarm is represented by a n- dimensional vector, $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$. The velocity of this particle is represented by another n-dimensional vector, $V_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. The previously best visited position of the ith particle is denoted as $P_i = (p_{i1}, p_{i2}, \ldots, p_{id})$. Where i=1, 2 …n. n and d represents the number of particles in a swarm and positions respectively. The formula for updating positions and velocities of particles using standard PSO and weighted improved PSO are given below:

Standard PSO: New positions and velocities of the particles are calculated by using the formula

$$V_{i,d}^{t+1} = v_{i,d}^{t+1} + c_1 \times rand1 \times (p_{i,d} - x_{i,d}) + c_2 \times rand2 \times (p_{g,d} - x_{i,d}). \quad (4)$$

$$X_{i,d}^{t+1} = X_{i,d}^{t+1} + v_{i,d}^{t+1} \quad (5)$$

where rand1 and rand2 are random values between the interval [0 1]. C_1, C_2 are cognitive and social coefficients. $x_{i,d}$ represents i^{th} position of d^{th} particle, $p_{i,d}$ and $V_{i,d}^{t+1}$ are position and velocities of a particle. Gbest represents the best particle and Pbest is a vector stores the positions corresponding to the kth particle's best individual performance.

Weighted Improved PSO (WIPSO): Here the inertia weight, denoted by w is introduced in velocity update equations. New positions and velocities of the particles using inertia weight are calculated by using the formula:

$$V_{i,d}^{t+1} = [w + v_{i,d}^{t+1} + v_{i,d}^{t+1} + c_1 \times rand1 \times (p_{i,d} - x_{i,d}) + c_2 \times rand2 \times (p_{g,d} - x_{i,d})] \quad (6)$$

$$X_{i,d}^{t+1} = X_{i,d}^{t+1} + v_{i,d}^{t+1} \quad (7)$$

In the above equation inertia weight w is calculated by,

$$\text{Chaotic inertia weight } w = \text{WIPSO-1} = (w_1 - w_2) * \left(\frac{max\_iter - iter}{max\_iter}\right) + w_2 \quad (8)$$

$$\text{Linear inertia weight } w_k = \text{WIPSO-2} = w_2 - \frac{w_2 - w_1}{max\_iter} + k \quad (9)$$

In the above equations, max_iter and iter are maximum iteration number and current iteration number. W_1 and W_2 are user defined weight values.

Forecasting Algorithm using FCM and PSO is Explained as Follows:

- Determine the parameters value of particle swarm optimization.
- Determine the evaluation function. Here Root Mean Squared Error (RMSE) is used as an objective function.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [y_i - \hat{y}_i]^2} \quad (10)$$

where $\hat{y}_i$ and y_i are predicted and current prices/demand values and n is the number of samples.

- Generate a random initial population.
- Calculate the evaluation function values of all particles in the current swarm. RMSE is calculated by means of fuzzy relation matrix and defuzzify the fuzzy forecasts.
- According to RMSE, Pbest and Gbest particles are determined.
- Update PSO parameters if necessary.
- New positions of the particles for normal PSO and weighted improved PSO are calculated by using the formulas given in equations 4 and 6.
- Repeat Steps 4–7 until maximum iteration is reached.

The differences between the proposed method and the method presented in Aladag C.K. *et al*., (2012) are that the proposed method uses variants of PSO for dealing the forecasting problems. The proposed method provides a higher forecasting accuracy rate than the existing methods. Through the proposed work, it is proved that weighted improved PSO performs better than standard PSO.

RESULTS AND DISCUSSION

Dataset Selection for the Proposed System: In this work two different datasets: Electricity dataset (synthetic dataset) and Weather dataset (real dataset) are used for demonstrating the performance of standard PSO and weighted improved PSO. Electricity dataset contains region name, date with hour, price and demand. It shows the demand and price for every half an hour. This Australian Electricity Market dataset is collected from January 2011 to June 2014. The sample electricity dataset is shown in Table 1. Based on these data the user can able to predict the future value of the electricity price/demand. Another real dataset - Tamilnadu weather dataset contains the following fields: Date, place, max_temp, min_temp in Celsius and rainfall during last 24 hours. The data is collected from the period January 2012 to June 2014. The sample weather dataset is shown in Table 2. The above datasets is divided into training and testing set. In electricity dataset the training set is taken from the period January 2011 to December 2013 and testing set is analyzed from the period from January 2014 to June 2014. In weather dataset the training set is taken from the period January 2012 to December 2013 and testing set is analyzed from the period from January 2014 to June 2014. In addition to the above two datasets, this algorithm can also be applied for other datasets like calculating the volume of product sales, water demand forecasting and wind forecasting.

Performance Analysis of Variants of PSO: In the proposed work, FCM clustering algorithm is applied to variants of PSO. Variants of PSO include standard PSO and weighted improved PSO. Parameter settings for variants of PSO are shown in Table 3. In this work, acceleration constants $C_1$and C_2 are set in the range of 0.2 to 2. In most of the existing works, combinations of $C_1$and C_2 values are set to 4 and it should not exceed beyond 4. Similarly weights can be set to any values. In the proposed work maximum and minimum weight is set to 0.4 and 0.9 respectively since which give better accuracy when comparing with other values.

Table 1: Sample Data set for Electricity applications

Region	Settlement date	Total demand	Total price
NSW1	6/1/2006 3:30	7451	18.31
NSW1	6/1/2006 4:00	7262.58	17.33
NSW1	6/1/2006 4:30	7192.3	16.92
NSW1	6/1/2006 5:00	7252.37	17.31
NSW1	6/1/2006 5:30	7544.07	18.66
NSW1	6/1/2006 6:00	8020.28	21.15
NSW1	6/1/2006 6:30	8986.43	25.87
NSW1	6/1/2006 7:00	9922.95	30.54
NSW1	6/1/2006 7:30	10337.4	32.67

Table 2: Sample weather data set for Certain cities in Tamilnadu

Date	Place	Max-temp	Min-Temp	Rainfall
10/25/2013	Chennai	31	25	2
10/25/2013	Coimbatore	30	23	2
10/25/2013	Madurai	33	24	0
10/25/2013	Salem	31	23	0
10/25/2013	Trichy	32	25	0
10/26/2013	Chennai	31	25	1
10/26/2013	Coimbatore	30	23	0
10/26/2013	Madurai	35	25	0
10/26/2013	Salem	32	22	1
10/26/2013	Trichy	34	25	1

Table 3: PSO Parameter Setting

Parameter Name	Value
Swarm size	50
Initial inertia weight	1.5
Acceleration constants $C_1$and C_2	0.2 to 2
Maximum iteration No	100
W_1 and W_2	0.9, 0.4

Table 4: Performance Comparison of proposed method with existing method for Weather applications

Algorithm	MSE	RMSE
SPSO (Standard Particle Swarm Optimization)	0.12567	0.3545
WIPSO_1 (Weighted Improved Particle Swarm Optimization_1)	0.09005	0.300
WIPSO_2 (Weighted Improved Particle Swarm Optimization_2)	0.09432	0.307

Table 5: Performance Comparison of proposed method with existing method for Electricity Dataset

Algorithm	MSE	RMSE
SPSO (Standard Particle Swarm Optimization)	65.99	8.12
WIPSO-1 (Weighted Improved Particle Swarm Optimization-1)	54.45	7.37
WIPSO-2 (Weighted Improved Particle Swarm Optimization-2)	56.78	7.53

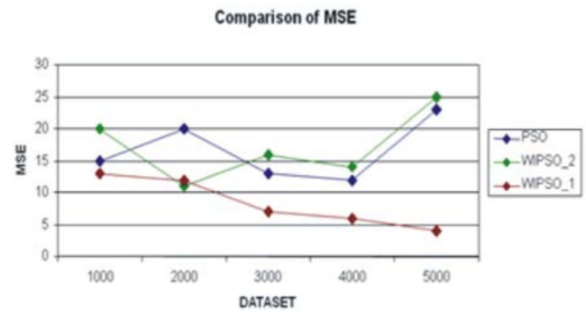

Fig. 2: Comparison of Error rate for standard PSO with WIPSO

Two different data sets are used to evaluate the performance of the proposed approach. The results obtained from the proposed method are compared with existing approaches. Performance is measured using MSE (Mean Squared Error) and RMSE (Root Mean Squared Error). MSE and RMSE values for weather and electricity dataset are shown in Table 4 and 5.

All the models have been executed 100 runs and the best result of all runs is taken to be the final result in the training phase and to forecast the testing data in the testing phase. Error rate for standard PSO with WIPSO is shown in Figure 2. From the figure and the resultant Table it is observed that WIPSO_1 works well than standard PSO.

CONCLUSION

Prediction using FCM algorithm along with variants of PSO is compared. The presented weight improved PSO algorithm has been applied to the real time problem. The performance of the WIPSO strategy has been compared to the standard PSO strategy using two different applications. The results show that WIPSO_1 gives better accuracy compared to standard PSO and WIPSO_2. Here the accuracy depends on information sharing among their population members to enhance their search processes using a combination of deterministic and probabilistic rules. Our Future work will focus on consideration of multi-observed variables and providing dynamic window size to predict the future values.

REFERENCES

1. Ale, J.M. and G.H. Rossi, 2000. An Approach to Discovering Temporal Association Rules. Proc. 2000 ACM Symp, Applied Computing (SAC ’00), pp: 294-300.

2. Song Q. and B.S. Chissom, 1993. Fuzzy time series and its models, Fuzzy Sets and Systems, 54: 269-277.
3. Huarng, K., 2001. Heuristic models of fuzzy time series for forecasting, Fuzzy Sets and Systems, 123: 369-386.
4. Chen, S.M., 1996. Forecasting enrollments based on fuzzy time series, Fuzzy Sets and Systems, 81: 311-319.
5. Cheng C.H., T.L. Chen, H.J. Teoh and C.H. Chiang, 2008. Fuzzy time series based on adaptive expectation model for TAIEX forecasting. Expert Systems with Applications, 34: 1126-1132.
6. Li S.T., Y.C. Cheng and S.Y. Lin, 2008, FCM-based deterministic forecasting model for fuzzy time series, Computers and Mathematics with Applications, 56: 3052-3063.
7. Hakan Aladag Cagdas, Ufuk Yolcu, Erol Egrioglu and Ali Z. Dalar, 2012. A new time invariant fuzzy time series forecasting method based on particle swarm optimization, Soft Computing, 12: 3291-3299.