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Power system short-term load forecasting based on PSO clustering analysis and Elman neural network

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Abstract:-This paper proposes a new approach based on particle swarm optimization (PSO) clustering analysis for short-term load forecasting (STLF). PSO is an intelligent evolutionary computation technique, it is a population-based stochastic search process, used to group historical load and weather data to each cluster which have highest similar characteristic data point. A forecasting model for each day in 24 points is established though selecting the data of learning samples by PSO clustering and using Elman neural network. This method gives sufficient play to the ability of processing non-linear problems by artificial neural network and intelligent evolutionary computation technique. The simulation results of daily and weekly loads forecasting for actual power system show that the proposed forecasting model can effectively improve the accuracy of short-term load forecasting.

Keywords: -STLF, Clustering Analysis, PSO

1. INTRODUCTION

Short-term load forecasting is an essential action in electric power operations. It is required for unit commitment, energy transfer scheduling and load dispatch. With the emergence of load management strategies, the short-term forecast is playing a broader role in utility operations. The development of an accurate, fast and robust short-term load forecasting methodology is of importance to both the electric utility and its customers. Lots of technologies have been used to solve this problem, including Regression model[1], Kalman filtering[2], Box & Jenkins model[3], Artificial Neural Networks[4], Chaos theory[5] and etc.

Artificial Neural Networks (ANN) that using non-linear modeling methods have been more and more regarded as an effective approach to the STLF problem[6][7]. The model proposed in this paper uses the Elman neural network using PSO algorithm carries on clustering analysis to the historical load data. The data of learning samples which have higher similar characteristic grouped by PSO clustering are used for the input variables in the model of Elman neural network. The grouping of similar daily load patterns allows prediction algorithms to reduce the forecasting error.

The rest of the paper is organized as follows: Elman neural network model based on PSO clustering is overviewed in Section 2. Section 3 presents how PSO algorithm to do the clustering analysis for the historical data. Simulation results are summarized in Section 4.

2. ELMAN NEURAL NETWORK WITH PSO CLUSTERING

Neural networks (NN) are useful for analyzing an objective variable in the presence of strong non-linearity and uncertainty. It has represented a very interesting and attractive way forward for STLF and this has been confirmed by the amount and quality of accounts presented in the literature.

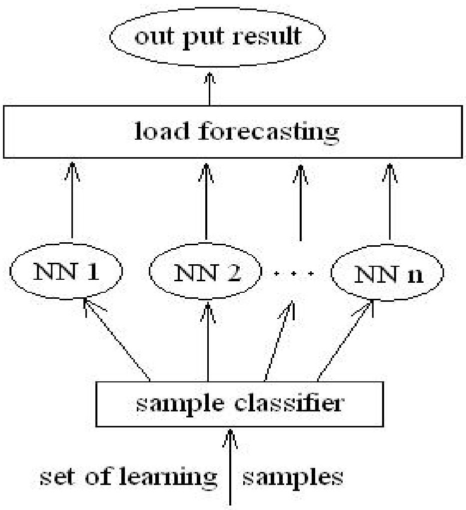

Fig1. Elman neural network model based on PSO clustering

The Elman network commonly is a two-layer network with feedback from the first-layer output to the first layer input[8]. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. The experiment we use Elman network for STLF show that this neural network play effectively a great role to improve the accuracy of the daily load forecasting.

Fig.1 is the structure of forecasting model this paper proposed. Firstly, the effect of the sample classifier is to group set of learning samples to each cluster by using the PSO clustering analysis. Then we can decide the forecasting day load belong to which cluster by calculating the Euclidean distance, and select the best samples to train the Neural networks (NN), then input data vectors to NN to do the forecasting. The number of NN is equivalent to cluster numbers we group.

3. DATA CLUSTERING USING PARTICLE SWARM OPTIMIZATION

3.1 Particle swarm optimization

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kenney and Eberhart in 1995[9]. The method has been developed through a simulation of simplified social models. PSO is based on swarms such as fish schooling and bird flocking. According to the research results for bird flocking, birds are finding food by flocking (not by each individual). PSO must also have a fitness evaluation function that takes the particle's position and assigns to it a fitness value. The position with the highest fitness value in the entire run is called the global best (P_g). Each particle also keeps track of its highest fitness value. The location of this value is called its personal best (P_i) .The basic algorithm involves casting a population of particles over the search space, remembering the best (most fit) solution encountered. At each iteration, every particle adjusts its velocity vector, based on its momentum and the influence of both its best solution and the best solution of its neighbors, then computes a new point to examine. The studies shows that the PSO has more chance to "fly" into the better solution areas more quickly, so it can discover reasonable quality solution much faster than other evolutionary algorithms. The original PSO formulate is described as

(1) and (2):

$$V_{id} = w\ V_{id} + c_1\ rand\ (P_{id} - X_{id}) + c_2\ rand\ (P_{gd} - X_{id}) \quad (1)$$

$$X_{id} = X_{id} + V_{id} \quad (2)$$

Where d is the number of dimensions (variables), i is a particle in the population, g is the particle in the neighborhood with the best fitness , V is the particle velocity vector, X is the location vector, and P is the position vector for a particle's best fitness yet encountered. Parameters c_1 and c_2 are the cognitive and social learning rates, respectively. These two rates control the relative influence of the memory of the neighborhood to the memory of the particle. $rand$ is a random number between (0,1). w is the inertia weight, it can adjust the moving speed value of the particles, as given below[10]:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} t_n \quad (3)$$

where $w_{\max}$ and $w_{\min}$ are the maximum and minimum weight value, respectively, t_n is the current number of iterations (or generations), and $t_{\max}$ represents the maximum number of iterations.

3.2 Historical data clustering using PSO

Data clustering is the process of grouping together similar multi-dimensional data vectors into a number of clusters or bins. The clustering aims at identifying and extracting significant groups in underlying data.

In order to reduce the forecasting error and improve the accuracy of the STLF, we use PSO algorithm to group historical load and weather data into different clusters, assign the highest similar characteristic data point to each cluster and the least similar characteristic data in the other clusters.

Traditional cluster algorithm such as well-know clustering technique K-means may get stuck at local optimal solution, depending on the choice of the initial cluster centers. It can't make sure to solve the global optimal solution every time. The proposed clustering analysis algorithm based on PSO needs the less parameter to decide and base on the minimum object function J_e to search automatically the data cluster centers of n-dimension Euclidean space R^n.

The paper introduce how to utilize the PSO clustering to distinguish the N historical data points into K groups, decide and update the center of each cluster. Each historical data point vector z_p including the information of daily historical load data and the next day's weather data with n dimensions. The data point vector z_p can be centralized to the closest cluster center m_j. The formula to decide the weight of the similarity is by using the Euclidean distance:

$$D = \left\| z_p - m_j \right\| \quad (5)$$

where: $p = 1,2,\ldots, N$, $j = 1,2,\ldots, K$

In the context of clustering, a single particle represents the K cluster cancroids vectors. That is, each particle X_i is constructed as follows:

$$X_i = (m_{i1}, \ldots, m_{ij}, \ldots, m_{iK}) \quad (6)$$

where m_{ij} refers to the j -th cluster centroid vector of the i -th particle in cluster C_{ij} .

The length of each particle is $K \times n$ words. C_j is the subset of data point vectors that form cluster j . Therefore, a swarm represents a number of candidate clusterings for the current load data vectors.

Using the proposed clustering analysis algorithm based on PSO, our historical data vectors for STLF can be clustered as follows:

Step1): Initialize each particle to contain K randomly selected cluster centroids, namely initialize positions vector X and velocity V of all particles in the population randomly. Here the position X of the particle is the center position of each cluster.

Step2): Evaluate the fitness (object) function for each particle. The method is assign each data point vector z_p , p =1,2,…, N , to cluster C_j j =1,2,…, K using equation (5).And the fitness function for this PSO clustering is given by:

$$J_e = \sum_{j=1}^{K}\sum_{p=1}^{N} \forall z_p \in C_j \left\| z_p - m_j \right\| \tag{7}$$

Step3): Compare particle's fitness evaluation with particle's best solution P_i . If current value is better than P_i , then reset P_i to the current particle's value and position.

Step4): Compare particle's fitness evaluation with the population's overall previous best. If current value is better than P_g (the global version of the best value), then reset P_g to the current particle's value and position.

Step5): Update the cluster centroids, namely change velocities and position using equation (1) and (2).

Step6): Repeat Step2)-Step5) until the maximum number of iterations is completes or a stop criterion is satisfied.

4. SIMULATION RESULTS

The proposed model is based on PSO clustering analysis and Elman neural network, The historical data being used in the forecasting should be grouped into each cluster by the PSO clustering analysis showed in section 2. A number of these shot-term forecasting historical data which have highest similar characteristic will be the training samples to input for Elman neural network. The data used in the experiments come from the power system in Shanghai city, China, in the year of 2001. In the experiments the load data be separated into two parts belonged to learning samples and forecasting samples, the forward are six-month period historical data already been grouped to each cluster, the latter are one month period data. All the data used in the experiments were firstly transferred to the interval of [0,1], after forecasting the real value will be transferred again.

For the PSO clustering analysis in section 2, used 20 particles and 4 clusters, let $c_1 = c_2$ =2.0 and $w_{\max}$ =0.4, $w_{\min}$ =0.1, $t_{\max}$ =1000, these values were chosen to ensure good convergence[11][12].Each historical data point vector z_p including 26 dimensions there are 24 hour load of the previous day corresponding the 24 dimensions, the other two dimensions corresponding the day's maximum and minimum temperature.

For Elman neural network, according engineering judgment and experience, used a three layered feed forward architecture with one input layer, one output layer and one hidden layer of neurons, with the structure {26-12-1}, the network training function that updates weight and bias values according to Levenberg-Marquardt optimization.

Calculate the historical data of the previous day, by using the minimum Euclidean distance to decide the forecasting day belong to which cluster and choose 20 closest learning samples to be the input of the Elman neural network. The forecasting result as follows:

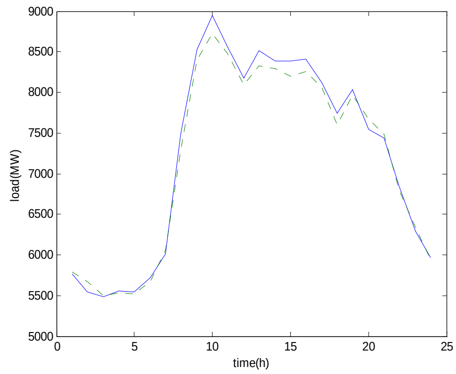

Fig.2. Real load (solid curve) and forecasting load (dotted curve) using ANN based PSO clustering model

Fig.2 and Fig.3 both the forecasting load of 12/9/2001, the first use PSO clustering to group the historical learning samples, the latter use merely the previous data by the sequence date before the forecasting day. According to table1 and this two forecasting curve in figures, we can see clearly that the proposed forecasting model in this paper effectively improve the accuracy of short-term load.

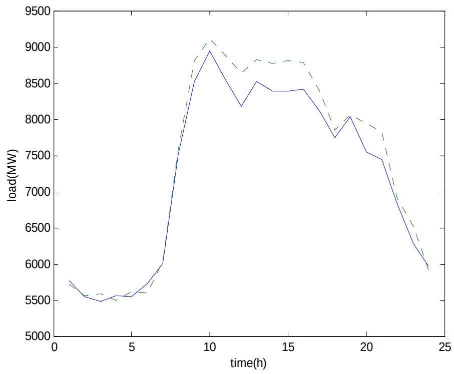

Fig.3 .Real load (solid curve) and forecasting load (dotted curve) using traditional ANN forecasting model

Tab.1 the percentage error of Fig2 and Fig3

hour	Relative error(%) of Fig2	Relative error(%) of Fig3
1	-0.3748	0.9214
2	-2.2737	-0.3723
3	-0.2116	-1.8754
4	0.5691	1.2727
5	0.2701	-1.3638
6	0.9684	2.1311
7	-0.8865	-0.3226
8	2.6676	-0.8639
9	1.5290	-3.3427
10	2.4172	-1.9287
11	1.0531	-3.8134
12	1.0260	-5.5543
13	2.2388	-3.5941
14	1.1443	-4.5157
15	2.2054	-5.0324
16	1.8670	-4.3954
17	0.6925	-3.4123
18	1.7336	-1.4465
19	0.8144	-0.3550
20	-1.6608	-5.2164
21	-0.6040	-5.1964
22	0.6335	-1.1087
23	-0.7884	-3.6228
24	0.2910	0.7165
Max error(%)	2.6676	5.5543
MAPE(%)	1.2050	2.5989

Table2 is the continuous load forecasting error in a week, and the result is satisfactory.

Tab.2 the forecasting error in a week

Date	Max error(%)	Min error(%)	MAPE
13/9/2001	2.7467	0.0202	1.2206
14/9/2001	4.8870	0.2293	2.0353
15/9/2001	5.5098	0.0761	2.2706
16/9/2001	7.5234	0.0568	2.2129
17/9/2001	4.1700	0.3488	2.0441
18/9/2001	6.0908	0.0055	2.6561
19/9/2001	5.3686	0.1962	2.3884

5. CONCLUSION

This paper presents an application of PSO clustering analysis and Elman neural network for short-term load forecasting in power system short-term. The historical learning samples have been assigned into each cluster which centralized highest similar characteristic data before selected the training samples. This method pre-treat the learning samples, effectively improve the accuracy of the load forecasting. The simulation results of daily loads forecasting show that the proposed forecasting model is an effective method of short-term load forecasting.

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