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A Parallel Network Clustering of Electric Loads Based *PSO*[1]

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Abstract: - A new parallel neural network clustering algorithm based particle swarm optimisation is presented. A large number of pieces of evidence are clustered into subsets.A nonlinear connection function is adopted in this neural network clustering algorithm, the centre of connection function is used to a particle, the whole neural network clustering object function can be expressed. A numerical example has been used to illustrate the effect of the algorithm on the characteristics clustering of electric loads. Many sets of load data measured from a power system have been dealt with using the method. The results of the study clearly indicate that the proposed method is very useful to load characteristics clustering for power system.

Key-Words: - characteristics clustering, clustering algorithm, load characteristics, neural network, *PSO*

1 Introduction

The process of grouping a set of physical or object into classes of similar object is called clustering, cluster analysis has been studied extensively for many years, focusing mainly on distance-based cluster analysis. Cluster analysis tools based on *k*-means, .*k*-medoids, and several other methods have also been built into system. Unlike classification, clustering and unsupervised learning do not rely on predefined classes and class-labeled training examples. Clustering is a form of learning by observation, rather than learning by examples. There are a large number of clustering algorithm. The choice of clustering algorithm depends both on the type of data available and on the particular purpose and application. In general, major clustering methods can be classified into partitioning methods, hierarchical methods, density-based methods, grid-based methods and model-based methods.

Neural network approach i approach to clustering tends to represent each cluster as an exemplar. New objects can be distributed to the cluster whose exemplar is the most similar, based on some distance measure. The attributes of an object assigned to a cluster can be predicted from the attributes of the clusters exemplar. There are two prominent methods of the neural network approach to clustering .The first is competitive learning, and the second is self-organizing feature maps. Several algorithm have discussed [1-6]

The particle swarm optimization (PSO) is a parallel evolutionary computation technique developed by Kennedy and Eberhart based on the social behavior metaphor. In this paper, A new neural network clustering algorithm based particle swarm optimisation is firstly presented. A large number of pieces of evidence are clustered into subsets by this algorithm. A nonlinear connection function is adopted. We regard the centre of connection function as a particle. A novel PSO use the group intelligence behavior to solve the optimization problem in this neural network clustering. A numerical example has been used to illustrate the effect of the algorithm on the characteristics clustering of dynamic loads. Many sets of load data measured from a power system in three years have been dealt with using the method. Experimental results show load characteristics have rule though they are random and time-varying proceedings.

The subsequent sections of the paper: In section 2 we describe architecture of the neural network clustering. In section 3 we describe the particle swarm optimization to solve the optimization problem. and a new neural network clustering algorithm based particle swarm optimisation and application in characteristics clustering of electric loads is discussed in section 4. In Finally, in section 5, conclusions are drawn

2 Architecture of The Neural Network

2.1 Kohonen Training Algorithm

The Kohonen SOM is a type of articialneural network. ANNs simulate the activity of the human brain. Part of the attractiveness of using ANNs is to perform subjective analyses, as opposedto the

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typically more objective analyses offered by general analytical procedures. The Kohonen SOM, like other ANNs, is used to perform tasks such as grouping, classification, forecasting and optimization. The SOM takes inputs in the form of vectors and classifies these inputs into groups . What sets the SOM approach apart from most other ANN approaches is that it is an unsupervised learning process, which means that n there is no prior known classification, as opposed to the supervised learning process of feedforward, backpropagation ANNs[7-8].

2.2 Architecture of The Parallel Neural Network Clustering

The neural network consists of two layers of neurons: an input layer and an output layer.too. Consider a sequence of training sample x_i,i=1,2,3…n. Each input sample x is tagged with its correct class membership. The number of class is m. There are $m \times n$ lines of connection in network. Unlike kohonen neural network, we adopt nonlinear connection function, we will discuss it in section 4. Fig 1 shows architecture of the neural network clustering

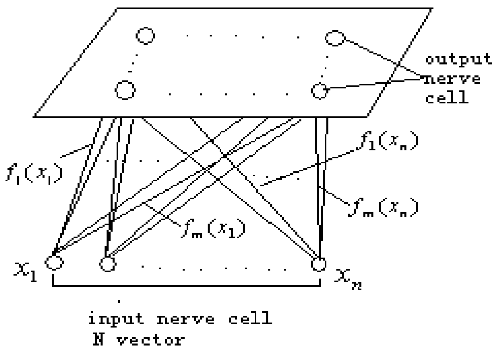

Fig 1 shows architecture of the neural network clustering

In data mining applications ,very large training samples sets of millions of samples are common. Hence, this restriction limits the scalability of some algorithms, where they can become inefficient due to swapping of the training samples in and out main and cache memories. In this paper ,first partitions the data into L subsets that individually fit into memory, and then we train L neural network using L subsets samples.

3 *PSO* to solve the optimization problem

3.1 Particle Swarm Optimization

The particle swarm optimization (PSO) is originally designed by Kennedy and Eberhart and has been compared to genetic algorithms for efficiently finding optimal or near-optimal solutions in large search spaces. The technique involves simulating social behavior among individuals (particles) “flying” through a multidimensional search space, each particle representing a single intersection of all search dimensions. The particles evaluate their positions relative to a goal (fitness) at every iteration, and particles in a local neighborhood share memories of their “best” positions, then use those memories to adjust their own velocities, and thus subsequent positions.

PSO technique is used to solve continuous combinatorial optimization problems [9,10], The inherent rule adhered by the members of birds and fishes in the swarm, enables them to move, synchronize, without colliding, resulting in an amazing choreography was the basic idea of PSO technique [11], task assignment problem are discussed in [12], nonlinear inertia weight variation for dynamic adaptation in particle swarm optimisation is discussed in [13] and Structural reliability assessment based on particles swarm optimisation is discussed in [14]

Let x and v denote a particle coordinates (position) and its corresponding flight speed (velocity) in a search space, respectively. The best previous position of particle is recorded and represented as *pbest*. The index of the best particle among all particle in the group is presented as *gBest.* To ensure convergence of PSO, this indicates that use of a constriction function may be necessary. At last, the modified velocity and position of each particle can be calculated as shown in the following formulas:

$$v_{i+1} = K \times [w \times v_i + \varphi_1 \times rand() \times (pBest - x_i) + \varphi_2 \times rand() \times (gBest - x_i)] \quad (1)$$

$$x_{i+1} = x_i + v_{i+1} \quad (2)$$

where i is pointer of iterations, x_i is the current position of particle at iteration i, v_i is the velocity of particle at iteration i, w is the inertia weight factor, φ_1, φ_2 is the acceleration constant, $rand()$ is the uniform value in the range[0,1], K is the constriction factor , is a function of φ_1, φ_2 as reflected in (3)

$$K = \frac{2}{\left|2 - (\varphi_1 + \varphi_2) - \sqrt{(\varphi_1 + \varphi_2)^2 - 4(\varphi_1 + \varphi_2)}\right|} \quad (3)$$

The inertia weight is set according to the following equation

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (4)$$

Where $iter_{\max}, iter$ is the maximum number of iterations, and the current number of iterations, respectively.

To ensure uniform velocity through all dimensions, the maximum velocity is as

$$v^{\max} = (x^{\max} - x^{\min}) / N \quad (5)$$

Where N is a chosen number of iterations.

3.2 *PSO* Algorithm

The algorithm is can be described in the following steps.

Step 1)Input parameters and boundaries of variable.:
Number_of_Agents; Weight, weight_up; Maxiter
Initialize randomly the particles

Step 2) Calculate the evaluation value of each particle. Compare each particle's evaluation with its *pBest*. The best evaluated value among the *pBest* is *gBest*. ;iter=0;

Step 3) iter=iter+1

Step 4) Each particle is evaluated according to its updated position. If the evaluation value of each particle is better than the previous *pBest*, the currentvalue is set to be *pBest*. If the best *pBest* is better than *gBest*, the value is set to be *gBest*.

Step 5) Update the inertia weight *w* given by （4）
or weight_up = (weight-0.4) *
(Maxiter - iter)/Maxiter +0.4;
Modify the velocity *v* of each particle according to（1）. If *v*＞*v*max, then *v* =*v*max. If *v*＜–*v*max, then *v* =-*v*max.
change the position of each particle according to（2）.

Step 6) If pbest[gbest] <=E_Cutoff || (iter >= Maxiter))
Then the particle that generates the latest *gBest* is the optimal value
exit
Else goto Step 3

4 A Parallel Network Clustering of Electric Loads Based *POS*

4.1 Nonlinear Connection Function:

The architecture of neural network is shown in Fig. 2, where $x = (x_1; x_2; : : : ; x_n)^T \in R^n$ is the input vector, $y = (y_1; y_2; : : : ; y_m)T \in R^m$ is the practical output vector and ˆ $y \in R^m$ is the predicting output vector of neural network, $f(x_i,x_i')$ is the nonlinear conection function. In this paper , connection function is defined as :

$$f(x_i, x_i') = \exp\left(-\frac{1}{2*\omega_i}\left\|x_i - x_i'\right\|^2\right) \quad (6)$$

x_i is the input sample of I dimension, x_i' is medoids of sample of I dimension, w_i is the width of this dimension, experimental result suggest that the value of w_i is equal to 0.1

4.2 Objective Function:

The whole neural network clustering object function can be expressed as

$$\min \quad S = \sum_{j=1}^{m} S_j \quad \text{where , } S_j \text{ is}$$

$$S_j(X_h) = \sum_{h=1}^{H-k}\sum_{g=1}^{H-k}\left(1 - \exp(-\sum_{i=1}^{n}\left|x_{hi} - x_{gi}\right|)\right), h \neq g \quad (7)$$

$j \in \{1,2,\ldots,m\}$ is label of output .neuron, $h \in \{1,2,\ldots,H-k\}$ is the number of clustering samples in one neuron. $i \in \{1,2,\ldots,N\}$ is sample dimension. x_{hi} is the data of h sample in I dimension and x_{gi} is the data of g sample in I dimension

4.3 Design of the Neural Network Clustering Algorithm Based on *POS*

The algorithm is can be described in the following

Step 1)Input parameters and boundaries of variable.:
Number_of_Agents; Weight, weight_up; Maxiter
nitialize randomly the particles

Step 2) partitions the data into L subsets

Step 3) do {

Step 4) do {input one sample;
calculate $f(x_i,x_i')$,
clustering output neuion }
while all sample

Step 5) calculate S_j and S ; S is result of this train neural network clustering }
while L training neural network clustering

Step 6) x_i' ,the medoids of sample of $f(x_i,x_i')$ is regarded as a $m \times n$ dimension particle.

Step 7) change the position of each particle based pso

Step 8)If pbest[gbest] <=E_Cutoff || (iter >= Maxiter))
Then the particle that generates the latest *gBest* is the optimal value
Exit Else goto Step 3

4.4 Application in characteristics clustering of electric Loads

As open access market principles are applied to power system, power system has changed from the cost based operations to bid based operations. It created competition and trading mechanisms for market participants. [15-18]

We input sample *x*, with 12 dimension in access database. The recorder is 234.The result of clustering samples in every neuron of output layer is shown in table 1

Table 1The clustering samples in every neuron of output layer

output . neuron number	Clustering samples bumber
1	40,51,54,73,76,88,93,95,115,117,130,139,141,142,168,172,185,190,201,206,209,212,213,224,231
2	28,57,61,63,79,87,129,145,151,157,158,163,165,171,183,204,207,214,228
3	7,12,17 ,42,43,64,89,98,100,103,110,136,148,161,181,191,195,199,221,230,232
4	1,4,,5,6,8,19,20,22,25,27,29,36,48,50,65,66,68,69,71,72,77,78,82,83,84,96,99,101,104,106,107,111,120,124,126,128,131,133,134,138,159,170,173,177,182,186,,188,192,196,197,198,200,203,219,220,222,223
5	45,56,58,81,86,90,116,146,166,174,225
6	0,2,24,34,62,80,94,102,105,108,112,123,136,148,161,181,191,195,199,221,230,232
7	10,13,18,30,38,46,47,49,53,59,60,74,75,85,91,118,121,127,135,137,140,143,144,147,152,153,154,160,184,187,189,210,211,216,217,226,234
8	11,16,26,31,37,41,67,92,114,149,162,233
9	3,9,14,15,21,23,32,33,39,44,52,55,70,97,113,132,150,156,167,169,175,176,179,193,202,205,208,215,218,229

The distributing pattern for clustering samples is shown in Fig. 2

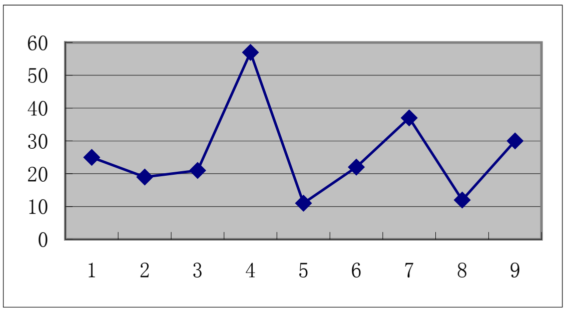

Fig.2 The distributing pattern for clustering samples

A new neural network clustering algorithm based on pso is firstly presented for the characteristics clustering of dynamic loads With the development of measurement-based modeling approach, the characteristics clustering and synthesis of electric dynamic loads arise.

In accordance with the problem that some parameters can be identified easily and other parameters are difficult to be identified in the load modeling of induction motor, we elucidate the relations between the parameter sensitivity and the parameter identifiability through the analytic sensitivity analysis.

5 Conclusion

A novel PSO use the group intelligence behavior to solve the optimization problem in this neural network clustering The algorithm for the characteristics clustering of dynamic loads. Many sets of load data measured from a power system in three years have been dealt with using the method. Experimental results show load characteristics have rule though they are random .We will obtain the global load model for describing the nonlinear characteristics of the electric loadr. It will automatically produce the If-Then rules, whose premise parameters and consequent parameters are adjusted by using a Back-Propagation algorithm in combination with the least squares method. The simulation results also show the feasibility of the method.

References:

[1] Jiawei Han, Micheline kamber Data Mining Concepts and Techniques Morgan Kaufmann Pub. 2001,P225.

[2] U. Bergsten, J. Schubert, and P. Svensson. Applying data mining and machine learning techniques to submarine intelligence analysis. In *Proceedings of the Third International Conference on Knowledge Discovery and Data Mining* (KDD'97), pp: 127–130, Newport Beach, August 1999

[3] T. Uchiyama，M. A. Arbib，An algorithm for competitive learning in clustering problems，Pattern Letters ， vol. 27,no. 10 ，pp.1415-1421，1994

[4] L. Xu，A. Krzyzak，E. Oja，Rival penalized competitive learning for clustering analysis，RBF net ， and curve detection ， IEEE Transactions on neural networks， vol. 4，no.3,pp. 636-649，June. 1993

[5] J. F. Yang ， C. M. Chen ， A dynamic k-winners-take-all neural network ， IEEE Transactions on SMC，vol. 27，no. 3，pp. 523-526，June 1997

[6] L. P. Wang，On competitive learning，IEEE Transactions on neural networks，Vol. 8，No. 5，pp. 1214-1217，Sep. 1997

[7] T. Kohonen, E. Oja, O. Simula, A. Visa, J. Kangas, Engineering application of the self-organising map, Proc. IEEE , vol.84 ,no.10, pp:1358_ 1384., 1996

[8] IZ. Qiuming, C. Yao, L. Luzheng, A global learning algorithm for a RBF network, Neural

Network, pp 527–540. Dec. 1999

[9] K.E. Parsopoulos, M.N. Vrahatis, Recent Approaches to Global Optimization Problems Through Particle Swarm Optimization, Natural Computing 1, Kluwer Academic Publishers, The Netherlands, 2002, pp. 235–306.

[10]H. Yoshida, K. Kawata, Y. Fukuyama, S. Takayama, Y. Nakanishi, A particle swarm optimization for reactive power and voltage control considering voltage security assessment, IEEE Trans. Power Syst. Vol.15 ,no:4,pp1232–1239., 2000

[11] J. Kennedy, R. Eberhart, Particle swarm optimization, vol. IV, in: Proceedings of IEEE International Conference on Neural Networks (ICNN'95), Perth, Australia, 1995, pp. 1942–1948.

[12]He,S Wu, Q.H Wen,J.Y, Saunders, J.R,; Particle swarm optimization for task assignment problem,Biosystems vol.78, no.1,pp.135-147 ,December, 2004,

[13]Chatterjee, A,Siarry,P Nonlinear inertia weight variation for dynamic adaptation in particle swarm optimization Computers and Operations Research. vol: 33, no: 3, pp. 859-871, March, 2006

[14]Elegbde,Charles Structural reliability assessment based on particles swarm optimization vol: 27, no: 2, pp. 171-186, April, 2005

[15].Ma Rui, He Renmu, et al. Multiobjective optimisation tranaction model incorporating load static voltage characteristics. *Proceeding of the CSEE*,vo2.2 no.9,pp.1-5,2002.

[16]Ma Rui,Yan Hongwen A New Data-Mining FrameworkBased on Decision-Tree for Competitive Bidding Assessment In Power Market Automation Of Electric Power Systems ,volume 26, Number 8,.2002, pp.22-25

[17]Rui Ma, Renmu He, Hongwen Yan. Novel Multi-objective Optimal Block and Group Bidding Model for Hydrothermal Power Market. Proceeding of the CSEE, vol.24, no 11, 2004,pp.53-57.

[18]Ma Rui. A novel bi-Objective fuzzy optimal short-term trade planning model considering environment proection and economy profit in deregulated power system. *Proceeding of the CSEE*,vo2.2 no.4,pp.104-108,2002.