

An Improved Mamdani Fuzzy Neural Networks Based on PSO Algorithm and New Parameter Optimization

Lei Meng^{*1}, Shoulin Yin², Xinyuan Hu³

^{1,2,3}Software College, Shenyang Normal University

No.253, HuangHe Bei Street, HuangGu District, Shenyang, P.C 110034 - China

*Corresponding author, email: 8871346@qq.com¹; 352720214@qq.com²; 1138074916@qq.com³

Abstract

As we all know, the parameter optimization of Mamdani model has a defect of easily falling into local optimum. To solve this problem, we propose a new algorithm by constructing Mamdani Fuzzy neural networks. This new scheme uses fuzzy clustering based on particle swarm optimization (PSO) algorithm to determine initial parameter of Mamdani Fuzzy neural networks. Then it adopts PSO algorithm to optimize model's parameters. At the end, we use gradient descent method to make a further optimization for parameters. Therefore, we can realize the automatic adjustment, modification and perfection under the fuzzy rule. The experimental results show that the new algorithm improves the approximation ability of Mamdani Fuzzy neural networks.

Keywords: PSO algorithm, Mamdani Fuzzy neural networks, Fuzzy clustering, Gradient descent method

Copyright © 2016 Institute of Advanced Engineering and Science. All rights reserved.

1. Introduction

Fuzzy neural network [1, 2] combine fuzzy system and neural network, it absorbs the advantages of fuzzy system and neural network, which not only owns the fitting ability and learning ability of neural network, but has strong structural knowledge expression ability of fuzzy logic. Fuzzy neural network learning mainly has two parts: the structure identification and parameter estimation [3]. Structure identification means that it determines the rules number of the fuzzy system, the number and shape of the membership function according to certain performance requirements. The traditional way makes a acquisition through expert knowledge. In recent years, many researchers use fuzzy clustering method to get the initial fuzzy rule base, which avoids the blindness and randomness of the traditional method. Parameter learning makes further optimization for parameters after determining the initial structure.

Deka [4] proposed a new approach to river flow prediction using a fuzzy neural network (FNN) model which combined the learning ability of artificial neural networks with the merits of fuzzy logic. Zhang [5] combined fuzzy control with artificial neural network control, both played to the advantages of fuzzy control was robust, and finally through numerical computation of structural language experience, positive identification in parallel, it greatly increased the stability of mill running processing. Ghiasi [6] presented the development of an intelligent model based on the well-proven standard feed-forward back-propagation neural network for accurate prediction of TEG purity based on operating conditions of reboiler. Capability of the presented neural-based model in estimating the TEG purity was evaluated by employing several statistical parameters.

Although the Particle Swarm Optimization (PSO) has the ability of global search and fast convergence speed, it has poor local search ability at the late training. Meanwhile, gradient descent method has better local search ability.

Therefore, to solve the above problems, this paper proposes fuzzy clustering based on PSO algorithm to acquire initial parameters of fuzzy systems when optimizing parameters of Mamdani Fuzzy neural networks. Then it uses the combined method between PSO and gradient descent method to make further optimization for parameters of Fuzzy neural networks. The experimental results show that the new method improves the approximation ability of Mamdani fuzzy neural network. The paper's structures are as follows. In section2, we introduce PSO algorithm. Section3 illustrates Initial structure of Mamdani Fuzzy neural networks. Fuzzy neural networks and the new algorithm is represented in section4 and section5 respectively. We

explain parameter learning in section6. It conducts some experiments for our new algorithm in section6. Finally, we give a conclusion in section7.

2. PSO Algorithm

PSO algorithm [7-9] is a global optimization technique based on swarm intelligence, it makes intelligent search for solution space through the interaction of particles, then it aims to find the optimal solution.

Supposing in a D -dimension target searching space, each particle is regarded as a point in the space. There are m particles to form a group. $z_i = (z_{i1}, z_{i2}, \dots, z_{iD})$ is position vector of i -th particle. $v_i = (v_{i1}, v_{i2}, \dots, v_{iD})$ is the flying speed of i -th particle. The position Z of each particle is a potential solution. It can calculate the current fitness value of each particle according to fitness function. It will adjudge which particle is the optimal solution according to the fitness value. Before t iterations, the i -th particle searches optimal position recorded as $p_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. At each iteration, particle updates speed and position through (1) and (2).

$$v_{id}^{t+1} = wv_{id}^t + c_1 rand_1() \cdot (p_{id}^t - z_{id}^t) + c_2 rand_2() \cdot (p_{gd}^t - z_{id}^t) \quad (1)$$

$$z_{id}^{t+1} = z_{id}^t + v_{id}^{t+1}, \quad d = 1, 2, \dots, D \quad (2)$$

Where $c_1 = 2$ and $c_2 = 2$ is acceleration coefficient. $rand_1$ and $rand_2$ is the random number ranging [0,1], which is used to keep the population diversity. w is inertia weight factor which has an important effect on the optimal performance. Bigger w is conducive to jump out of minimum point and smaller w is conducive to algorithm convergence. We always use (3) to update.

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} iter \quad (3)$$

Where $iter$ is current iterations, $iter_{\max}$ is the maximum iterations.

3. Initial Structure of Mamdani Fuzzy Neural Networks

Fuzzy c-means clustering [10, 11] based on PSO algorithm can divide known data into C categories. Supposing the optimal particle is $z_i = (z_1, z_2, \dots, z_C)$. $z_i = (z_{i1}, z_{i2}, \dots, z_{iD-1}, z_{iD})$ is the corresponding clustering center. Each cluster center has a corresponding fuzzy rule. $D-1$ clustering centers are the input. The D -th clustering center is output. C is the number of fuzzy rules. Membership function can use Gaussian function to express.

$$\mu_{A_j^i}(x_i) = e^{-\frac{(x_i - m_{ji})^2}{2(\sigma_{ji})^2}}, \quad j = 1, 2, \dots, C \quad (4)$$

Where m_{ji} and σ_{ji} are center and variance of Gaussian function respectively. The initial value of m_{ji} is z_{ji} . The width of membership function can be calculated by :

$$\sigma_{ji}^2 = \frac{\sum_{k=1}^n (\mu_{jk})^q (x_{ki} - m_{ji})^2}{\sum_{k=1}^n (\mu_{jk})^q}, \quad q \geq 1 \tag{5}$$

The fuzzy rule system adopts the Gaussian function, product inference engine, singleton fuzzifier and center average defuzzifier to get the system output:

$$y = \frac{\sum_{j=1}^C \alpha_j w_j}{\sum_{j=1}^C \alpha_j}, \quad w_j = z_{Dj}, \quad \alpha_j = \prod_{i=1}^{D-1} \mu_{A_i'}(x_i) \tag{6}$$

4. Fuzzy Neural Networks

Fuzzy neural network is divided into four parts as figure1.

- a. Input layer. Each neuron accepts a data signal, and transfer to next layer.
- b. Membership function layer. Raw data is divided into C category through fuzzy cluster. Therefore, each group have C neurons. Its membership function is as formula (4).
- c. Fuzzy reasoning layer. Each node represents a fuzzy rules, its function is to match the former of fuzzy rules, and calculate the compatibility of each rule. This layer has C neurons. The *i*-th neuron only accepts output of *i*-th in the former group as α_j in (6).
- d. Output layer. Its function is to realize accurate calculation, output is as *y* in (6). Objective function of the network training is defined as (7):

$$E = \frac{1}{2N} \sum_{i=1}^N (y_i - y')^2 \tag{7}$$

Where *y* is the actual output of fuzzy system. *y'* is desired output.

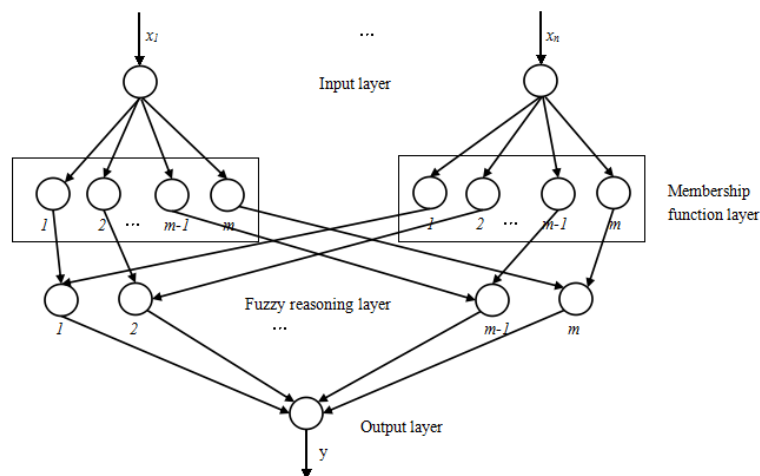


Figure 1. Fuzzy neural network

5. The Improved Mamdani Fuzzy Neural Networks Based on PSO Algorithm and New Parameter Optimization

5.1. Fuzzy c-means Clustering Based on PSO Algorithm

Its processes are as follows.

- Making fuzzy c-means clustering for sample data $X = \{x_1, x_2, \dots, x_n\}$. Generating C clustering centers. C clustering centers form one particle. Repeating N times and producing N particles z_1, z_2, \dots, z_N . It starts to real-number encoding for z_1, z_2, \dots, z_N . And $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, z_i is one-dimensional row vector of $C \times D$ column.
- Calculating the membership matrix U of sample data for each particle.
- Calculating fitness value of every particle and finding individual optimal value p_i and global optimum value p_g .
- Updating speed and position of each particle according to (1) (2) and generating particle swarm of next generation.
- If it reaches the maximum iterations, then stopping iteration. Finding the optimal solution at the last generation. Otherwise, go to step b.

5.2. Parameter Learning

Mamdani Fuzzy neural networks [12-15] determine initial parameters of the fuzzy rule base through fuzzy clustering based on PSO algorithm. Traditional gradient descent method is sensitive to the initial value and easy to fall into local optimal. However, particle swarm optimization algorithm has strong global search ability and fast convergence speed. When one point is near optimal point, it is unable to accurately determine the position of the optimal solution, that is, its local search ability is weak. Therefore, this paper regards formula (7) as objective function when parameter learning. It first uses PSO to make global optimization for initial parameters of the fuzzy rule base, when it is up to number of maximum iterations or objective function is less than a certain threshold, it uses gradient descent method to adjust $(m_{ji}, \sigma_{ji}, w_j)$ and it will has higher accuracy, and finally gets the ideal fuzzy rule base.

6. Experimental Results

We use two approximation function to verify the paper's new scheme.

- $f^1(x) = \frac{\sin x}{x}$;
- $f^2(x_1, x_2) = 0.5(1 + \sin 2\pi x_1 \cos 2\pi x_2)$

Under the MATLAB platform, we make approximation experiments and get figure2,3. Two functions select 200 for input/output data in the respective domain respectively. Setting number of clustering is 21, number of particle swarm is 30, number of maximum iterations is 500, the largest threshold is 0.1×10^{-5} .

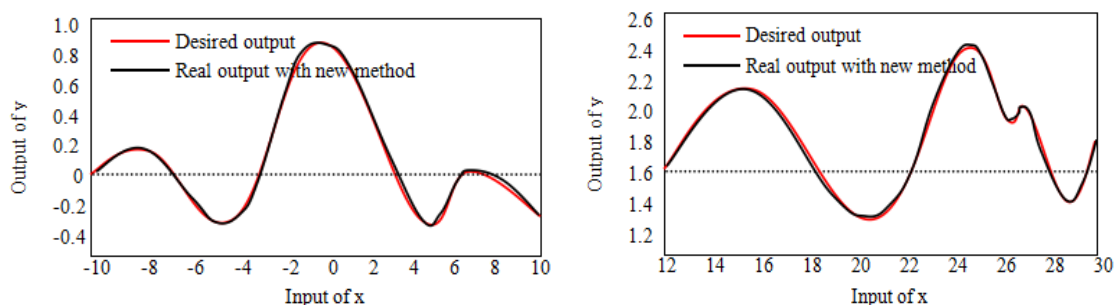


Figure 2. The approximation result of function f^1

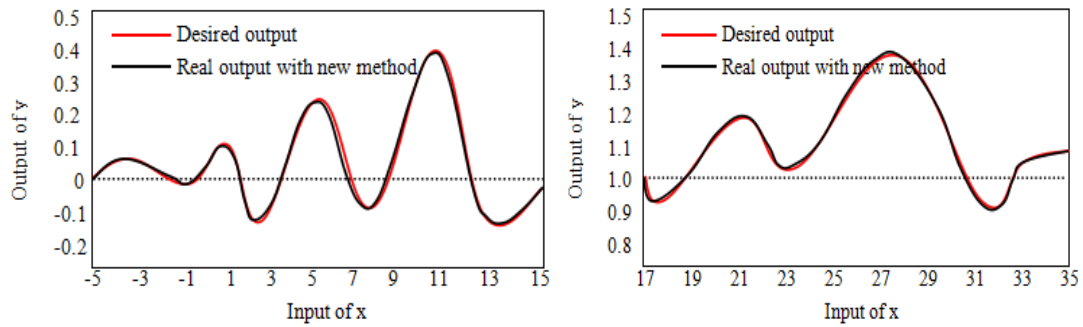


Figure 3. The approximation result of function f^2

We also make comparison with PSO algorithm and this paper's new method and get figure4. As can be seen from the fig4, though PSO and new scheme has the similar trend, at the turning point, it shows the obvious gap between the two curves. What's more, we obtain the error figure5. The new algorithm can reach the convergence in a short time.

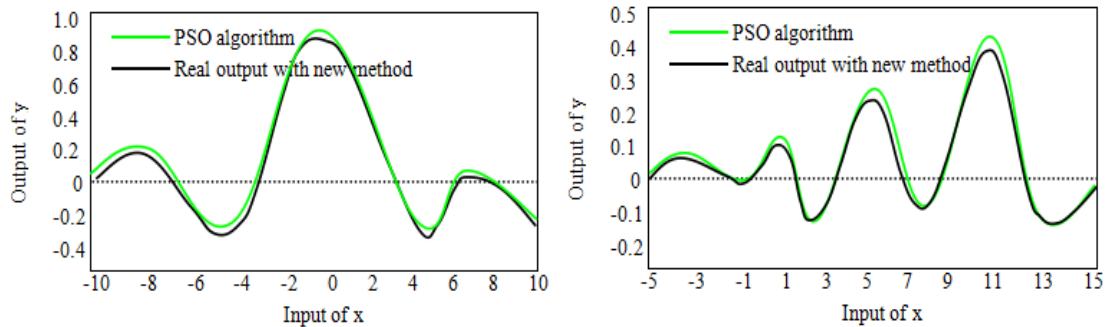


Figure 4. Comparison with f^1 and f^2 respectively

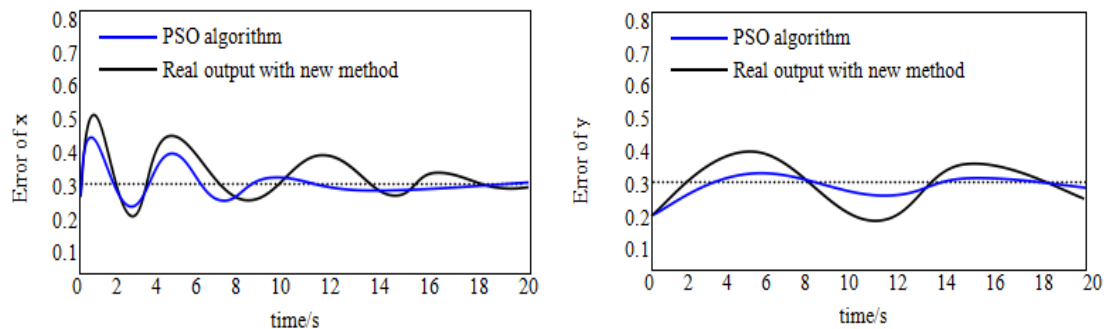


Figure 5. The errors at x-axis and y-axis using different method

7. Conclusion

Fuzzy clustering based on particle swarm optimization (PSO) algorithm generates an initial fuzzy rule base. Then it uses particle swarm optimization algorithm and gradient descent method to study the initialization parameters, which makes full use of the global search ability of particle swarm algorithm and local search ability of gradient descent method. That makes the parameters in the fuzzy rule base has higher accuracy. Finally, experimental results show that the new method improves the Mamdani fuzzy neural network approximation ability effectively.

Acknowledgment

The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

References

- [1] Chaves P, Kojiri T. Stochastic Fuzzy Neural Network: Case Study of Optimal Reservoir Operation. *Journal of Water Resources Planning & Management*. 2014; 133(6): 509-518.
- [2] Zhou YH, Hong-Wei MA. Synchronized Control of Shearer Traction Motors Based on Dynamic Fuzzy Neural Network. *Coal Mine Machinery*. 2014.
- [3] Chen HF, Zhao W, Chen HF, et al. Recursive identification and parameter estimation. *Taylor & Francis Usa*. 2014.
- [4] Deka P, Chandramouli V. Fuzzy Neural Network Model for Hydrologic Flow Routing. *American Society of Civil Engineers*. 2014; 10(4): 302-314.
- [5] Zhang J, Wang JM, Yang ZG, et al. Application of Fuzzy Neural Network in Mill Load Control. *Instrument Technique & Sensor*. 2014.
- [6] Ghiasi MM, Bahadori A, Zendehboudi S. Estimation of triethylene glycol (TEG) purity in natural gas dehydration units using fuzzy neural network. *Journal of Natural Gas Science & Engineering*. 2014, 17(2):26–32.
- [7] Zhi XH, Xing XL, Wang QX, et al. A discrete PSO method for generalized TSP problem[C]// *Machine Learning and Cybernetics*. Proceedings of 2004 International Conference on. IEEE. 2014; 4: 2378-2383.
- [8] Hsieh YZ, Su MC, Wang PC. A PSO-based Rule Extractor for Medical Diagnosis. *Journal of Biomedical Informatics*. 2014; 49(6): 53-60.
- [9] Inbarani HH, Azar AT, Jothi G. Supervised hybrid feature selection based on PSO and rough sets for medical diagnosis. *Computer Methods & Programs in Biomedicine*. 2014; 113(1): 175-185.
- [10] Yang X, Zhang G, Lu J, et al. A Kernel Fuzzy c-Means Clustering-Based Fuzzy Support Vector Machine Algorithm for Classification Problems with Outliers or Noises. *Fuzzy Systems IEEE Transactions on*. 2014; 19(1): 105 - 115.
- [11] Zarinbal M, Zarandi MHF, Turksen IB. Relative entropy fuzzy c-means clustering. *Information Sciences an International Journal*. 2014; 260(1): 74-97.
- [12] Soldatova OP, Lyozin LA. Research of Classification Tasks Solving Using Neural Fuzzy Production Based Network Models of Mamdani–Zadeh. *Vestn. Samar. Gos. Tekhn. Univ. Ser. Fiz.-Mat. Nauki*. 2014: 136–148.
- [13] Dahal K, Almejalli K, Hossain M A, et al. GA-based learning for rule identification in fuzzy neural networks. *Applied Soft Computing*. 2015; 35: 605–617.
- [14] Sebastiao A, Lucena C, Palma L, et al. Optimal tuning of scaling factors and membership functions for mamdani type PID fuzzy controllers//Control. Automation and Robotics (ICCAR), 2015 International Conference on. IEEE, 2015: 92-96.
- [15] Shokri BJ, Ramazi H, Ardejani FD. Prediction of Pyrite Oxidation in a Coal Washing Waste Pile Applying Artificial Neural Networks (ANNs) and Adaptive Neuro-fuzzy Inference Systems (ANFIS). *Mine Water & the Environment*. 2014; 33(2): 146-156.