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Fuzzy neural network optimization and network traffic forecasting based on improved differential evolution

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HIGHLIGHTS

- This paper combines the differential evolution algorithm with the BP algorithm, and proposes an improved differential evolution BP algorithm to optimize the fuzzy neural network forecasting network traffic.
- An improved differential evolution algorithm using the adaptive mutation operator and Gaussian disturbance crossover operator aims to improve the mutation of standard differential evolution algorithm and the design of crossover operators.
- Simulation results show that the convergence speed and forecasting accuracy of the proposed algorithm are better than that of the traditional fuzzy neural network algorithm.

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ABSTRACT

The traditional fuzzy neural network often uses BP algorithm to optimize parameters when conducting parameter identification. However, BP algorithm tends to be trapped in local extremum. In view of the shortcomings of this method, this paper combines the differential evolution algorithm with the BP algorithm, and proposes an improved differential evolution BP algorithm to optimize the fuzzy neural network forecasting network traffic. In order to solve problems such as slow convergence speed and tendency of premature convergence existing in differential evolution algorithm, an improved differential evolution algorithm using the adaptive mutation operator and Gaussian disturbance crossover operator aims to improve the mutation of standard differential evolution algorithm and the design of crossover operators. To validate the effectiveness of it, this optimized fuzzy neural network forecasting algorithm is applied to four standard test functions and the actual network traffic. Simulation results show that the convergence speed and forecasting accuracy of the proposed algorithm are better than those of the traditional fuzzy neural network algorithm. It improves not only the generalization ability of the fuzzy neural network but also the forecasting accuracy of the network traffic.

1. Introduction

With the fast development of Internet and network technique, the network scale grows rapidly, and the network topological structure becomes more and more complicated, meanwhile, problems in network performance and network service quality have become very prominent. Users hope to get superior and more guaranteed service through Internet, while network service providers want to improve the controllability and manageability of the Internet and then enhance its utilization through the optimization of network resources [1]. Under this condition, we need to master the operation condition of current network to take relevant management steps, and we also need to predict the network traffic, which is the basic work of internet control. Therefore, if the network resources are limited, it will greatly enhance the network performance and service quality to build network traffic predicting model to make real-time forecasting, control or adjust the network in time [2].

In recent years, many researchers at home and abroad have focused on the network traffic forecasting algorithm and have put forward a variety of forecasting algorithms. At first, it is thought that the network traffic is subject to Poisson distribution or approximate to the Markov process, and the forecasting model based on autoregressive (Autoregressive) [3] or autoregressive moving average (ARMA) [4] is generally used. But in recent years, researches on network traffic have found that network traffic has

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auto-correlation properties [5,6], and Poisson process cannot fully describe the characteristics of network traffic any longer. Based on ARMA model, linear models such as Moving average model (ARIMA) and Markov-Modulated Poisson process can make the sequence more stable through several times of difference [7,8]. Compared with the traditional stochastic model, they can better describe the nature of Internet such as multi-construction, outburst continuity and self-similarity. As the representative of the linear forecasting they have been widely used, but the results of the experiments show that as the forecasting steps increase, the forecasting error of the model will gradually accumulate. So they are only suitable for short-term forecasting. With intelligent processing functions such as learning, memory and computing, artificial neural network works as a powerful tool in solving large-scale problems. The forecasting method of neural network can describe the nonlinear characteristics of network traffic, which shows that forecasting method of the neural network is better than the linear forecasting method. At the same time, when conducting the training, the neural network can memorize signals in a nonlinear way; the effect of forecasting steps on forecasting results is relatively small; it can do distributed processing and has good learning and adaptation ability [9]. These advantages presented above indicate that the forecasting method of neural network is effective for network traffic forecasting [10–14]. Fuzzy logic can put the human past experience and knowledge into the fuzzy rules, which then can give the complex research objects the abstract attribute [15]. Fuzzy Neural Network (FNN) combines the knowledge expression ability of fuzzy reasoning and self-learning ability of neural network, and it has been widely used in many fields such as adaptive control, nonlinear system identification and pattern recognition [16,17].

The design of fuzzy neural network includes network structure identification and parameter identification. The traditional fuzzy neural network often uses BP algorithm to optimize parameters when conducting parameter identification [18]. However, BP algorithm tends to be trapped in local extremum and has its inherent limitations. DE (Differential Evolution) algorithm is a stochastic heuristic search algorithm. A new individual is first produced based on the simple variation and crossover operation of difference. Then the new individual will be compared with the original one in terms of fitness value, and the individual with better fitness value will be preserved.

Besides, differential evolution (DE) algorithm can also use individual local information and group global information to do cooperative search. It has been used in many fields because of its availability, robustness and strong global search capability [19]. However, as a kind of optimization algorithm, DE algorithm has the characteristics of slow convergence, tendency of premature convergence and so on. In view of these characteristics, many scholars have put forward some improvement measures. Oiman et al. introduced adaptive mutation scale factor and used a normal distribution to generate cross operator, Brest et al. proposed an improved algorithm with the gradual reduction of population [20], Ma et al. proposed a Memetic evolutionary algorithm based on local fast convergence algorithm [21]. These improved algorithms improve the optimization ability of DE algorithm to some extent.

Based on the thorough analysis of the existing research results, this paper proposes a fuzzy neural network algorithm combining improved differential evolution algorithm with BP optimization (IDEBP). In the improved differential evolution algorithm, the mutation and crossover operator design of standard differential evolution algorithm is improved by using the adaptive mutation operator and Gauss perturbation crossover operator. IDEBP algorithm is used to optimize the structural parameters of the fuzzy neural network, and it is also applied to 4 standard test functions and network traffic to verify the validity of the algorithm. The simulation results show that the algorithm has a higher forecasting accuracy. Operators and system administrators are interested in the mixture of traffic carried in their networks for several reasons. Knowledge of traffic composition is valuable for network planning, accounting, security, and traffic control. Traffic control includes packet scheduling and intelligent buffer management to provide the quality of service (QoS) needed by applications. It is necessary to determine to which applications packets belong, but traditional protocol layering principles restrict the network to processing only the IP packet header [22].

2. Fuzzy neural networks

The fuzzy neural model studied in this paper is multilayer fuzzy neural network, and its model structure is shown in Fig. 1 [14]. In the b node of the L layer of the net structure, input is set as $I_b^{(L)}$ and output as $O_b^{(L)}$. h, i, j, k, l are used to respectively represent neurons labeling of the first layer, the second layer, the third layer, the fourth layer and the fifth layer. Input output relationships between each layer are expressed as follows. The first layer is the input layer, and each neuron of this layer represents an input variable.

$$I_h^{(1)} = x_h,\ O_h^{(1)} = I_h^{(1)} \tag{1}$$

In this formula, $h = 1, 2, \ldots, m$, and these figures represent input quantity.

The second layer is fuzzy layer, and Gauss function is used for fuzzy processing.

$$I_h^{(2)} = O_h^{(1)},\ O_i^{(2)} = e^{-\left(\left(I_i^{(2)}-c_i\right)^2/\sigma_i^2\right)} \tag{2}$$

In this formula, c_i and σ_i represent the center and width of the membership function. They are both variable parameters that need to be adjusted.

The third layer is the rule layer, using sum–product to do reasoning. The joint strength between this layer and the second layer is 1, and rule neurons complete the operation of fuzzy logic "and".

$$O_j^{(3)} = \min_{i\in I_j}\left(O_i^{(2)}\right) \tag{3}$$

In this formula, I_j represents index sets of the second layer neurons that are connected with the j neurons of the third layer; $O_i^{(2)}$ represents the output of the i neurons of the second layer.

The fourth layer is the conclusion layer, that is to say, normalization processing is made for the output fuzzy reasoning data of the rule layer. Gauss type is taken as each neuron' membership function of this layer to meet the stability requirements of the network. The function is expressed as follows:

$$O_k^{(4)} = \max_{j\in I_k}\left(O_j^{(3)} w_{kj}^2\right) \tag{4}$$

In this formula, I_k represents the index sets of all the neurons of the third layer that are connected to the fourth layer' k neurons.

The fifth layer is the clarification layer and is also called the defuzzy layer. To make all the neurons and its weights of this layer defuzzificated. Area center algorithm is used to express the fuzzy process. The final output relation can be expressed as follows

$$O_l^5 = \frac{\sum_{k\in I_l} O_k^4 \sigma_{lk} c_{lk}}{\sum_{k\in I_k} O_k^4 \sigma_{lk}} \tag{5}$$

In this formula, I_l represents index sets of the fourth layer's neurons that are connected to the l neuron of the fifth layer, and c_{lk} and σ_{lk} respectively represent the membership function' center and width of the output language variable of the fourth layer k neuron. The k neuron is connected to the l neuron of the fifth layer,

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