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Application of BP Neural Network Optimization Based on PSO Algorithm in Energy Development

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To study the application effect of BP Neural Network Optimization based on PSO Algorithm in energy development. Adopt certain technical means to analyze the results and characteristics of BP Neural Network based on PSO Algorithm and explore its feasibility in energy development and application. After a series of research and analysis, it was found that the BP Neural Network Optimization based on PSO Algorithm can balance the relationship between energy and economic growth in energy development, which is conducive to the healthy development of the ecological environment. The research results of the BP Neural Network Optimization based on PSO Algorithm provide an important reference for the development and utilization of energy, so it has certain application and promotion value.

1. Introduction

People's quality of life and economic level have been increasing in the rapid socio-economic development environment. The energy consumption of various projects has become more serious. The waste of energy has not only restricted the development of the economy, but caused great impact on the ecological environment. The research and development of energy-saving technologies and equipment has received great attention from all sectors. The BP Neural Network based on PSO Algorithm came into being in this environment. The purpose of energy development is to reduce energy consumption and promote long-term and healthy growth of the energy economy. In order to maximize the use of energy and increase the use of existing energy, many scholars who study energy development believe that in the process of energy development, using the BP Neural Network based on PSO Algorithm to establish a data model, we can quickly obtain the optimal energy development plan and establish a project for energy development, which is significant for environmental protection and efficient energy use. The neuron network theory tries to simulate the basic characteristics of the human brain, such as fault tolerance, self-adaptation and self-organization, especially when dealing with complex information, background ambiguity, or unclear inference rules, it has unique advantages. The BP Neural Network based on PSO Algorithm is widely used in the development and production of various industries. During the energy development process, the BP neural network using the PSO algorithm can play a role of mutual coordination and mutual support, and is one of the keys to promote the development of energy.

2. Literature review

Artificial neural network (ANN) is a nonlinear system composed of a large number of simple processing units, which is used to simulate the structure and function of human brain nervous system. It has good nonlinear mapping ability, adaptive learning ability and parallel information processing ability. Its study began in the 1940s. Then, it experienced a slow and arduous development process. Until the 1980s, the American physicist J.J. Hopfield established a fully interconnected neural network model. Rumelhart, McClelland and other scholars proposed Back Propagation (BP) learning algorithm. The research on artificial neural networks has achieved rapid development. In some industrially developed countries such as the United States and Japan, there has been an upsurge in competing for research and developing artificial neural networks. At present, the application of artificial neural network theory has penetrated into many fields. Great achievements

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have been achieved in intelligent control, pattern recognition, adaptive filtering and signal processing, sensing technology and robot, nonlinear optimization, knowledge processing, biomedical engineering, financial forecasting and management. In the past ten years, the development of artificial neural network shows that it is a new subject with wide application prospects. Its development will have an important impact on the current and future level of science and technology. Yu et al. proposed a combined method for short-term gas load forecasting based on an improved BP neural network. Using real-coded genetic algorithms, the network is optimized. First, several improvements have been made to the standard neural network to increase the convergence speed of the network. It includes improved additional momentum factor, improved adaptive learning rate, and improved momentum and adaptive learning rate. Then, the global search capability of the optimized genetic algorithm is used to determine the initial weights and thresholds of the BP neural network, so as to avoid falling into a local minimum. Such improvements can help to predict efficiency and maximize the performance of the model (Yu and Xu, 2014). Yuan et al. constructed a BP neural network optimized by genetic algorithms to predict and identify tower crane faults. By improving the structure of the BP neural network, it proved that the tower crane failure was effective and accurate (Yuan et al., 2013). Gao et al. studied the application of an optimized BP neural network method in short-term traffic flow prediction. In order to overcome the shortcomings of traditional BP neural networks, genetic algorithm is used to optimize the weights and thresholds of BP neural network for training samples. Then, through the test sample, the optimized network was tested. The RO network is subjected to a 30-minute short-term forecast. Studies have shown that the model has superiority in convergence speed and prediction accuracy (Gao et al., 2013).

At present, domestic and foreign researches on group intelligent algorithm optimization neural network mainly focus on the improvement of group intelligent optimization algorithm represented by PSO algorithm. Group intelligent optimization algorithms have become an important research direction in the field of artificial intelligence, and a large number of research results are published in magazines and periodicals. Every year, several research projects on the theory and application of PSO algorithms in China are funded. At present, the research of PSO and BP neural network and its application in various fields are also very numerous. To fully understand the characteristics of gas nanosensors between temperature and sensitivity, Zhao developed a backpropagation neural network based on particle swarm optimization (PSO) to fit the temperature-sensitive characteristics of SnO_2. The simulation results show that the particle swarm optimization algorithm can optimize the structure of the BP network and greatly improve the temperature fitting accuracy of the BP neural network. The optimized BP network has better generalization performance than the traditional BP network (Zhao, 2013). Liu et al. used a BP neural network based on particle swarm optimization (PSO) algorithm (also known as PSO-BP) to predict the high-speed grinding temperature of titanium-based composites. In addition, a comparison was made between GD BP (gradient descent training BP neural network), LM BP (BP neural network trained based on Levenberg Marquardt (LM) algorithm) and PSO-BP. The results show that the PSO-BP method is superior to the other two methods (such as GD BP and LM BP) in predicting the grinding temperature with respect to convergence speed, fitting accuracy, and prediction accuracy (Liu et al., 2016). In order to improve the prediction accuracy of pest occurrence cycle, a prediction method based on rough set theory and improved PSO-BP neural network was proposed. It uses inertia weight to improve the particle swarm optimization algorithm. The improved particle swarm optimization algorithm is used to optimize the weights and thresholds of BP neural networks. Finally, a pest prediction model was established using rough set and improved PSO-BP network. Research shows that the improved particle swarm optimization algorithm can reduce the number of iterations with an average accuracy of 94.8% (Bai et al., 2014). In order to overcome the shortcomings of traditional BP network in cementing prediction, particle swarm optimization (PSO) algorithm based on stochastic global optimization is introduced into neural network training. Particle swarm optimization algorithm is used to optimize the weight of BP network. Research shows that the training time of this method is shorter than that of BP network. The prediction accuracy is high. It can improve cementing quality and achieve cementing quality prediction and tracking analysis (Ni et al., 2014). Sha et al. proposed a short-term load forecasting method based on EMD and PSO-BP neural networks. The method uses EMD to automatically divide the historical load sequence into several independent intrinsic mode functions (IMFs). Using BP neural network, each IMF component is optimized for training and prediction. Studies have shown that this method is more accurate than the EMD-BP model (Sha et al., 2013).

In summary, the research of PSO algorithm mainly focuses on the design of its algorithm structure and performance. It mainly includes the selection and optimization of parameters, the diversity of population, the analysis of convergence, the topology structure and the integration of algorithms. The research focuses more on the design of the algorithm. To solve specific problems, the improved PSO algorithm is combined with BP neural network or other optimization algorithms. It is more widely used in forecasting areas, such as prediction of temperature. There are almost no applications in the development of energy. Therefore, based on the above research status, the PSO algorithm and BP neural network are combined and used in the field of energy development to make up for the gap in this field.

3. Method

The artificial neural network method is used to predict the ground settlement of the tunnel. The design of BP network structure includes: determination of input variables and output variables (determination of the number of neurons in the input layer and the output layer); determination of the number of hidden layers and number of neurons in each hidden layer; preprocessing of network data; selection of transfer functions; selection of training methods and their parameters. The selection of network input variables usually follows two criteria: First, the selected independent variables should be those closely related to the predicted object; second, there shall not be a strong linear relationship between the selected independent variables. At the same time, the input layer functions as a buffer memory, and the number of inputs of the network should generally be equal to the number of inputs of the application. The transfer function chosen is a hyperbolic tangent function, featuring fast convergence speed, the training result is closer to the target vector, and the training error is small. For the actual situation of the settlement prediction of the tunnel, the training function Mar-quardt with the fastest convergence speed and the least number of trainings is selected. The initialization of network weights adopts a method with a random non-zero value close to zero. The application shows that this method can effectively avoid the network computing from entering the saturation region too early. Encode the connection weights between all neurons in the original BP neural network into individuals represented by real strings. An example is given for the simplest BP neural network (Figure 1).

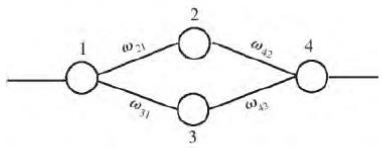

Figure 1: Simple BP Neural Network

4. Research results and discussion

4.1 BP Neural Network Model based on PSO Algorithm

4.1.1 Training BP neural network using PSO algorithm

Table 1: Training effect corresponding to different number of the hidden layers

Hidden layer	Number of training	Running time /s	Momentum coefficient	Target of error
1	47	5	0.001	0.02110
2	23	1	0.001	0.00573

The BP algorithm is an algorithm with gradient descent error, and the major disadvantage is low convergence speed and easily falls into local extremes. If there are too many hidden nodes, the performance of the neural network will become weak, the learning process will not converge for a long time, and the fault tolerance and performance of the network will be reduced due to overfitting. For its mechanism, on the contrary, its local search ability is strong. The PSO algorithm can reach the vicinity of the optimum point quickly. The advantages of PSO algorithm are obvious. As an intelligent optimization algorithm based on biological population, the copy and migration operation can effectively prevent the algorithm from falling into the local extreme point. Similarly, if the trend is a fixed step and the value is relatively large, the individual will cross the optimal point in the calculation process, resulting in premature and slow convergence. In the PSO and BP hybrid algorithm, the copy and migration operations through the PSO algorithm are added to the BP neural network training process, and the two algorithms work in parallel. Constructing the BP model network based on PSO algorithm will exert the global optimization ability of PSO algorithm and the ability to easily jump out of the minimum point, but exert the local optimization ability of BP algorithm. Two kinds of algorithms complement each other. The BP neural network using PSO algorithm is mainly used for the complex attribute changes. In practice, seismic attributes are easily affected by many factors. BP neural network cannot reach effective accuracy in a long time. However, in the process of improving accuracy, neural networks are prone to came to a deadlock. Through combination of the PSO algorithm and the BP algorithm, the training speed of the network is effectively accelerated, and the output accuracy is improved. The training effect parameters are compared as shown in Table 1.

4.1.2 Reservoir prediction using BP neural network model based on PSO algorithm

The application area is the Yongjin Oilfield of the Junggar Basin, and the Xishanyao Formation of the Jurassic is one of its important layers. However, the thin interbedded reservoirs of Xishanyao are buried deep (5600~6000m), and the inhomogeneities are strong; The physical properties of reservoirs are poor, the velocity of sands and mudstones is difficult to distinguish, and the correspondence to reflection sync-phase axis of the formation is not clear. Only natural gamma curves and lithology correspond clearly. The predicted objects are different even in the same work area and the same reservoir, and the corresponding sensitive seismic attributes are also different. New properties continue to emerge. For example, Liner et al. proposed a new seismic attribute: SPICE (exponential imaging of correlative events). This attribute was developed based on the singularity analysis and wavelet transform of offset seismic data. Therefore, the optimization results of seismic attributes directly affect the accuracy of prediction. The area provides data of 4 wells, and the corresponding well coordinates are used as a reference to extract the most recent seismic attributes to constitute the sample. The maximum amplitude, arc length, RMS, and instantaneous frequency (Fig. 2) with good correlation are taken as the input, corresponding to the sample data, and the thickness of the sand body obtained in the logging is used as the output. The BP Neural Network based on PSO Algorithm is adopted for training. After the training ends, the optimized network weight (i.e., the connection weight coefficient of the hidden layer) is output, and the thickness of the reservoir sand body in the entire area is predicted. The maximum amplitude, arc length, RMS, and instantaneous frequency (Fig. 2) with good correlation are based on the four seismic attributes and reservoir parameters with good correlation at a given well point. A complex network system is formed through training and learning, and a nonlinear relationship between seismic attributes and reservoir parameters is established. Seismic data and logging data reflect the underground geologic bodies and there is a certain relationship. It is difficult to characterize this kind of relationship with a functional expression, and difficult to describe quantitatively. However, the BP Neural Network Model based on PSO Algorithm can realize the mapping of nonlinear complex relationships between the input and the output. At the drilled wells (such as Permanent 1 Well, Permanent 7 Well, etc.), multivariate linear regression was used to study the attribute data, and the log curves obtained from logging were compared with the relationships obtained using the BP neural network and the BP Neural Network based on PSO Algorithm, respectively. This technique is applied to all completed drilling wells in the area, and finally the data body of the entire area reservoir can be obtained. Figure 3 shows the results predicted by the original BP neural network model and the BP Neural Network based on PSO Algorithm.

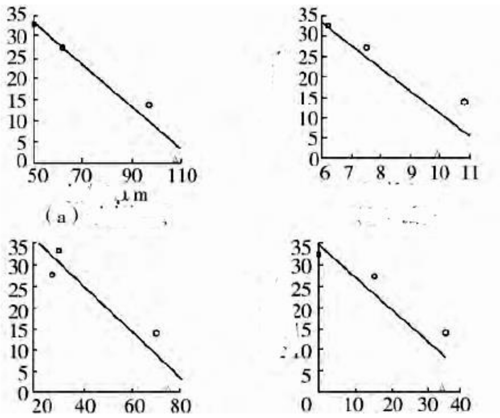

Figure 2: Relevance of the max magnitude, arc length, RMS amplitude and dominant frequency

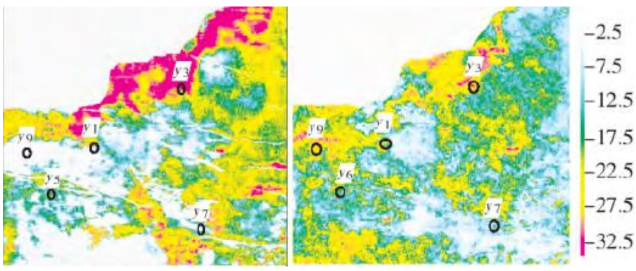

Figure 3: Prediction of BP neural network model and the BP Neural Network based on PSO Algorithm

4. 2 Determination of normalized intervals

Figure 4 shows the simulation results of different normalization intervals using the postreg function in the MATLAB neural network kit. A linear regression analysis is performed on the training results of the networks established after normalizing at different normalization intervals. The returned performance parameter r (Relevance coefficients of the network output and the target output) is used for description. The closer the r value is to 1, the closer the network output is to the target output, and the better the network performance. Figure 4 shows the comparison and simulation results of performance parameters r at different normalization intervals. Through the comparison of performance parameters, we can see that the effects are good and the network performance is relatively stable as the data is normalized to the interval [0 ~ 1] ~ [0.2 ~ 0.8], and the effect is the best as the data is normalized to [0.05 ~ 0.95].

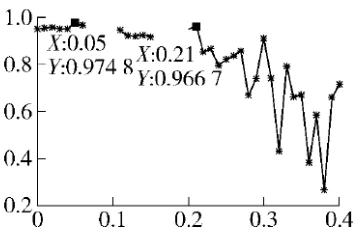

Figure 4: Simulation results with different normalization

4.3 Effective application of improved BP Network in energy development

The improved BP network structure and its algorithm are used to predict the long-term settlement of the ground in shield construction. A network containing four input neurons and one output neuron was established. Due to the large number of input samples, two hidden layer neural network structures were adopted to prevent function overflow and improve training speed and precision. The four input neurons are the time (days) after the shield passed, the soil cover thickness (m), the distance (m) from the centerline of the tunnel, the weighted average cohesion (kPa) of the cover soil, and the output neurons are settlement (mm). After repeated trials, the determined number of neurons in the hidden layer took 8 and 9 respectively. The parameters of the established BP network model and training results are: the number of hidden layers is 2 layers, the number of trainings is 77, the running time is 5s, the momentum coefficient is 0.001, and the error is 9.63 × 10 - 5; Figure 5 shows the predicted error convergence curve. Figure 6 shows the comparison between simulation results and original output results.

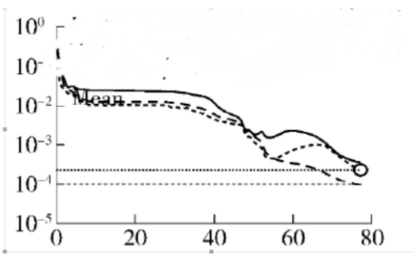

Figure 5: Error convergence curves of the ground long-term settlement predicted by the neural network

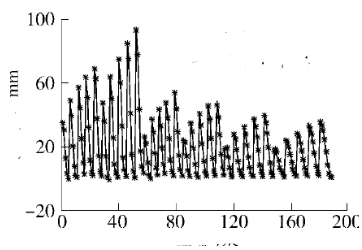

Figure 6: Comparison between simulation results and original output targets

5. Conclusion

With the rapid development of the social economy, new energy projects are constantly emerging. Although the use and development of energy resources have a positive effect on improving economic efficiency, the unrestrained development and irrational use of energy cause serious waste, which also bring negative impact on the stable development of the social economy, and negative impact on the environment. Based on the situation of China's energy consumption, this paper selects a reasonable energy development plan based on the energy needs of different groups, and constantly develops new energy-saving technologies to reduce energy consumption and control energy costs. With the application of energy-saving technologies, energy maximization can be achieved. In addition, with the implementation of proper measures, a neural network of PSO algorithms can be used for analysis of energy sources, providing a timely and rational theoretical basis for energy development. The experiment results proved that the BP neural network using the PSO algorithm provides an important basis for energy development.

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