Interval Water Demand Forecasting Model in Deep Confidence Network based on Wavelet Model or BP Neural Network

Qiang Wang
Human Resources Office, Shandong Vocational College of Industry, Zibo, 256414, China

Abstract: The traditional deep belief network interval water demand predictive model can achieve the purpose of predicting water demand, but the predictive model still has certain instability in water demand forecasting, so a deep belief network interval water demand predictive model based on wavelet model or BP neural network is proposed. Around the construction of a deep belief network interval water demand predictive model, firstly, we use the wavelet model to detect the depth of groundwater level and then perform the next step of reducing the water demand, and use the BP neural network to calculate the water demand to build the water demand predictive model. The experimental results show that deep belief network interval water demand predictive model based on wavelet model or BP neural network can improve the accuracy of certain water demand.

Keywords: Wavelet model; BP neural network; Water demand; Prediction

1. Introduction

There are many researches on water demand prediction, mainly involving the structure of water. According to the actual situation, the water consumption structure is divided into domestic water consumption demand, agricultural water consumption demand and industrial water consumption demand, so as to consider the reasons affecting the water consumption demand in the next step. The water consumption demand can often be more accurately predicted [1]. Water consumption forecast is to construct water demand predictive model for future water consumption. Considering the water supply and drainage planning of population growth and social and economic development comprehensively, based on the prediction of future water demanding changes and characteristics, we design water supply and drainage schemes. With the development of economy and society, human beings' demand for water resources is increasing day by day, and water resources are becoming increasingly important in social economy. Therefore, the accuracy of water demand predictive process and prediction results are constantly improving. Meanwhile, due to the updating and improvement of water demand forecasting methods, the forecasting results of water demand are more thorough, making the forecasting results more comprehensive and accurate. In the context of population and economic development, the water demand and water consumption constitutes, as well as the quality and quantity of water in the process of development will change. Therefore, it is of great practical significance to find ways to solve the problem of water resource demand and ensure the supply and balance of water resources. Deduction method to predict water consumption was popular in the early 20th century. This method adopts multivariate model, the initial list cannot fully reflect all the factors affecting water demand, and these potential important relationships may be ignored. Therefore, extrapolation is rarely used in the current prediction research [2]. In addition, there is another problem with the extrapolation method, that is to say, with the extension of the predicting time, the prediction error increases obviously and even loses. One important reason is that it is only static or semi-static (time-series only), some people even do not take into account the impact of social factors on water consumption, thinking that the future water supply system is just a simple system, but many practical factors have a significant impact on the water supply system.

2. To Establish a Deep Belief Network Interval Water Demand Predictive Model

In order to a deep belief network interval water demand predictive model, the first is to analyze the relationship between the data. The time series predictive method is used to supplement the lack of water resource information, and the corresponding model is:

$$Y_t = 3.4694 + 0.7377Y_{t-1},\ R^2 = 0.7026$$
$$(2.03)\quad (0.17)\quad F{=}18.9 \tag{1}$$

In the formula: the numbers in brackets above are the standard errors of the corresponding parameters. According to the requirements of econometrics, the corresponding parameter must be 2 greater than the standard deviation, and it can be considered as a valid parameter. R^2, that is, the explanatory rate of the model to the dependent variable. F, that is, the total validity test number of the model, the required value must be greater than the corresponding critical value.

2.1. Detection of groundwater level based on wavelet model

Wavelet model is a new neural network model, which combines the theory of wavelet transform with the idea of artificial neural network. The algorithm is composed of input layer, hidden layer and output layer, replaces the neuron excitation function of the traditional neural network hidden layer with wavelet function, and replaces the weight and threshold value of the corresponding input layer to the hidden layer and the hidden layer to the output layer with wavelet basis function. Wavelet transform has good time-frequency locality and self-learning function of neural network. It fully inherits the advantages of excellent time-frequency locality of wavelet transform, so that neural network has stronger fault-tolerant ability and convergence speed, and better prediction effect [3]. The Morlet wavelet is proposed as the excitation function of the hidden layer neurons of the wavelet neural network to establish the wavelet neural network model:

$$y_i(t)=\sum_{j=1}^{n} w_{ij} h_{a,b}\left(\frac{\sum_{k=1}^{m} w_{jk} x_k(t)-b_j}{a_j}\right) \tag{2}$$

Of which: x_k is the k th input samples of input layer. y_i is the i th output layer value of output layer. w_{ij} is the weight connecting node i of input layer and node j of hidden layer. w_{jk} is the weight connecting node j of hidden layer and node k of input layer. a_j is the elastic factor of j th hidden layer node. b_j is the extension factor and translation factor of j th hidden layer nodes. The error objective function is as follows:

$$E(W)=\frac{1}{2P}\sum_{\rho=1}^{P}\sum_{i=1}^{n}\left(d_i^{\rho}-y_i^{\rho}\right)^2 \tag{3}$$

Through a large number of training samples, we modify the parameters and weights of the neural network constantly to enable the neural network to carry out mode recognition on the samples, mode recognition feature function based on wavelet neural network model and research on numerical simulation method of groundwater flow based on wavelet neural model.

2.2. Downscaling water demand prediction

The data predicted by the water demand predictive model for the water consumption in production, operations and public services is the master planning data at the control unit scale. However, the population data in the master plan are all district scale, so the water demand data predicted by the water demand predictive model are all district scale [4]. In order to obtain the distributed water demand data on the scale of all planning control units, it is necessary to conduct downscaling calculation of the water demand predicted by the model before using water, and reduce the water demand data at district level to the scale of planning control units.

The domestic water consumption is in direct proportion to the population in the residential land control unit. The population in the residential land control unit is not only related to the population in the residential land control unit, but also related to the population density, plot ratio and other indicators in the residential land control unit, as well as the plot ratio of floor area and floor area ratio [5]. The formula for measuring the reduction ratio of household water consumption within the built-up area of the town is as follows:

$$V_{li}=Q_{DW}S_{7i}\rho_i r_i \tag{4}$$

$$d_{li}=S_{7i}r_i \tag{5}$$

$$V_l=\sum\sum Q_{DW}M_{7i}=\sum\sum Q_{DW}S_{7i}\rho_i r_i \tag{6}$$

$$\frac{V_{li}}{V_l}=\frac{Q_{DW}S_{7i}\rho_i r_i}{\sum\sum Q_{DW}S_{7i}\rho_i r_i}=\frac{\rho_i d_{li}}{\sum\sum \rho_i d_{li}} \tag{7}$$

In formula (4), d_{li} refers to the floor area of the residential land control unit; in formula (5), V_t refers to the total water demand value of living, and the distributed water demand prediction model is used to simulate the data. The scale reduction parameters in equation (6) include population density parameters and building area parameters in the residential land control unit. Taking the domestic water demand data simulated by the distributed water demand predictive model as the scale, assume that the domestic water demand on the domestic water control unit under the same population density at the district level is equal, a scale formula is established as follows:

$$\frac{V_{li}}{V_l}=\frac{\rho_i d_{li}}{\sum \rho_i d_{li}}=\frac{d_{li}}{\sum d_{li}} \tag{8}$$

Formula (7) shows that in order to obtain the distributed results of water demand, we need to use BP neural network to predict water demand in order to build a deep belief network interval water demand predictive model.

2.3. Use BP neural network to calculate water demand forecast

Artificial neural networks (ANNs) are a mathematical model used to simulate the information processing process of biological neural networks, as shown in Figure 1.

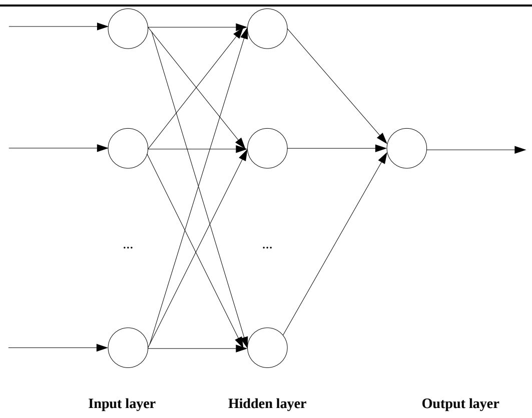

Figure 1. Structure of BP neural network

Back Propagation neural network is a kind of neural network based on error back propagation training algorithm. Its advantage is that when the number of hidden layers and nodes is large enough, the neural network can approximate any nonlinear mapping relationship and has good generalization ability [6]. Figure 1 shows a typical BP network model topology, consisting mainly of input layer, hidden layer and output layer. Figure 2 shows several neuron models in each cell layer. Adaptive learning rate adjustment; Improper selection of learning rate of BP algorithm is an important factor that leads to slow convergence rate. If the speed is too small, the convergence speed is too slow; if the speed is too large, oscillation or even divergence occurs [7]. In this case, adaptive learning rate adjusting method, that is, when two consecutive iterations have the same gradient, the deceleration time is too long, and then the step length doubles; in the continuous iteration process with opposite gradient direction, the descending speed is too fast and then the step length halves.

As for the additional momentum term W (k), the standard BP algorithm based on instantaneous negative gradient only makes instantaneous modification. Since the direction of gradient at the previous moment is ignored, the oscillation usually occurs in the learning process with slow convergence [8].

The purpose of the additional momentum term is to reduce the network sensitivity of the local details of the error-curved surface by suppressing the network limitation to local minima. The modified weight correction formula is as follows:

$$w(k+1)=w(k)+\alpha(k)\left[(1-\eta)d(k)+\eta d(k-1)\right] \quad (9)$$

$$\alpha(k)=2^{\lambda}\alpha(k-1) \quad (10)$$

$$\lambda=sign\left[d(k)d(k-1)\right] \quad (11)$$

It' s a dynamic factor, of which, $\alpha(k)$ is learning rate, $d(k)=-\frac{\partial E}{\partial w(k)}$ is the negative gradient at k moment, $0\le\eta<1$ is factor of momentum, and BP neural network is used to calculate the water demand forecast, in order to build a deep belief network interval water demand predictive model.

3. The Experimental Demonstration

In order to ensure the effectiveness of deep belief network interval water demand predictive model based on wavelet model or BP neural network proposed in this paper, we carry out an experimental demonstration, and adopt different prediction models to predict the water demand in the same area. In order to ensure the preciseness of the experiment, different water demand predictive models are used to predict the water demand.

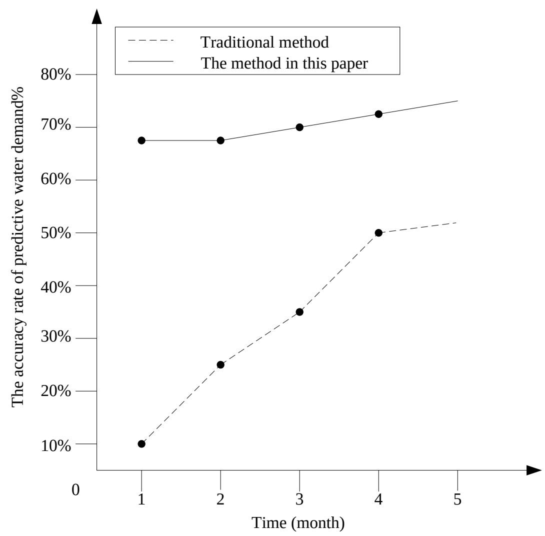

Figure 2. Comparison diagram of accuracy of water demand prediction model

Figure 2 represents the water demand-forecasting curve of the two methods. It can be analyzed that the deep belief network interval water demand predictive model based on wavelet model or BP neural network in this paper has certain advantages, especially clear in the first month. The accuracy difference value of deep belief network interval water demand predictive model based on wavelet model or BP neural network proposed in this paper has reached 60%,

However, with the increase of time, the accurate value has been increasing steadily. After 5 months of experiment, there is still a nearly 20% difference in the accurate value.

4. Conclusions

This paper conducts research and analysis on the deep belief network interval water demand predictive model based on wavelet model or BP neural network, builds water demand predictive model by using the wavelet model and BP neural network and carries out experimental demonstration. The experiment demonstration shows that the proposed water demand predictive model has high accuracy and stability.

5. Acknowledgment

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