Research on flow and pressure prediction of urban water supply pipeline network based on GA-BP algorithm

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Abstract. In order to realize the optimal scheduling and energy saving of urban water supply pipeline system, a method of flow and pressure prediction of water supply pipeline network based on genetic algorithm and BP neural network is proposed in the paper. The flow and pressure prediction models of urban water supply network are built, then tests and verifies the models by the dates obtained from the water supply monitoring system, so as to provide control basis for optimal operation of urban water supply pipeline network.

1. Introduction
The optimal operation of urban water supply pipeline network plays an important role in ensuring the safety and reliability of water supply and meeting the needs of users. In this paper, based on the actual data of a city's water supply pipeline network system, the BP neural network algorithm optimized by genetic algorithm is used to predict the flow and pressure of the future pipeline network. The algorithm provides technical support for the optimized operation of the water supply pipeline network, thereby improving the operating efficiency of the water supply pipeline network and saving energy.

2. Related methods for optimal operation of urban water supply pipeline network
In the aspect of optimal operation of water supply pipeline network, many scholars have been constantly studying. Chuanbin Yin[1] introduced the support vector machine (SVM) algorithm based on the structural risk minimization criterion, and used SVM dark to optimize the parameters of support vector machine kernel function, which shortened the prediction time, At the same time, the prediction accuracy of hourly peak water load is improved. Based on this, the author puts forward a macro pressure model based on the algorithm about support vector machine. Chenglin Guo [2] proposed to establish the optimal scheduling model of urban water supply pipeline network based on geographic information system (GIS). The optimal scheduling of water supply pipeline network was realized through the integrated development of MapInfo and VB. The flow of each pipe section of the pipe network was obtained by using recursive algorithm, and the water pressure was obtained by Hardy cross method. Gao Xiang [3] puts forward the research on optimal scheduling of water supply system based on immune algorithm, which is mainly divided into three parts: the principle of immune algorithm, the first level optimal scheduling model of water supply system and the solution of the first level optimal scheduling model of water supply system by using immune algorithm. In this paper, based on the scholars' research on urban water pipeline network, a neural network prediction algorithm is proposed to predict the flow and pressure of water supply pipeline network.
3. Flow prediction of urban water supply pipeline network based on GA-BP neural network

3.1. Flow prediction algorithm of water supply pipeline network based on GA-BP neural network

Due to the convergence speed of BP neural network is slow, which is not conducive to global optimization [4][5], this paper uses genetic algorithm to optimize BP neural network and establishes GA-BP neural network model to predict the flow of urban water supply pipeline network system. GA-BP traffic prediction algorithm is divided into building a BP neural network, GA optimizing the initial weights of BP neural network and GA-BP neural network training and prediction [6].

Firstly, the structure of BP neural network is determined. The number of nodes in the network layer needs to be determined according to the actual law. Here, the hourly flow of each period is predicted by the time information of daily water supply pipeline flow. The flow data is the variable category of input layer and output layer. 24 nodes are selected as the input layer of the model, that is, the flow data of 24 hours per day, and the next day 24 and 1 are the number of input and output nodes. Secondly, we need to determine the number of hidden layer nodes. Determine hidden layer node according to $m = \sqrt{n + k + u}$, the number of hidden layer nodes is determined to be 9 when each reference index is predicted to be the optimal solution.

Then, the genetic algorithm is introduced to optimize the weights and thresholds of BP neural network. The weights and thresholds of the initial neural network model can be set as random numbers. The real number coding is used to code the real string composed of the initial weights and thresholds. The fitness function uses the reciprocal of the absolute sum of the errors between the predicted and measured values, performs crossover and mutation operations, and then calculates the fitness Degree function, decoding to get the optimal initial weight and threshold [7]. The crossover probability and mutation probability are calculated according to the following formula:

\[
p_c = \begin{cases} 
  p_{c1} \frac{(p_{c1} - p_{c2})(f' - f_{avg})}{f_{max} - f_{avg}} & f' > f_{avg} \\
  p_{c1} & f' \leq f_{avg}
\end{cases}
\]

\[
p_m = \begin{cases} 
  p_{m1} \frac{(p_{m1} - p_{m2})(f'' - f_{avg})}{f_{max} - f_{avg}} & f'' > f_{avg} \\
  p_{m1} & f'' \leq f_{avg}
\end{cases}
\]

Among them, $f_{max}$ is the fitness of the best individual in the population; $f_{avg}$ is the average fitness of the population; $f'$ is the larger fitness of the two crossed individuals; $f''$ is the fitness of the individual to be mutated.

3.2. Simulation results and analysis of flow prediction of water supply system based on GA-BP

The simulation platform of this experiment is matlab2013a. The structure of the model after running the algorithm is shown in Figure 1. The expected error $E = 0.004$ and the training times $r = 100$ are set. The population size is 50, the crossover probability is 0.6, the mutation probability is 0.08, and the number of iterations is 100.
GA-BP algorithm is used to predict the flow of urban water supply pipeline network. The three weeks flow data of a monitoring node from May 1 to 22, 2020 are selected as training samples. The BP flow prediction model and GA-BP flow prediction model are trained by the sample data to predict the flow trend of the following week.

According to figure 2, it can be clearly seen that the error of GA-BP traffic prediction model is smaller and the prediction effect is better, which can provide basic technical support for the research of optimization adjustment. The results of the flow prediction model constructed by GA-BP flow prediction algorithm are consistent with the real flow change curve, even in some periods, the predicted value of water supply pipeline is consistent with the actual data, which shows that the model is reliable for urban water supply pipeline flow prediction, and has certain reference value and practical value.

| time | actual value | BP forecast | GA-BP forecast | BP relative error | GA-BP relative error | time | actual value | BP forecast | GA-BP forecast | BP relative error | GA-BP relative error |
|------|--------------|-------------|----------------|------------------|---------------------|------|--------------|-------------|-----------------|------------------|---------------------|
| 1    | 829.65       | 825.43      | 830.21         | 0.51%            | 0.07%               | 13   | 838.26       | 840.24      | 832.84         | 0.24%            | 0.07%               |
| 2    | 828.04       | 828.18      | 822.38         | 0.02%            | 0.68%               | 14   | 846.2        | 840.67      | 840.67         | 0.65%            | 0.65%               |
| 3    | 828.72       | 836.71      | 820.64         | 0.96%            | 0.97%               | 15   | 856.54       | 810.63      | 843.86         | 5.36%            | 1.48%               |
| 4    | 826.95       | 836.23      | 820.35         | 1.12%            | 0.8%                | 16   | 844.45       | 811.47      | 831.36         | 3.91%            | 1.55%               |
| 5    | 832.74       | 813.15      | 820.42         | 2.35%            | 1.48%               | 17   | 857.83       | 820.08      | 835.06         | 4.4%             | 2.65%               |
| 6    | 832.22       | 811.54      | 823.23         | 2.48%            | 1.08%               | 18   | 839.51       | 834.43      | 828.23         | 0.61%            | 1.34%               |
| 7    | 835.97       | 825.93      | 824.34         | 1.2%             | 1.39%               | 19   | 829.04       | 822.69      | 827.57         | 0.77%            | 0.18%               |
| 8    | 846.16       | 833.37      | 835.61         | 1.51%            | 1.25%               | 20   | 853.17       | 809.98      | 839.04         | 5.06%            | 1.66%               |
| 9    | 848.02       | 833.56      | 833.2          | 1.71%            | 1.75%               | 21   | 850.19       | 835.87      | 823.42         | 1.68%            | 3.15%               |
| 10   | 836.04       | 821.5       | 822.22         | 1.74%            | 1.65%               | 22   | 846.27       | 820.84      | 818.6          | 3.0%             | 3.27%               |
From Table 1, it can be clearly seen that the relative error of GA-BP neural network algorithm prediction is small, and the establishment of GA-BP traffic prediction model is relatively reliable, which can provide basis for optimal scheduling.

4. Prediction of water supply system pressure based on neural network algorithm

4.1. Pressure model of urban water supply pipeline network

Since the flow parameters of the water supply pipeline network cannot meet the accuracy of the micro model [8], the pressure factor needs to be considered. The effluent flow rate and pressure of the water plant and the distribution of the pipe network in the local area are the key factors that affect the pressure data. In the pressure model of the pipeline network in this paper, the input of the model is the effluent flow of a monitoring node in the urban water supply pipeline network, and the pressure measurement data of the monitoring node is the output. The specific expression is:

\begin{equation} H_j = f_{\text{bpnet}}(Q_1, \ldots, Q_j) \end{equation}

In the above formula, the pressure measurement data at the pressure measurement position at time j is \( H_j \), the water flow at time j is \( Q_j \), and \( f_{\text{bpnet}} \) is used to solve the nonlinear mapping between the data. After the pressure model of the water supply pipeline is established, the pressure data of the curve at different positions of the water supply pipeline is analyzed through neural network structure, training network model and data comparison. The input node of the model is 24, which is the flow of 24 hours a day, and the output node is 24, which is the pressure of 24 hours. The range of the number of hidden layer nodes can be calculated by \( m = \sqrt{n + k + u} \). When the number of hidden layer nodes is 4, the predicted reference indicators are optimal, and the model structure is shown in Figure 4.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Figure3.png}
\caption{Structure diagram of pressure model about pipeline network}
\end{figure}

In the training of the sample, select the flow data of urban water supply pipeline network from May 1st to 8th as the input variable. Select the hourly average pressure at a certain location of the pipeline as the output variable. Select the hourly output traffic data of a node in 24 periods on May 09 for testing.

4.2. Simulation results and analysis of water supply system pressure prediction based on BP neural network

Run MATLAB for simulation. The data in this paper comes from the pressure value of a certain location in a certain city on May 9 in 24 periods, and the data is simulated. The simulation results are shown in Figure 4.
Figure 4. Prediction of water supply pipeline pressure

It can be seen from Figure 4 that the predicted value of hourly average pressure at this node is basically consistent with the real value, and its relative error is small, which can meet the prediction requirements of water supply network pressure model.

| time | actual value | estimate | relative error | time | actual value | estimate | relative error | time | actual value | estimate | relative error |
|------|--------------|----------|----------------|------|--------------|----------|----------------|------|--------------|----------|----------------|
| 1    | 0.435        | 0.4386   | 0.8%           | 9    | 0.433        | 0.4208   | 2.81%          | 17   | 0.435        | 0.4325   | 0.57%          |
| 2    | 0.435        | 0.4405   | 1.26%          | 10   | 0.434        | 0.4229   | 2.56%          | 18   | 0.44         | 0.4284   | 2.64%          |
| 3    | 0.436        | 0.4442   | 1.88%          | 11   | 0.435        | 0.4224   | 2.90%          | 19   | 0.434        | 0.4271   | 1.59%          |
| 4    | 0.435        | 0.4456   | 2.16%          | 12   | 0.435        | 0.4173   | 4.06%          | 20   | 0.434        | 0.4209   | 3.02%          |
| 5    | 0.436        | 0.4427   | 3.05%          | 13   | 0.434        | 0.4247   | 2.14%          | 21   | 0.434        | 0.4329   | 0.25%          |
| 6    | 0.431        | 0.4394   | 0.1%           | 14   | 0.435        | 0.4346   | 0.09%          | 22   | 0.434        | 0.4230   | 2.53%          |
| 7    | 0.433        | 0.4233   | 2.24%          | 15   | 0.436        | 0.4347   | 0.29%          | 23   | 0.436        | 0.4285   | 1.72%          |
| 8    | 0.437        | 0.4196   | 3.98%          | 16   | 0.434        | 0.4341   | 0%             | 24   | 0.435        | 0.4312   | 0.87%          |

By analyzing the prediction results of different pressure measuring points in Table 2, the relative error between the predicted data and the actual value can be well analyzed, and the pipeline pressure prediction model can be determined. According to the analysis of the data in the table, the relative errors of the pressure measurement points are very small, and the relative errors at all times are less than 5%. This shows that the pressure prediction model has good prediction effect and high accuracy, and can provide technical support for the optimization of scheduling research.

5. Conclusion

In this paper, the data obtained from the monitoring system of urban water supply pipeline network are processed, and the BP neural network algorithm optimized by genetic algorithm is used to predict the flow data in the future, and the neural network algorithm is used to predict the pressure trend of each position of the pipe network. It can provide basic technical support for the later optimal operation of water supply network, to achieve real-time pressure control of water supply pipeline network and reduce the cost of water supply.
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Reference
[1] Chuanbin Yin. Study on optimal operation of urban water supply system[D]. Tianjin University, 2005.
[2] Chenglin Guo. Study on optimal operation of water supply network based on GIS [D]. Nanhua University, 2007.
[3] Gao Xiang. Research on optimal operation of water supply system based on immune algorithm[D]. Harbin Institute of technology, 2007.
[4] Xinyue Ge, Yihuai Wang, Xin Zhou. Application of GA-BP neural network in NB IOT water quality monitoring system[J]. Modern electronic technology, 2020, 43 (24): 30-33 + 37.
[5] Shaofeng Xie, Yun Zhao, Guohong Li, Zhihao Zhou. GPS precipitable water prediction based on GA-BP neural network [J]. Surveying and Mapping Science, 2020, 45 (03): 33-38.
[6] Xitong Lu. Study on optimal operation of urban water supply system [D]. Xi'an University of science and technology, 2019.
[7] Jianbin Guo, Cheng Qian, Xiangkai Zhu, Jiawang Lei, Jinxiang Ye. Study on vibration prediction of hydraulic unit based on GA-BP [J]. Hydropower energy science, 2020, 38 (10): 133-135.
[8] Stvan Selek, Jozsef Gergely Bene, Csaba Hos. Optimal (short-term) pump schedule detection for water distribution systems by neural evolutionary search[J]. Applied Soft Computing Journal, 2017, 12(08):2336-2351.