Prediction of Drag Reduction Rate in Turbulent Channel Flow Based on BP Neural Network

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Abstract. The technology of turbulent drag reduction by viscoelastic additives cannot be widely applied in practical engineering due to the difficulty in judging the effect of drag reduction. To solve this problem, the experiment of drag-reducing channel flow of polymer solution was carried out based on the comprehensive analysis of the factors affecting the drag reduction rate. Abundant drag reduction rate data were obtained. A three-layer BP neural network prediction model was established with polymer solution concentration, Reynolds number and injection flow rate as input parameters. Based on the test results, the prediction accuracy on drag reduction rate of the model was analysed. The prediction and model validation of drag reduction rate are carried out further according to the historical data in literature. The results show that the predicted drag reduction rate of BP neural network is close to the real drag reduction rate in the drag-reducing flow of polymer solution. The prediction is with high accuracy and with good generalization ability. It is expected to be applied to practical projects and to promote the development of turbulent drag reduction technology by additives.

1 Introduction

With the intensification of the world energy crisis, Turbulent drag reduction in the flow-related engineering technology is becoming more and more important. Toms [1] first discovered in 1948 that a very low-concentration polymer solution can significantly reduce the resistance of turbulent flow. This phenomenon is called The Toms Effect or additive drag reducer technique. After that, some scholars have found that adding viscoelastic polymer or some surfactant solutions to the pipeline or channel flow will reduce the drag [2-3], and under certain circumstances, the drag will be reduced. The rate can even be as high as 80% [4].

Regarding the prediction of Drag-reduction Rate (DR) brought by viscoelastic additives, Motier et al. [5, 6] proposed a prediction model suitable for the DR of pipelines with diameters in the range of 100-400mm, and proposed based on Virk The asymptotic theory of, introduces the maximum drag reduction rate (DR_m) into the prediction model; Karami et al. [7] established a prediction model of DR in the pipeline flow of additive drag reduction through experiments, which correlated the pipeline flow rate, medium concentration, medium temperature and pipe wall roughness and other factors; Cao et al. [8] proposed a DR prediction correction that considers the dispersion of additives in the pipeline; Jiang et al. [9] established a DR prediction model based on the turbulent additional stress by analyzing the relationship between the friction factor and the turbulent additional stress. These models are all empirical models based on

different factors that affect the drag reduction rate. However, there are many factors affecting the drag reduction rate of turbulence [10,11], and the drag reduction mechanism is complex. The drag reduction rate and these factors are a multivariate nonlinear dynamic system, the application of simple physical models and linear methods has certain limitations.

In recent years, with the development of neural network methods, because the method has strong nonlinear fitting and prediction capabilities, it has already had some applications in the prediction of turbulence-related fields [12]. Ling et al. [13] used a tensor-based neural network to predict the anisotropic stress tensor of turbulence and provided an improved Reynolds stress closure model; Lee et al. [14] proposed an adaptive controller based on neural network and applied it to the drag reduction of low Reynolds number (Re) turbulent channels; Based on the artificial neural network method, Ouyang et al. [15] established the nonlinear relationship between the bubble injection flow rate and other factors and the drag reduction effect, and used genetic algorithm to determine the factors with greater and lesser impact, and the optimization of parameter design using microbubble turbulence to reduce drag is realized. It can be seen that the neural network does not need to understand the explicit relationship between the drag reduction rate and many influencing factors, and can approximate any non-linear continuous function with a certain degree of accuracy. It is suitable for solving complex problems related to turbulence, and extract reasonable rules between output and input data.

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This paper intends to use the BP neural network method to establish a prediction model for the drag reduction rate caused by wall injection of polymer solution in channel turbulent flow. First, carry out indoor channel drag reduction experiments to obtain sample data of key influencing factors such as drag reduction rate and polymer solution concentration; then train a prediction model, and combine the experimental data to verify the feasibility of using this model to predict drag reduction rate. This method based on BP neural network method to obtain the drag reduction rate avoids the complicated experimental process compared with the traditional method, and can guide the application of drag reducer on-site operation.

2 Drag Reduction Experiment

2.1 Experimental method

The main purpose of the experiment is to provide samples and test data for establishing a model for predicting the drag reduction rate after the injection of a polymer solution in the channel turbulence. The polymer solution used in this experiment is Polyethylene oxide (PEO) aqueous solution with a molecular weight of 4.3 million. In order to achieve this goal, a drag reduction flow experiment loop system as shown in Figure 1 was built. It mainly includes water storage tank, centrifugal pump, flow meter, test section, injection system, etc. The test section is a rectangular channel of 6.00m×0.25m×0.02m (length × width × height). One side is equipped with an injection cavity with a narrow slit. In the middle of the injection cavity is a hollow cavity containing the injected solution. The upper surface of the cavity is provided with injection holes, and the lower surface is level with the inner wall of the channel. There are slits with a length of 200mm and a width of 0.50mm, which forms an angle of 30° with the incoming flow direction, as shown in Figure 2. The injection cavity can be connected with an injection pump to inject polymer solution into the channel, and the injection flow can be achieved by adjusting the frequency of the peristaltic pump. On the centerline of the other side wall of the channel, a pressure measuring hole is set at 0.15m and 0.45m from the front edge of the injection slot. The differential pressure is measured by a high-precision differential pressure gauge with an error of ±1 Pa. It can be used to calculate wall shear stress and drag reduction rate.

Fig. 1. Schematic diagram of drag reduction experiment loop system

Fig. 2. Cross section of injection cavity

In this experiment, the turbulent velocity field after the PEO solution was injected under three flow Re numbers in the channel was measured. Three different concentrations of PEO solution (50ppm, 100ppm, 200ppm) were injected under each Reynolds number, each concentration Inject 5 times with different flow rates (1.0L/min, 1.25L/min, 1.5L/min, 1.75L/min, 2.0L/min). In order to analyze the drag reduction effect of the polymer solution and the drag reduction effect under different concentrations and different injection flow conditions, the drag reduction rate DR is the most intuitive description. The drag reduction rate DR in this experiment is calculated by the following formula using the pressure difference of the test section. The expression of the drag reduction rate is as follows:

$$DR = \frac{\Delta P_w - \Delta P_d + \Delta P}{\Delta P_w} \times 100\% \quad (1)$$

In the formula, ΔP_w is pressure difference in measuring section in pure water flow, ΔP_d is the pressure difference in the pressure measurement section after the PEO solution is injected, ΔP is the small pressure difference increase relative to the pure water flow after water injection.

The experiment has obtained 45 sets of drag reduction rate data under different conditions. The conditions involved mainly include the concentration of the PEO solution, the injection flow rate and the Reynolds number flowing in the channel. The specific influence of these three factors will be analyzed below.

2.2 Analysis of influencing factors

The molecular structure of the high molecular polymer with drag reduction effect is linear. The longer the main chain and the fewer branches, the better the drag reduction effect.

Figure 3 shows the drag reduction rate after injecting different concentrations of PEO solution when the constant injection flow rate is 2L/min. It can be seen from the figure that the drag reduction rate in the channel increases with the increase of the concentration of the injected solution, but the increase range is decreasing, up to 26.33%. This shows that the drag reduction effect in turbulent flow will increase with the increase of the concentration of the injected solution, but there is a saturated effective concentration, which is consistent with the general turbulent drag reduction conclusion. This is because when the concentration of the injected solution is low, as the concentration of the injected solution increases, the more obvious the drag reduction effect, the greater the

drag reduction rate. As the concentration of the injected solution continues to increase, the viscosity of the fluid will increase under a certain flow pressure, resulting in an increase in viscous resistance and a decrease in drag reduction efficiency. Therefore, when the concentration of the injected solution increases to a certain number, the drag reduction rate tends to stabilize. With the increase of Reynolds number, the drag reduction rate in the channel gradually decreases, indicating that the increase of the flow velocity in the channel leads to the degradation of the polymer, which affects the final drag reduction effect.

Fig. 3. Drag reduction rate under different injection concentrations

Fig. 4. Drag reduction rate under different injection rate

Figure 4 shows the drag reduction rate in the channel at different injection flow rates when the injection concentration in the channel is 200 ppm. The abscissa in the figure is the injection volume flow of the PEO solution. It can be seen from the figure that as the injection flow increases, the drag reduction rate increases, but the increase is not large. It can be seen from the figure that as the injection flow increases, the drag reduction rate increases, but the increase is not large, indicating that the change in the injection flow rate of the polymer solution can affect the change of the drag reduction rate, and under the experimental conditions, the two are positively correlated.

3 BP neural network modeling and prediction

3.1 BP neural network

BP neural network is a feedforward network trained by error back propagation proposed by Rumelhart et al. [18]. It can learn and store a large number of input-output pattern mapping relationships without revealing the mathematical equation describing this mapping relationship in advance. The entire learning process of the BP neural network consists of the forward propagation of the input signal and the backpropagation of errors. The threshold and weight of the neural network are adjusted according to the error signal of the back propagation. The sign of the end of the neural network is that the error signal reaches the set training goal or the number of iterations reaches the set value.

3.2 Neural network model creation

This article takes the BP neural network with a single hidden layer as the research object. From the data obtained in Section 1.2, it can be seen that the number of input layer nodes of the neural network is 3, and the number of output layer nodes is 1. The number of hidden layer nodes is determined by empirical formula. The formula is as follows:

$$n_1 = \sqrt{n + m} + a \quad (2)$$

In the formula, n_1 is the number of hidden layer neurons, n is the number of neurons in the input layer, m is the number of neurons in the output layer; a is a constant, the value is [1,10]. Through trial and error method, the number of neurons corresponding to the least training times and the least error is selected, and the number of hidden layer nodes is finally determined as 8. Therefore, the topological structure of the BP neural network is finally determined to be 3:8:1, and the structure is shown in Figure 5.

Fig. 5. BP neural network structure diagram established in this paper

3.3 Neural network model parameter setting

This article is based on Matlab software, writes a program and uses the newff function in the toolbox to create a network to learn and train selected samples. The parameter settings of the established BP neural network model are shown in Table 1, where tansig is used as the transfer function of hidden layer neurons, and the linear function purelin is used as the transfer function of output layer neurons.

Table 1. BP neural network parameters

Parameter category	Settings
Training function	trainlm
The maximum number of iterations	2000
Learning rate	0.01
Target error	0.001

3.4 Forecast results and analysis

From the 45 sets of data obtained in the experiment, 27 sets of data are selected as calculation samples, as shown in Table 2. Select 70% of the 27 sets of data as the training sample, and 30% as the test sample, establish a BP neural network prediction model for channel turbulence drag reduction, and compare the predicted drag reduction rate with the real value. Use the remaining 18 sets of data (as shown in Table 3) to validate the model.

Table 2. 27 sets of calculated sample drag reduction rate data

PEO solution concentration /ppm	Injection rate/ L/min	Re	DR /%
50	1.0	20000	12.08
50	1.5	20000	14.28
50	2.0	20000	16.16
100	1.0	20000	20.06
100	1.5	20000	20.84
100	2.0	20000	22.45
200	1.0	20000	24.11
200	1.5	20000	25.14
200	2.0	20000	26.33
50	1.0	30000	9.14
50	1.5	30000	11.31
50	2.0	30000	12.29
100	1.0	30000	17.01
100	1.5	30000	20.54
100	2.0	30000	21.52
200	1.0	30000	22.46
200	1.5	30000	23.94
200	2.0	30000	24.89
50	1.0	40000	8.38
50	1.5	40000	10.70
50	2.0	40000	11.65
100	1.0	40000	17.10
100	1.5	40000	19.79

100	2.0	40000	21.36
200	1.0	40000	21.06
200	1.5	40000	22.13
200	2.0	40000	23.04

Table 3. 18 sets of validation sample drag reduction rate data

PEO solution concentration /ppm	Injection rate/ L/min	Re	DR /%
50	1.25	20000	13.10
50	1.75	20000	15.10
100	1.25	20000	20.68
100	1.75	20000	21.83
200	1.25	20000	24.65
200	1.75	20000	25.75
50	1.25	30000	9.90
50	1.75	30000	11.50
100	1.25	30000	18.13
100	1.75	30000	20.38
200	1.25	30000	23.10
200	1.75	30000	24.30
50	1.25	40000	9.23
50	1.75	40000	10.88
100	1.25	40000	18.18
100	1.75	40000	20.33
200	1.25	40000	21.58
200	1.75	40000	22.53

3.4.1 Forecast result

The predicted value of drag reduction rate of the calculated sample based on the BP neural network model is compared with the real value, and the comparison results are shown in Table 4.

Table 4. Calculate the prediction result and error of the sample drag reduction rate

Actual drag reduction rate /%	Forecast drag reduction rate /%	Relative error /%
16.16	14.8004	8.41
11.31	12.1588	7.50
17.10	16.0823	5.95
22.13	22.9469	3.69
17.01	18.4546	8.49
24.11	23.6681	1.83

20.84	21.8181	4.69
10.70	11.1096	3.83

Comparing the predicted results with the actual measurement results, it is found that the predicted value of drag reduction rate is in good agreement with the expected value. The average prediction error is 0.0655, the mean square error is 0.0455, and the goodness of fit R^2 is 0.9529, indicating that the established BP neural network model can better predict the drag reduction rate.

3.4.2 Model verification

The conditional parameters in the remaining 18 sets of drag reduction rate data are used as the input parameters of the BP neural network prediction model. The comparison result of the model's drag reduction rate prediction output and the expected output is shown in Figure 6.

Fig. 6. Validation sample prediction results

Analyzing and verifying the sample prediction results, it is found that the predicted output curve of drag reduction rate is in good agreement with the expected output curve. The maximum relative error in the predicted value of drag reduction rate is 8.72%, the average error is 0.0476, the mean square error is 0.0542, and the goodness of fit R^2 is 0.9714, and the prediction accuracy is good. The model can be used to predict the drag reduction rate.

4 Conclusions

(1) The established three-layer BP neural network prediction model has a good fitting result for the complex non-linear relationship between PEO solution concentration, Reynolds number, injection flow rate and drag reduction rate. The average error, mean square error and relative error of the prediction results are relatively small, and the goodness of fit R^2 is close to 1.

(2) The proposed method can quickly integrate the existing experimental data of drag reduction rate, and use the experimental data to establish a neural network model to predict the drag reduction rate under new input conditions, which can effectively reduce the experimental workload and time.

In this study, the drag reduction rate prediction is only carried out for the channel drag reduction flow in which

the polymer solution is injected into the wall. In order to expand the scope of application of this prediction method, the amount of training data will be increased in future research, and input parameters with universal significance will be fully excavated. Combined with literature data, a comprehensive prediction of the drag reduction rate in the drag reduction flow of viscoelastic additives is realized.

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