A Study on Roughness Coefficient Using BP Neural Network

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***Abstract*—Since 1999, Xiaolangdi reservoir plays an important role in flood control, irrigation and repair and maintenance of the healthy life of Yellow River. At the same time, process which the water and sediment flow into the downstream has been changed by the regulation of reservoir and trigger a number of new phenomenon. The abnormal phenomenon that a flood peak increased in August 2004 , July 2005 , August 2006, August 2007 along the lower Yellow River occurred after the density current is poured. The fundamental reason for this phenomenon is the decrease of integrated roughness coefficient. Comprehensive roughness coefficient is an important parameter for the river flow dynamics and mathematical model,whose correct or not directly influence the accuracy of the model. After analyzing the factors influencing roughness, a BP neural network model is built to calculate the roughness. Median grain size of bed load, sediment concentration, median grain size of suspended load, Froude number is the input of the model, the roughness coefficient is the output of the model. Through the verification of the roughness coefficient in the course of the "04.8", "05.7", "06.8",”07.8”, the results show that the neural network model can calculate roughness coefficient accurately..**

***Index Terms*—roughness, PSO, BP neural network**

I. INTRODUCTION

Comprehensive roughness coefficient is an important parameter for the river flow dynamics and mathematical model, whose correct or not directly influence the accuracy of the model. In order to ensure the similar to the scour of prototype, many model ignore the accuracy of the hydraulic friction characteristics which influence the value. So it has an important theoretical and practical value to study the society, many scholars have conducted a special study. Kennedy is the earliest man to get the relations between the average velocity and depth, which indirectly give the calculated relationship of roughness. After Einstein in 1952 introduced an idea of splitting the resistance, the resistance to the alluvial river issue has been the rapid development of a variety of roughness coefficient calculation method. Since the roughness coefficient is not affected only by just a factor, while there are a number of factors, therefore, establishment of a certain roughness coefficient with factors, is unscientific and imprecise, which requires us to establish a Kind of scientific and effective ways to predict.

An artificial neural network (ANN), often just called a “neural network” (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation . In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. In more practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. As roughness coefficient is influenced by multi-factors and non-linear, so BP artificial neural network (ANN) model is introduced in this paper to calculate roughness coefficient.

II. METHODOLOGY

A. BP neural network

An artificial neural network (ANN), also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation. In most cases an ANN is an adaptive system that changes its structure based onexternal or internal information that flows through the network.

In more practical terms neural networks are non-linear statistical data modeling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

In recent years, neural network has been widely applied to the different scope, in which BP network is commonly used. The model created in this paper is a BP neural network with three-layer network (Figure1).

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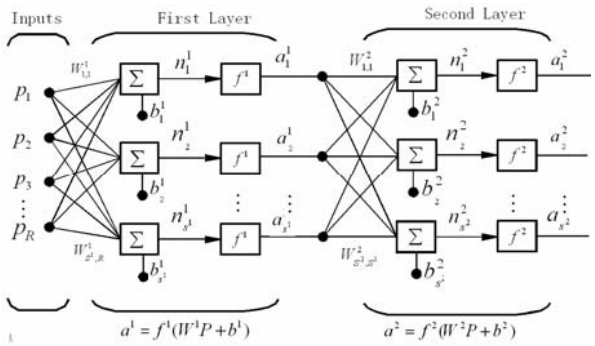


Figure 1. Three-layer BP network structure

In the Figure 1, p is input of neuron. Each layer has its own weight matrix $\overrightarrow{W}$, its bias vector $\vec{b}$, a net input vector $\vec{n}$, and an output vector $\vec{a}$. $\overrightarrow{W}$ is an $S \times R$ matrix, and $\vec{a}$ and $\vec{b}$ are vectors of length S respectively. The superscripts of symbols identify the layers. Also shown in Figure 1 are R input, S^1 neurons in the first layer, and S^2 neurons in the second layer. Different layers can have different numbers of neurons. The outputs of layers one and two are the inputs for layers two and three. Thus layer 2 can be viewed as a one-layer network with $R = S^1$ inputs, $S = S^2$ neurons, and an $S^1 \times S^2$ weight matrix $\overrightarrow{W}^1$. The input of layer 2 is $\vec{a}^1$, and the output is $\vec{a}^2$. The other layer also can be drawn using same abbreviated notation.

First, the output of the network will be computed. In the hidden and output layers, the net input to unit *i* is of the form:

$$s_i = \sum w_{ji} y_i + \theta_i \tag{1}$$

Several types of transfer functions are used; however, the most frequently used is the sigmoid function. This transfer function is usually a steadily increasing S-shaped curve. The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. In this study, two S-shaped transfer functions in a MATLAB neural network toolbox were used: the tansig function and logsig function. The two functions are of the form:

$$\tan sig\ (n) = \frac{2}{1 + e^{-2n}} - 1 \tag{2}$$

$$\tan sig\ (n) = \frac{1}{1 + e^{-n}} \tag{3}$$

The learning process of BP neural network is made up of 2 parts. 1) Signal transmission towards; 2) the error information is transmitted in the reverse direction.

(1) BP network signal transmission

To assume the network has m layers, making $Out_j^{\ m}$ express the output of the joint j in the m layer, so $Out_j^{\ 0}$ equals to In_j, namely the jth input. And making $W_{ij}^{\ m}$ express the connecting right value from $Out_i^{\ m-1}$ to $Out_j^{\ m}$, $\theta_j^{\ m}$ expresses the threshold value of the jth joint in the mth layer. The training steps of BP network are as following.

To make every right value and threshold value belongs to one random number in (-1, 1).

②To select one data pair (Ink, Tk) in data group, Input variable is put in the import layer (m=0), making $Out_i^{\ 0} = In_i^{\ k}$ (Including any i point), in the formula k represents the training figure number.

(2) Reverse error transmission of BP network and modifying the weight value.

④Calculate error value of each joint in outputting layer:

$$\delta_j^{\ m} = Out_j^m(1 - Out_j^m)(T_j^k - Out_j^m) \tag{4}$$

The error is getting by the difference between the real outputting data and expected value.

⑤Calculate the error value of each joint of front every layer:

$$\delta_j^{\ m-1} = F'(S_j^{\ m-1}) \sum_i W_{ij}^{\ m} \delta_i^{\ m} \tag{5}$$

This is get by reverse spreading the error by chasing floor (m=m, m-1,1).

⑥Revise right value and threshold value from one layer to another layer in reverse direction:

$$W_{ij}^{\ m}(t+1) = W_{ij}^{\ m}(t) + \eta \delta_j^{\ m} Out_i^{\ m-1} + \sigma[W_{ij}^{\ m}(t) - W_{ij}^{\ m}(t-1)$$

$$\vartheta_j^{\ m}(t+1) = \theta_j^{\ m}(t) + \eta \delta_j^{\ m} + \sigma[\theta_j^{\ m}(t) - \theta_j^{\ m}(t-1)]$$

In the formula representatives the learning times; η is the learning speed [η∈ (0, 1)]; σ is a momentum factor [σ∈ (0, 1)]

These accumulated inputs are then transformed to the neuron output. This output is generally distributed to various connection pathways to provide inputs to the other neurons; each of these connection pathways transmits the full output of the contributing neuron. Second, the error between the real output and the expected output will be computed. If the expected error is not satisfied, the precision, weights and biases will be adjusted according to the error.

. B PSO Algorithm

Particle swarm optimization (PSO) is a kind of evolutionary computation, which is an iterative optimization instrument similar to genetic algorithm. PSO analog prey behavior of birds. Such a scenario: a group of bird search food at random. In this area, there is only one food, however all birds don't know where the food is, but know the distance to the food. Then the what is optimal strategy to find food? Currently the simplest and most effective method is to search the food from the region around the bird food. PSO get inspiration from this model to solve this kind problem. Each optimization is to search a bird in space which is called as "particle". All particles have fitness value determined by optimization function, every particle also has one velocity to determine direction and distance. Then particles follow the optimization particle to search PSO as one random particle (random solution), iterative method is used to

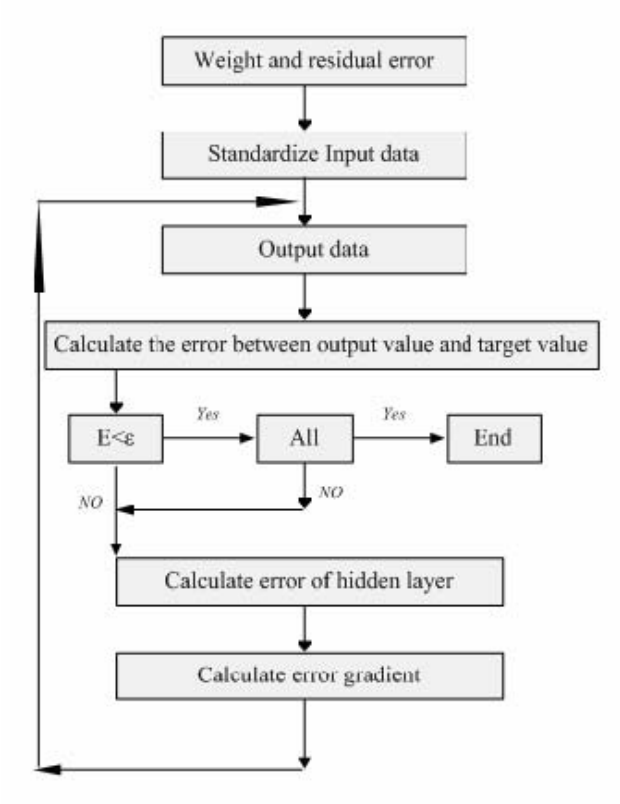


Figure 2. Flowchart of BP neural networks algorithm

find the optimal solution. At each iteration, the particles update themselves by tracking two "extreme" particles. The first is the optimization solution found by particles. This kind of solution is called as PBest, the other is the optimization found by species. This kind of extremum is called as global extremum.

When the two optimization are found, particles update themselves by equation 1 and equation 2 to find their own velocity and location.

$$v = v + c_1 \times rand() \times (pbest - present) + c_2 \times rand() \times (gbest - present) \quad (1)$$

$$present = present + v \quad (2)$$

Where v is the particle's velocity, present is the particle's position currently. Rand() is random number among (0,1). c_1, c_2 is learning factor. Commonly $c_1 = c_2 = 2$. The velocity in any dimension is limited in maximum velocity, if the updated velocity exceeds Vmax, then the velocity is Vmax

C training BP neural network using PSO

The optimization of PSO algorithm to BP neural network is to replace gradient descent method to train the weight and threshold value. The key is to build the reflecting relationship between weight and threshold value connecting dimension space and neural network.. in this paper, learning process mainly is the update process of weight and threshold value. The weight and threshold value in BP algorithm corresponds to the particles' position.

The fitness function of particle is Minimum mean-variance MSE

$$MSE = \frac{1}{P}\sum_{i=1}^{p}\sum_{j=1}^{N}(t_i - O_j)^2$$

Where N is the dimension of output matrix; P is the sample number.

The steps of PSO training weight value of neural network are as followings

(1) modeling neural network's structure, including input layer, hidden layer, output layer and neuron number
(2) initial particle swarm.
(3) Fitness function's determination.
(4) Fitness grade is calculated according to equation3
(5) Update pbest and gbest;
(6) Update w.
(7) Update velocity and position of any particle;
(8) Optimization solution

III. EXPERIMENTAL METHODS

A Experimental Equipments

The experiment is done in steel glass channel in Yellow River Institute of Hydraulic Research with rectangle profile, length of 22 meter , width of B=0.3m, height of H=0.5m,and roughness of n=0.010,slope of river bed of i=1/1000 and 3.8/1000. To ensure stability and uniformity, 10 meter at center is selected as experimental paragraph, electromagnetic flow meter is used to measure flow and rotor current meter is used to measure velocity. The channel test system can be seen in Figure3.

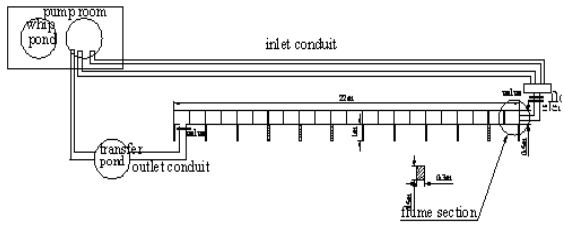


Figure 3. Sketch of flume

B Test Conditions

In test, water depth is strictly controlled to make uniform flow in order to compare roughness coefficients in conditions of different sediment concentration.

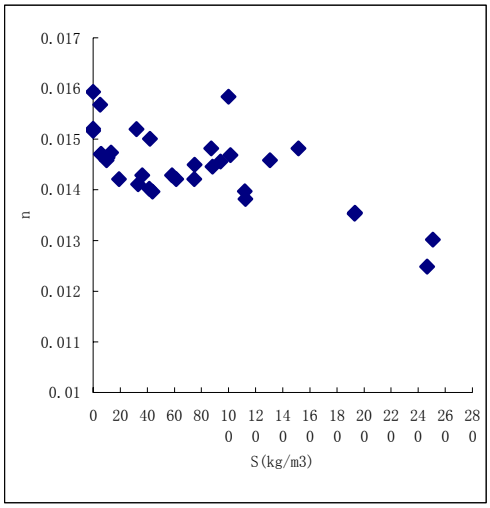
TABLE I. EXPERIMENT PARAMETERS

$\gamma_s/(t.m^{-3})$	d/mm		J(%)
	Scope	d_{50}	
2.65	0.0001-0.1	0.0060-0.010	0.38
S/(kg.m^{-3})	**Q/(L.s^{-1})**	**h/cm**	**B/h**
2.5-290	20-30	9.5-20	1.5-3.15

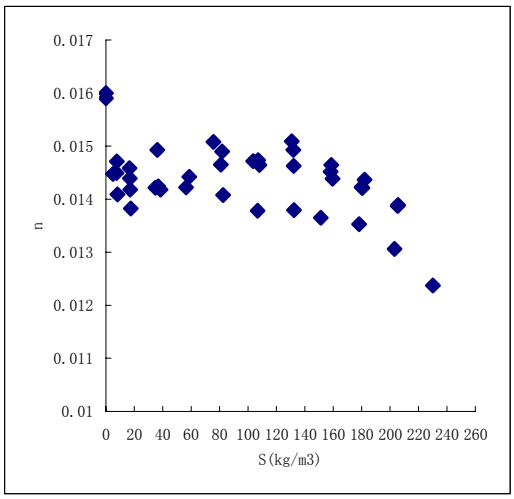
IV. TEST RESULTS AND ANALYSIS

A The Regularity of Roughness Coefficient

Fig.4 shows as sediment concentration increases, roughness coefficient decreases. When sediment concentration is larger than 60 to 100 kg/m^3, roughness coefficient has little changes. But when sediment concentration is larger than 100 kg/m^3, roughness coefficient decreases obviously. The writer believes the reason is that sediment-bearing water changes from Newtonian fluid into Bingham fluid. In view of Bingham fluid's large viscosity, resistance and high energy loss, the drag reduction phenomenon is caused by slip velocity at the intermediate layer between solid and fluid.



（a） $d_{50} = 6.35\mu m$



(b) $d_{50} = 9.17\mu m$

Figure 4. The relationship between roughness and sediment concentration

V. INFLUENCES OF ROHGHNESS

A Influence of Particle size on roughness coefficient

Constituents of bed mainly refers to the size of sand and gradation, and the impact of sand particle size on the roughness coefficient is obvious. At present, there are many research results in this study area. Though different researchers has different achievements, it is necesaary for the size of sand to the roughness. According to the observed data, the relationship of roughness and medium partical size indicates that the roughness coefficient decreases with the increasing medium partical size for fine sand. Though partical size of bed is one of the influencing factors to the roughness, to the hyper-concentration water flow, the influence of partical size can be ignored.

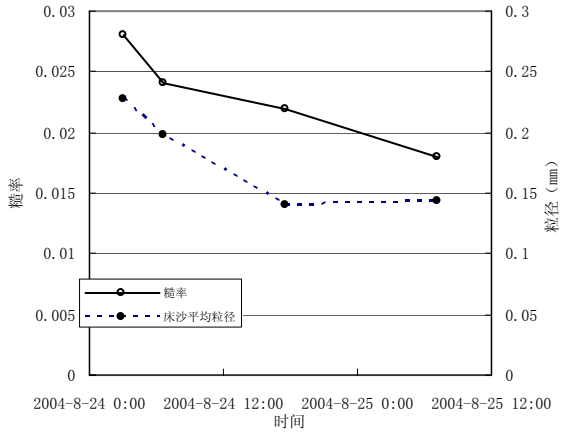


Figure 5. Relationship of partical size with roughness coefficient in "04.8"

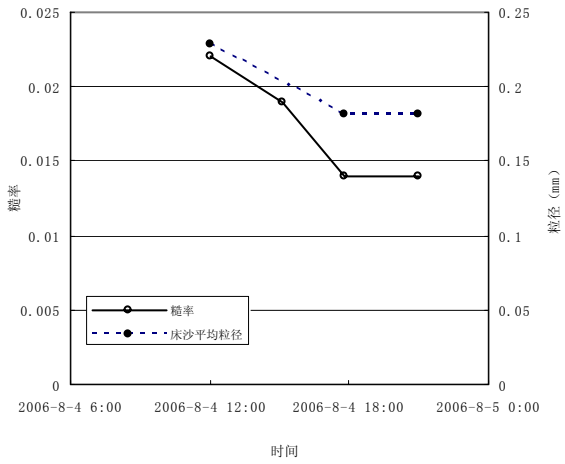


Figure 6. Relationship of partical size with roughness coefficient in "06.8"

（2）Influence of sediment concentration on roughness

The infuence of concentration on roughness mainly because the concentration can affect water flow structure and vertical velocity distribution.

①relationship of concentration with roughness

At present some scholars thought that the concentration is the major affecting factor influencing roughness coefficient. In order to understand roughness coefficient change with hyper-concentration water flow in the flood situation.，Jiang has counted massive actual material in Yellow River, the Weihe River, who Discovered that the river course roughness coefficient has the close relationship with the water power, which can be seen in Fig. 7 and 8.

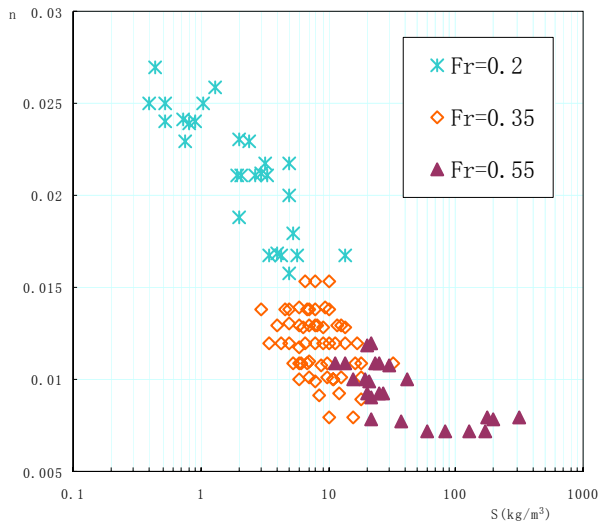


Figure 7. Relationship of roughness and concenration in Huayuan kou station

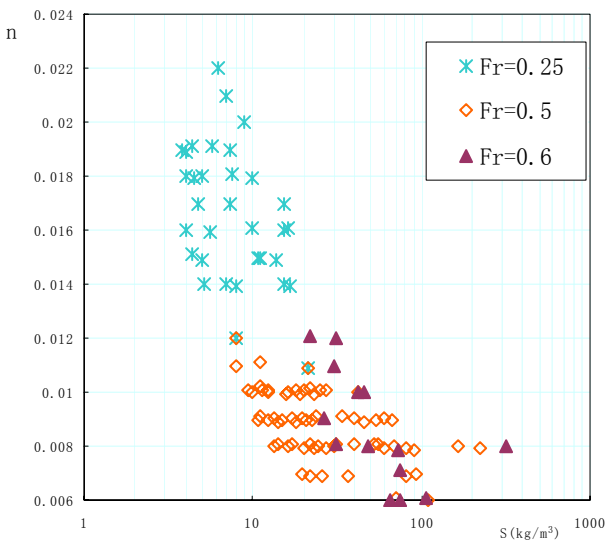


Figure 8. Relationship of roughness and concenration in Jiahetan station

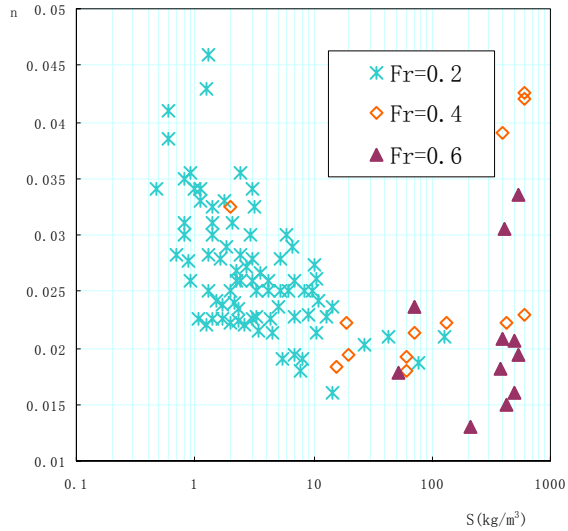


Figure 9. Relationship of roughness and concenration in Huayuan kou station

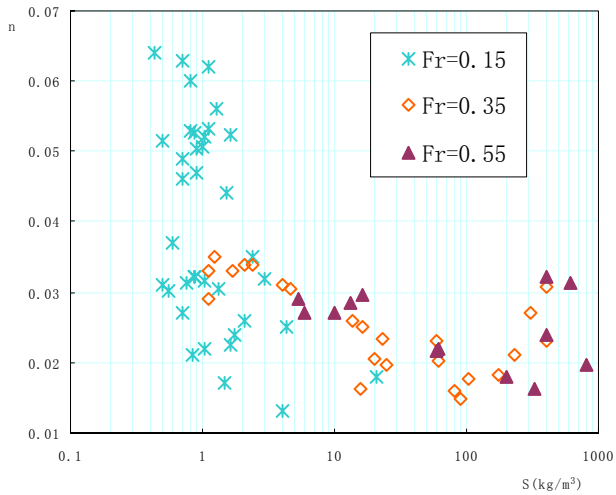


Figure 10. Relationship of roughness and concenration in Huayuan kou station

VI. ANN-BASED ROUGHNESS COEFFICIENT MODEL

A. Background

Since 1999, Xiaolangdi reservoir plays an important role in flood control, irrigation and repair and maintenance of the healthy life of Yellow River. At the same time, process which the water and sediment flow into the downstream has been changed by the regulation of reservoir and trigger a number of new phenomenon. The abnormal phenomenon that a flood peak increased in August 2004, July 2005, August 2006, August 2007 along the lower Yellow River occurred after the density current is poured. After analysis, the reason triggering the abnormal phenomenon can be considered as the drag reduction in the course. The factors affecting roughness coefficient includes Median grain size of bed load,

sediment concentration, median grain size of suspended load, Froude number.

B. BP model on roughness coefficient

Though neural network model can be seen as one kind of "black box" model, the process to built the model is complex as other models. During the building the model, the contents should be considered as follows: network type, pre-processing data, enough training sample, input pattern, network topology, parameter estimation, model testing.

B.1 Data pre-processing

Data processing is a preliminary work which includes size of training sample, utility replacement, statistics, Spatial information processing and handling of singular value.before the data is pre-processed, the data is divided into two groups which are training sample and testing sample. The data in "04.8","05.7","06.8" flood period are as the training sample, and the data in "07.8" flood period are as testing sample.

B.2 Determination of BP Neural network

Determination of input pattern is the key to an excellent neural network. Too few or too many input nodes can affect either the learning or prediction capability of the network. Therefore, we use input variables and the lag time as the input to make forecasts for future values. Since there are no suggested systematic ways to determine the appropriate number of neurons, the best way to select input variables is by trial-and-error. Median grain size of bed load, sediment concentration, median grain size of suspended load, Froude number is the input of the model, the roughness coefficient is the output of the model. We develop a model for the BP algorithms (Figure 2)

$$n = f\{d_{b50},\ S,\ d_{s50},\ Fr\}$$

Where n -roughness coefficient; d_{b50} - median grain size of bed load; S -sediment concentration; d_{s50} - median grain size of bed load; Fr -Froude number

When the number of hidden layers are 6, the model is stable and can get the ideal result. The structure of topology is 4-6-1. For better performance in our experiments, we use a small learning rate of 0.10 and the associated momentum factor of 0.95 in the training.the expired error is 0.0001

C. Results

BP neural network was applied to the lower stream of Yellow river, Following figures summarize the performance of the BP.

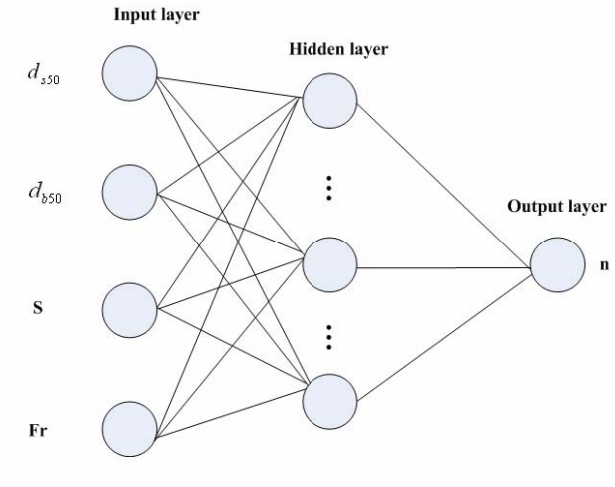


Figure 11. Structure of back-propagation (BP) neural networks of roughness coefficient

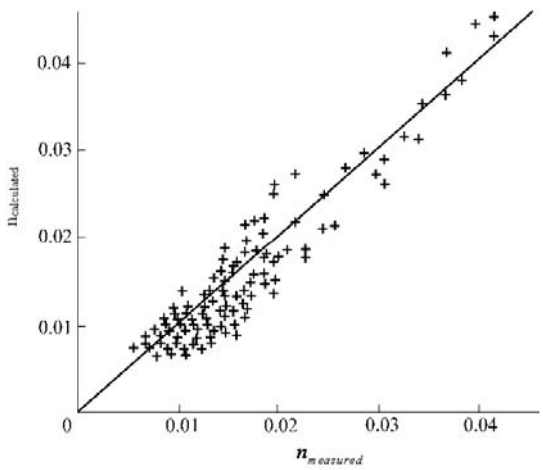


Figure 12. Calculated and observed roughness coefficient in huyuankou

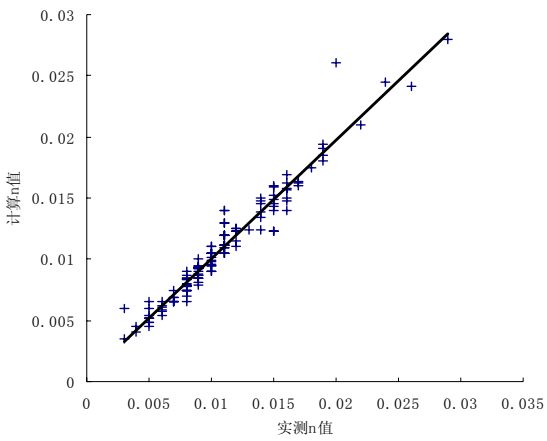


Figure 13. Calculated and observed roughness coefficient in huyuankou

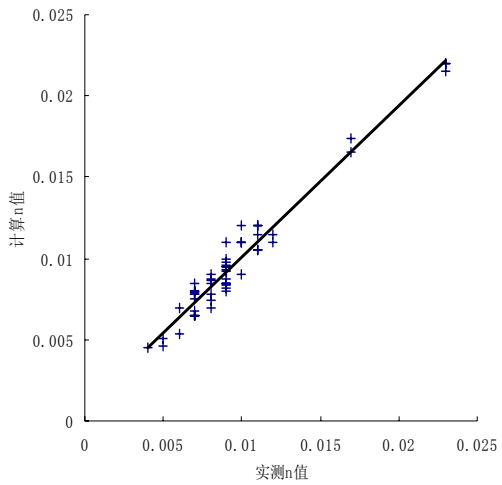


Figure 14. Calculated and observed roughness coefficient in huyuankou

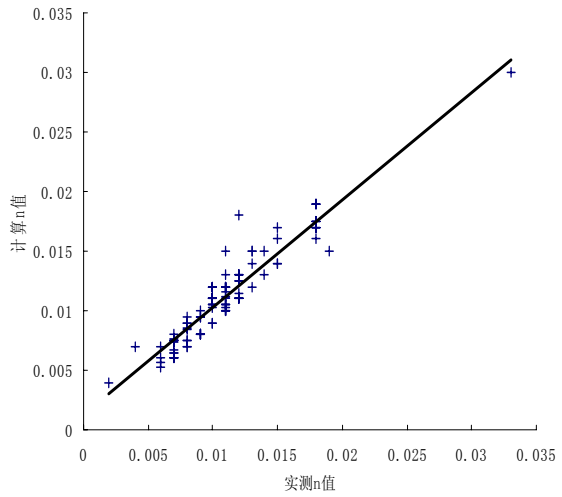


Figure 15. calculated and observed roughness coefficient in huyuankou

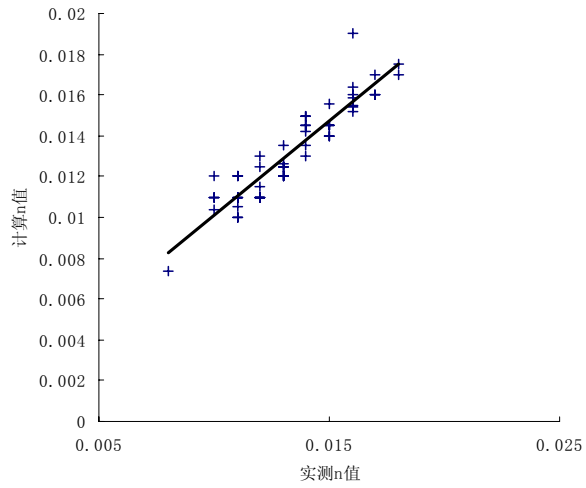


Figure 16. Calculated and observed roughness coefficient in huyuankou

Figure 12-16 shows the comparison of the measured and calculated roughness coefficient during "04.8","05.7","06.8" flood period. It can be seen that BP model is capable of calculating roughness coefficient well. As compared with the recession phase, the flood peak phase is not well predicted. BP model has the high practicability and good accuracy for roughness coefficient calculating. the BP model produces promising results and its advantages can be utilized by developing or using new algorithms in future studies. The BP neural networks will probably yield a reasonably good result if there is adequate data.

VII. CONCLUSIONS

An artificial neural network (ANN) is a mathematical methodology which describes relations between the input and output data irrespective of processes behind and without the need for making assumptions considering the nature of the relations. They are dependent on the particular samples observed and require tedious experiments and trial-and-error procedures. However, several distinguishing features of ANNs – adaptability, nonlinearity, and arbitrary function mapping ability – make them valuable and attractive tools for simulations of complicated hydrologic processes. The comparison study of ANN with measured roughness coefficient indicates that ANN performs well on the roughness coefficient calculation.

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