A Modified Radial Basis Function Method for Predicting Debris Flow Mean Velocity

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Abstract. This study focused on a model for predicting debris flow mean velocity. A total of 50 debris flow events were investigated in the Jiangjia gully. A modified radial basis function (MRBF) neural network was developed for predicting the debris flow mean velocity in the Jiangjia gully. A three-dimensional total error surface was used for establishing the predicting model. A back propagation (BP) neural network and the modified Manning formula (MMF) were used as benchmarks. Finally, the sensitivity degrees of five variables that influence debris flow velocity were analyzed. The results show that the mean error and the relative mean error of the 10 testing samples were only 0.31 m/s and 5.92%, respectively. This proves that the MRBF method performed very well in predicting debris flow mean velocity. Gradient of channel and unstable layer thickness have a greater impact on debris flow mean velocity than the other three influencing variables. This proves that the proposed MRBF neural network is reliable in predicting debris flow mean velocity.

Keywords: *debris flow; disaster risk reduction; mean velocity; radial basis function; sensitive variables sequence.*

1 Introduction

Debris flow is a common geological disaster in mountainous areas [1]. It is a type of sudden, ferocious and destructive natural disaster [2-6]. The mean velocity of debris flow is a significant parameter in disaster reduction work. Thus, the accuracy of predicting debris flow mean velocity is crucial for the design of debris flow reduction constructions.

Nowadays, there is still no widely accepted formula for calculating debris flow mean velocity [7]. Formulas used for calculating debris flow velocity include the dilatant fluid model, the Manning-Strickler formula and the Chezy formula. Studies on a constitutive model of debris flow dynamics started in the 1970s [8-11]. Calculation methods for velocity can be divided into two types based on the debris flow properties, i.e. viscous calculation formulas and turbulent calculation formulas. The most popular approach is the use of a dynamic model, such as the Bingham viscous fluid model, the dilatant fluid model, the generalized viscoplastic model, the Voellmy model, or the friction model. All

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these models have been used to predict the velocity of debris flow and all work successfully [12-14]. However, debris flow is a complex and open system that is influenced by many variables. There is a complicated nonlinear relationship between debris flow intensity, probability and impact variables [15]. It is difficult to establish an accurate and widely applicable physical mechanism model.

Artificial intelligence (AI) machine language could provide many excellent methods for debris flow velocity prediction. Artificial neural networks (ANNs) have a strong ability for nonlinear fitting and can realize arbitrary complex nonlinear mapping. ANN learning rules are simple and can be implemented easily. Meanwhile, ANNs have very strong robustness, memory ability, nonlinear mapping ability and self-learning ability. Recently, ANNs have been applied to debris flow evaluation, risk assessment and damage range prediction [16,17]. Nevertheless, there are only few applications of neural networks in debris flow velocity prediction.

The radial basis function (RBF) neural network is an excellent feed-forward neural network. The RBF neural network can get close to any nonlinear function with arbitrary longitude. In this paper, a modified RBF method is proposed to establish a model to predict debris flow mean velocity. By comparing the modified RBF with the results calculated by a back propagation (BP) neural network, the modified Manning formula (MMF) and the standard RBF prediction model, it was shown that MRBF could achieve satisfying results. Meanwhile, an analysis of debris flow variable sensitivity degree and ranking is also given.

2 Data Resources

2.1 Study Area

The Jiangjia gully is located in Yunnan Province, Southwest China (Figure 1). This area is covered with alpine forge landforms. The attitude in the eastern area is higher than in the western area. The maximum relative elevation of the eastern and western area is 2200 m. The basin's area is 48.5 km^2. Mountains in the area are steep and high. The eastern gully is narrow, while the western gully is wide. Debris flow can easily occur [18,19].

The strata in the study area are mainly shallow metamorphic rock. Sinian dolomite and Permian limestone appear, as well as a striped purple slate. The joints and folds are strongly developed, which can easily lead to the rock weathering. Abundant loose materials are distributed, which can be a material source for debris flow. In the Jiangjia gully, debris flows occur often, with the characteristics of high frequency and large scale. It is known as a natural museum of debris flow [20].

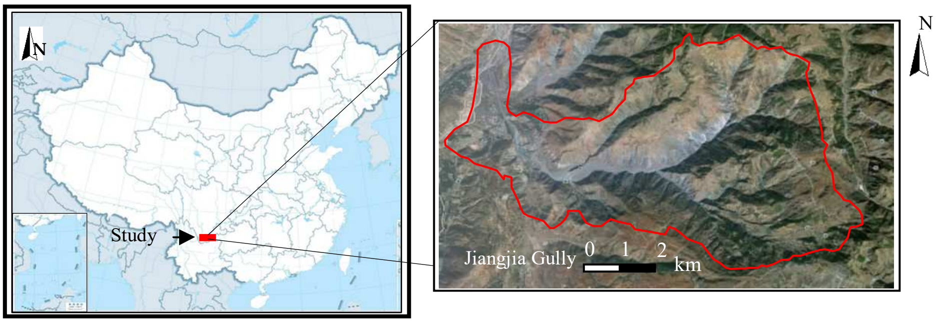

Figure 1 Geographical position of Jiangjia Gully in China.

2.2 Influencing Variables and Data

The data were collected from Xu [21]. This study used 50 groups of measured debris flow velocities from the Jiangjia gully in 1974 as study samples. 40 groups (80%) of measured data were randomly selected as training data, while the other 10 groups (20%) were used as testing data. Five debris flow velocity influencing variables were determined, i.e. x_1 = flow depth (cm), x_2 = gradient of channel (%), x_3 = density of debris flow ($t \cdot m^{-3}$), x_4 = grain size (cm) and x_5 = unstable layer thickness (m). The specific data can be seen in Table 1. The flow depth data were acquired by measuring the mud depth of ancient debris flow in the field. The ratio between elevation difference and horizontal distance in the debris flow main channel is called the gradient of channel. The density of debris flow and grain size data were obtained by in situ sieving analysis and the laboratory method. When the head of the debris flow scours the mud bed, the scoured layer is called the unstable layer. The thickness of the unstable layer was measured in the field.

3 Method

3.1 Radial Basis Function Neural Network

An artificial neural network (ANN) is created through interconnected artificial neurons. This artificial neural network is capable of learning and can be trained through a proper learning algorithm. There are many types of artificial neural networks, one of which is called the radial basis function (RBF) neural network. A radial basis function (RBF) neural network is a 3-layer feed-forward network with a structure similar to that of a multilayer forward network. The first layer is the input layer, which is composed of a signal source node. The second layer is the hidden layer. The neuron number in the hidden unit is different when solving different problems. Radial basis functions are used as activation functions. The third layer is a linear output layer. The output layer in the higher dimension space can realize the linear weighted combination of the output. The structure of the RBF neural network is shown in Figure 2. The most commonly used basis function is the Gauss function in Eq. (1). For any input vector $X \in R^n$:

$$R_i(x) = e^{\left(\frac{-\|X-C_i\|^2}{2\alpha_i^2}\right)} \quad i = 1,2,\ldots,p \tag{1}$$

where $R_i(x)$ is output of the ith hidden neuron, X is the n-dimension input vector, C_i is the center vector of the ith neuron, α_i is the basis width vector, which can usually be determined experimentally.

Table 1 Measured data of debris flow mean velocity and influencing variables in Jiangjia Gully in 1974.

No	y	x_1	x_2	x_3	x_4	x_5	No.	y	x_1	x_2	x_3	x_4	x_5
1	8.9	175	6.3	2.08	0.80	0.80	26	6.9	250	5.5	2.22	0.90	1.06
2	8.8	150	6.3	2.20	1.10	0.72	27	6.6	226	5.5	2.13	1.10	0.92
3	7.4	200	6.3	2.21	1.70	0.97	28	6	120	5.5	2.20	0.80	0.51
4	7.9	200	6.3	2.25	1.40	0.99	29	7.4	145	5.5	2.25	1.10	0.62
5	10	95	6.3	2.16	0.60	0.45	30	5	65	5.5	2.24	1.10	0.28
6	7.4	55	6.3	2.25	0.90	0.27	31	6.9	122	5.5	2.21	1.00	0.52
7	7.6	11	6.3	2.07	0.70	0.50	32	7.5	168	5.5	2.28	1.60	0.73
8	7.6	100	6.3	2.19	0.90	0.48	33	9.2	372	6.6	2.21	1.20	1.88
9	7.3	90	6.3	2.21	1.00	0.44	34	5.8	107	5.5	2.29	1.20	0.47
10	6.6	70	6.3	2.19	1.20	0.34	35	3.6	52	5.8	1.70	0.10	0.18
11	9.6	275	6.6	2.21	1.60	1.40	36	5.8	103	5.5	2.21	0.80	0.44
12	7.5	170	6.6	2.19	1.10	0.85	37	5.6	70	5.5	1.92	0.30	0.26
13	8.4	210	6.6	2.20	0.80	1.06	38	4.1	70	5.8	1.80	0.20	0.25
14	8.1	160	6.6	2.22	1.20	0.82	39	3.5	50	5.8	1.76	0.20	0.18
15	8.2	130	6.6	2.20	0.70	0.66	40	3.6	58	5.8	1.69	0.20	0.20
16	9.6	220	6.6	2.29	1.50	1.16	41	4.8	93	5.8	1.92	0.30	0.36
17	9.4	210	6.6	2.21	1.20	1.07	42	4.9	60	5.5	1.99	0.60	0.23
18	9.3	210	6.3	2.29	1.00	1.05	43	4.7	60	5.5	1.97	0.50	0.23
19	8.5	200	6.3	2.30	1.50	1.01	44	7.7	161	5.5	2.25	1.00	0.69
20	4	40	6.3	2.04	0.30	0.18	45	7.7	177	5.5	2.24	1.10	0.76
21	7.8	140	6.3	1.95	0.60	0.60	46	3.9	60	5.5	1.83	0.10	0.21
22	3.7	40	6.3	2.02	0.10	0.18	47	3.9	55	5.8	2.07	0.80	0.23
23	3.8	40	6.3	1.85	0.10	0.16	48	6.4	109	5.5	2.25	1.10	0.47
24	9.3	210	6.3	2.21	1.10	1.02	49	3.7	55	5.8	1.80	0.10	0.20
25	6.9	202	5.5	2.27	1.70	0.88	50	7.6	125	6.3	2.10	0.60	0.57

Note: y is the field investigated velocity of debris flow; x_1 is flow depth (cm); x_2 is gradient of channel (%); x_3 is density of debris flow ($t \cdot m^{-3}$); x_4 is grain size (cm); x_5 is unstable layer thickness (m)

The RBF neural network learning process comprises unsupervised learning and supervised learning. The unsupervised learning stage employs K-means clustering to cluster the training samples. After finding the cluster center C_i and α_i, the supervised learning is conducted. When C_i and α_i are determined, the RBF neural network becomes a linear function from input to output. The steps are as follows:

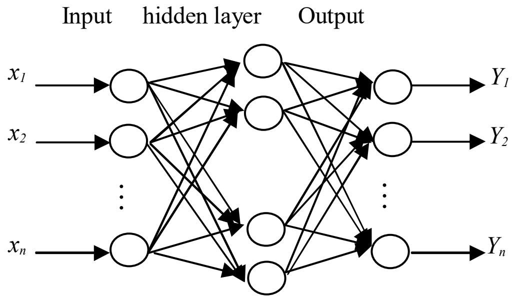

Figure 2 Network structure of RBF.

Step 1: Initialize the weights randomly
Step 2: Calculate output vector Y by the following Eq. (2):

$$y_i = \sum_{i=1}^{p} W_i R_i \quad (2)$$

where W_i is the weight of the ith hidden neuron to the output node.

Step 3: Calculate error ε_i for each neuron in the output by the following Eq. (3):

$$\varepsilon_i = y_i - y_i' \quad i = 1,2,\ldots,p \quad (3)$$

where y_i' is the desired output of the ith neuron in the output layer.

Step 4: Based on the least squares method, determine the weights between the hidden neurons and the output nodes in Eq. (4).

$$W = e^{(-\frac{p}{c_{\max}^2}\|X-C_i\|^2)} \quad i = 1,2,\ldots, p \quad (4)$$

where $c_{\max}$ is the maximum distance between the selected centers.

Step 5: Update the weights until the error meets the requirement as shown in Eq. (5):

$$W_{ij}' = W_{ij} + \mu\varepsilon_i R_j \quad i = 1,2,\ldots,m, j = 1,2,\ldots,p \quad (5)$$

where W'_{ij} is the updated weight and μ is the learning rate.

3.2 Establishment of Modified Radial Basis Function Neural Network Model

References [22,23] suggest that through changing the hidden neuron number and the width of the basis function, the testing results using RBF are different. The MATLAB software was used to write a program to search for the optimal results. In fact, the number of hidden neurons used in the original RBF method was not valid. It is not easy to find the optimal solution using the original RBF. Trial and error was used to find the optimal solution and determine the hidden neuron number. The MATLAB toolbox provides a RBF neural network constructor function, *newrb* (*P, T, error-goal, spread*). *P* and *T* represent the input and output vectors of the training samples, respectively. *Error-goal* is the target error. *Spread* is the width of the basis function.

In the training stage, the program can adjust the parameters and the structure. It also adaptively increases the hidden layer neurons to reach the target error. This study adopted the function *newrb* to test the generalization ability of the RBF neural network and set the *error-goal* to 10^{-4}. If the *spread* is set to 0.8, the total error is the minimum and the adaptive hidden neuron number is 38. The results change with the number of neurons. Thus, the MATLAB constructor function *newrb (P, T, error-goal, spread, MN*) was used, in which *MN* is the number of neurons in the hidden layer. The neuron number and *spread* have an impact on RBF neural network fitting and generalization. If the fitting degree is too low, there will be no inherent laws. If the fitting degree is too high, the generalization ability for the training samples will become weak.

Thus, it is key to choose the best available neuron number *MN* and *spread* value. Changing both these parameter values is a general way to get the optimal value. However, it is not easy to obtain the optimal value because RBF has a great blindness. When determining the neuron number and the *spread* value, it is necessary to test a large number of parameters. In this study, a three-dimensional total error surface was established. The x axis represents the neurons number, the y axis represents the *spread* value and z represents the total error of the ten testing data. The steps of generating the total error surface are as follows:

Step 1: Initialize the neuron number *MN* as 1, the step is 1;
Step 2: Initialize the width of the basis function *spread* as 0.1, the step is 0.1;
Step 3: Calculate the total errors of ten testing data using RBF;
Step 4: When the *spread* value is 20, set *MN* as 2, repeat *Step 2* and *Step 3* until *MN* is 50;
Step 5: Establish a three-dimensional surface with the produced 200×50 points.

The three-dimensional surface is shown in Figure 3. It determines the neuron number in the hidden layer and the width of the basis function.

Yu, *et al*. [24] selected a 3-layer BP neural network and used S function $f(x) = 1/(1+e^{-x})$ as the transfer function. They established a BP prediction model with MATLAB and used the training samples' mean error as the judgment standard. Finally, a 5:9:1 network was established. In this study, the BP method was chosen as the benchmark.

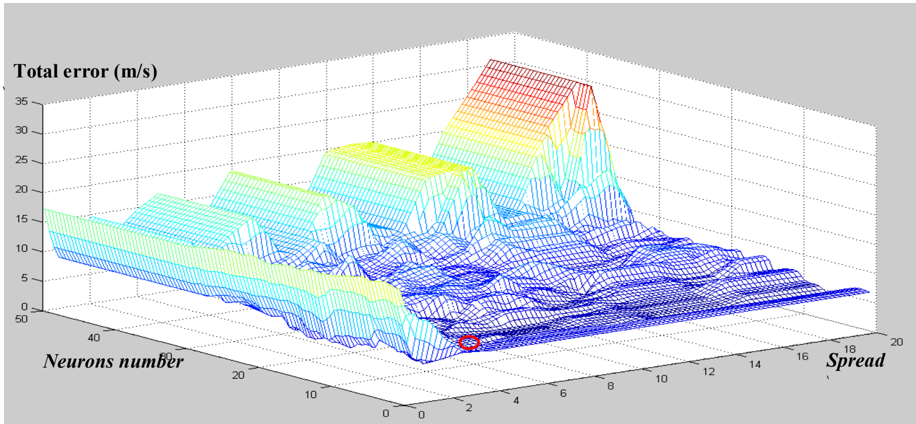

Figure 3 Impact of *spread* and neuron number in the hidden layer on the prediction total error.

Table 2 Comparison of predicted mean velocities of debris flow.

Sample No.	Real value (m/s)	BP		MMF		RBF		MRBF	
		Pred. value (m/s)	Fractional error (%)	Pred. value (m/s)	Fractional error (%)	Pred. value (m/s)	Fractional error (%)	Pred. value (m/s)	Fract-ional error (%)
41	4.8	9.15	90.63	6.42	33.85	6.12	27.58	5.55	15.66
42	4.9	6.03	23.04	4.34	11.48	5.29	7.96	4.82	-1.61
43	4.7	6.05	28.73	4.34	7.71	5.28	12.25	4.70	0
44	7.7	7.56	-1.83	8.38	8.78	7.90	2.57	7.05	-8.47
45	7.7	7.58	-1.56	8.92	15.87	8.14	5.65	7.19	-6.67
46	3.9	3.84	-1.53	4.34	11.22	5.03	29.06	3.60	-7.72
47	3.9	7.97	104.36	4.37	11.92	4.89	25.50	4.49	15.23
48	6.4	6.01	-6.09	6.95	8.67	6.17	-3.66	6.44	0.64
49	3.7	3.62	-2.22	4.37	17.97	3.84	3.74	3.75	1.35
50	7.6	8.85	16.47	5.83	23.35	9.93	30.72	7.73	1.72
Mean error (%)			**27.65**	**27.65**	**15.08**		**14.87**		**5.92**
Maximum error (%)			**104.36**	**104.36**	**33.85**		**30.72**		**15.66**

4 Results and Discussions

4.1 BP, RBF and MRBF Results and Their Comparisons

Figure 4(a) shows that both the BP and the RBF training results are acceptable, which means that they both have good learning ability. However, the total training error of RBF was only 0.46 m/s, while that of BP was 3.5 m/s. Therefore, the RBF generalization ability is better than that of BP. Figure 4(b) shows that the RBF testing curve floats around the measured value curve, the fitting result is good. In contrast, the BP testing curve fluctuates around the measured value, which has a poor ability in predicting debris flow mean velocity.

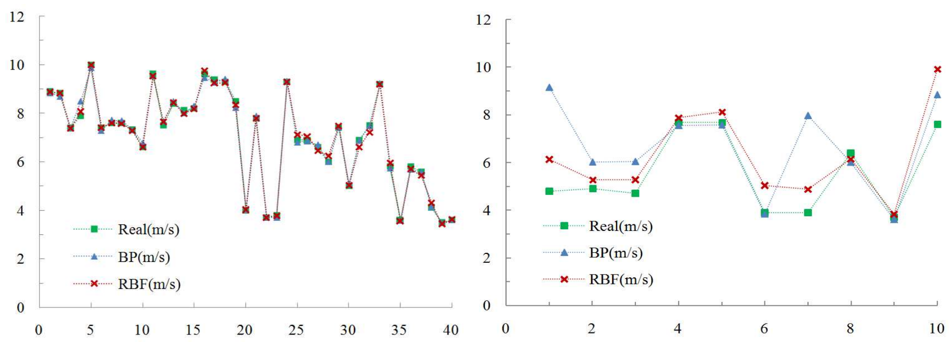

Figure 4 Results of training and testing mean velocities with BP and RBF.

The modified Manning formula (MMF) is an empirical formula, which is applicable for the Jiangjia area. Xu, *et al*. [25] has already introduced this formula in detail. In the present study, this method was used to calculate the mean velocities of the testing data. In Table 2, it can be seen that the mean velocity errors predicted by BP, MMF and RBF were 1.29 m/s, 0.84 m/s and 0.75 m/s, respectively. The BP maximum relative error was 104.36% and the mean error was 27.65%. The MMF results are given in Table 2, which shows that the maximum error and the mean error were 33.85% and 15.08%, respectively. The RBF maximum relative error was 30.72% and the mean relative error was 14.87%. The results of MMF and RBF are very close. However, in MMF, the debris flow velocity is only influenced by two variables: flow depth and gradient of channel. In this study, five variables were taken into consideration using the modified RBF. The mean velocity of debris flow does not depend only on grain size but also on several other variables at the same time. In a later study, more variables influencing the debris flow mean velocity need to be taken into consideration. Thus, the nonlinear method will become more important, which would be a good implement for calculating the mean velocity of debris flow using an empirical formula. Therefore, the accuracy using the RBF is further better than using BP and an empirical formula.

Yu, *et al.* [24] used the BP to train and predict the data. He found that the BP has poor prediction ability for testing data. In Table 1 of their paper, the maximum relative error is 101.22% and the average relative error is 27.64%. In our paper, the maximum relative error is 104.36% (using the same samples as Yu *et al.*), the average relative error is 27.65%, which is also the same as that of Yu *et al.*

40 groups of data were used as training data, while Xu, *et al.* [25] used 45 groups of data as training data. The remaining 10 groups were used as testing data. Xu, *et al.* selected five groups as testing data, which were different from the ones we selected. Meanwhile, we chose five variables, while Xu, *et al.* only chose four variables. Because we used different training data and different testing data, our relative average errors are different from those reported by Xu, *et al.*

Generally, RBF is superior to BP. BP is limited partly by its slow training performance, so the RBF neural network was developed instead. Theoretically, Both RBF and BP can be close to any nonlinear function with arbitrary precision. However, their approximation properties are not the same. An RBF neural network is different from a BP neural network in that it uses sigmoid activation functions utilizing basis functions in the hidden layer, which are locally responsive to input stimulus [26]. These hidden nodes are usually implemented with a Gaussian kernel. Also, Poggio and Girosi [27] have proved that the RBF neural network provides a better approximation method for continuous functions than BP. Furthermore, Zhi [28] found that the function approximation capability of RBF is superior to that of BP.

The hidden neuron number is generally determined by the complexity of the problem. Although more neurons make the network more accurate, this will lead to over-fitting. In the training phase, when the *spread* value was set to 0.8 and the neuron number was set to 38, the mean error of the training samples was only 0.012 m/s. However, the mean error of the testing samples was 0.75m/s. This means that RBF was already over-fitting in the training stage. Hence, 38 neurons in the hidden layer is too many. Meanwhile, in spite of the mean error of the testing samples using RBF being less than that of BP, the results were not satisfactory. The testing error should be controlled to be within 0.5 m/s. Thus, the neuron number in the hidden layer as well as the *spread* value needed to be reset.

It can be seen from Figure 3 that when the *spread* value is 6.8 and the neuron number is 14 (the location of the red oval), there appears a concave in the three-dimensional surface. In this case, the total error is minimum. In Figure 3, two regular patterns can be found: *a*) if the neuron number is fixed, with an increase of the *spread* value, the total error slightly decreases first and then increases; *b*) if the *spread* value is fixed, with an increase of the neuron number, the total error first increases slowly. Until the neuron number reaches a specific value, the total error increases sharply and is convergent at the maximum value.

In Figure 5, it can be seen that the MRBF testing values and the measured velocity values were almost the same. The total error was only 3.12 m/s. In the testing phase, the MRBF and RBF mean errors were 0.31 m/s and 0.75 m/s, respectively. The mean error using MRBF accounts for 41.33% of that using RBF. In Table 2, the maximum relative error of MRBF is only 15.66%. The mean error of the testing samples was only 5.92%. It can be seen that debris flow mean velocity is predicted better using MRBF than using RBF or BP.

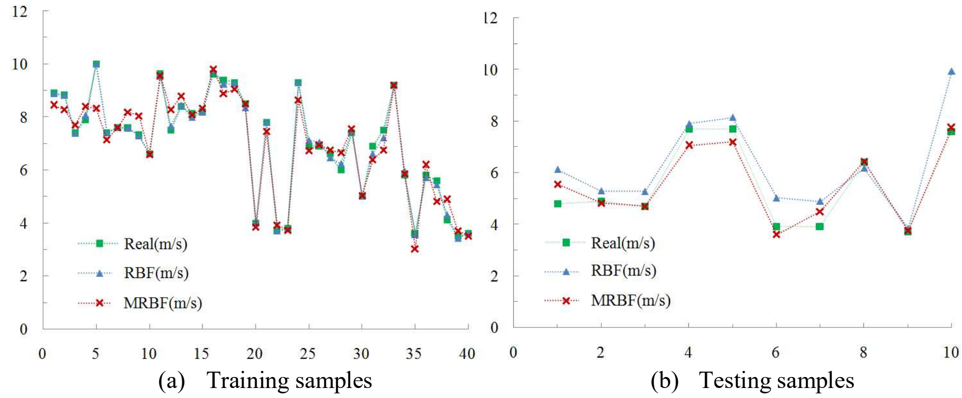

Figure 5 Results of training and testing mean velocities with RBF and MRBF.

Comparing RBF with MRBF (Figures 4(b) and 5), it was found that the greater the training error, the smaller the testing error. However, acting well in the training stage does not mean that it has better predicting ability. What should be focused on is the precision in the testing phase. BP ignores the essential regulation of the data, which leads to low prediction precision. If the neuron number is sufficient, the RBF neural network can approximate any nonlinear function with arbitrary precision and also has the ability of optimal generalization. In view of analysis of the mean error, the RBF neural network works well, but it is necessary to try different parameters values to get the optimal value. The higher the *spread* value, the smoother the fitting function. Meanwhile, using MRBF for predicting debris flow mean velocity is more accurate than using RBF or BP. The MRBF model can obtain better prediction results. However, the proposed MRBF model is only applicable to the study area. The variables that influence the mean velocity of different debris flow gullies are very different. Thus, if people want to predict debris flow velocity in other gullies, it is necessary to establish specific models using this method.

4.2 Analysis of Debris Flow Mean Velocity Sensitivity Variables

In order to figure out which variable has greater impact on debris flow mean velocity, this study tried to calculate the sensitivity of different variables. Variable sensitivity was calculated by reducing the variables one by one and comparing the 4-variable minimum mean prediction error with the 5-variable minimum mean prediction error. The formula used for calculating the influencing variable sensitive degree was as follows:

$$S_i = E_i / E \tag{7}$$

where S_i is the sensitive index, E_i is the mean prediction error of the default sensitive variable, E is the mean prediction error of the 5 variables. If $S_i < S_j$, it means that factor j is more sensitive than factor i. The results are shown in Table 3.

Table 3 Default variable test results of MRBF model for mean velocity of debris flow.

	5 variables	Depth	Gradient	Density	Grain size	Unstable layer thickness
Mean error(m/s)	0.31	0.47	0.70	0.46	0.49	0.61
S	-	1.52	2.26	1.48	1.58	1.97
Sensitivity ranking	-	4	1	5	3	2

Note: *S* is the sensitivity index

Table 3 shows that all 4 variable sensitive degrees are larger than 1. This means that if any one of them is left out, it will have an impact on the prediction results. The sensitivity index of the gradient and the unstable layer thickness are 2.26 and 1.97, respectively. This means that they have a greater influence on debris flow velocity than the other three variables. Thus, topography and sources have a larger contribution to the intensity and scale of debris flow. The importance ranking of the remaining three influencing variables is: grain size > depth > density.

5 Conclusions

This study selected five influencing variables, i.e. flow depth, gradient of channel, density of debris flow, grain size and unstable layer thickness. The

RBF mean testing error obtained was 0.75 m/s, which is much better than using BP (mean testing error was 1.29 m/s). It was also slightly better compared to using the empirical modified Manning formula (mean testing error was 1.29 m/s). The MRBF method was proposed, in which the parameters are changed to find the optimal value. Based on the minimum total error of the 10 testing samples, the relevant *spread* values and neuron numbers, a 3-dimensional surface was established.

By using the MRBF method, the minimum mean prediction error was 0.31 m/s (smaller than 0.5 m/s), which is satisfactory. The mean and maximum relative errors were 5.92% and 15.66%, respectively. The testing debris flow mean velocities were very close to the measured values. Thus, the accuracy using the MRBF model is reliable and the model can be used as an adequate method to simulate the variation regularity of debris flow velocity. The MRBF model also has the ability to deal with nonlinear data, especially for the complex study of changing debris flow dynamics.

It was also found that topography and sources are the main sensitive variables influencing debris flow velocity. The importance ranking of the five influencing variables is as follows: gradient ＞ unstable layer thickness ＞ grain size ＞ depth ＞ density. For later studies it is suggested that researchers should focus more on the following variables: gradient of channel and thickness of unstable layer.

Acknowledgements

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