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Prediction of the Production Rate of Chain Saw Machine using the Multilayer Perceptron (MLP) Neural Network

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Abstract

The production rate in rock cutting machines is one of the most influential parameters in designing and planning procedures. Complete understanding of the production rate of cutting machines help experts and owners of this industry to predict the production expenses. Therefore, the present study predicts the production rate of the chain saw machine in dimensional stone quarries. In this research, the method of artificial neural networks was used for modeling and predicting the production rate. In addition, in this modeling, 98 data were collected from the results obtained from field studies on 7 carbonate rock samples as the dataset. Four important parameters, including uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) Test, equivalent quartz content (Qs), and Schmidt Hammer (Sch) were considered as input data and the production rate was considered as the output data. The model was evaluated by the performance indices for artificial neural networks, including the value account for (VAF), root mean square error (RMSE), and coefficient of determination (R^2). For simulation, 10 models were created and evaluated. Finally, the best model, i.e. model No. 3, was selected with a $4 \times 3 \times 1$ structure, including 4 input neurons, 3 neurons in the hidden layer and 1 output neuron. The results obtained from the model's performance indices show that a very appropriate prediction has been done for determining the production rate of the chain saw machine by artificial neural networks.

Keywords: Chain Saw Machine; Production Rate; Artificial Neural Network; Carbonate Rocks.

1. Introduction

With the significant increase of construction, dimensional stones as one of the key parameters in this industry have gained a special place among construction materials. Furthermore, with the expansion of the construction industry, the increase in the production of dimensional stones is inevitable. On the other hand, taking the required measures for increasing the efficacy and productivity of the dimensional stones industry is significantly important. The proper evaluation and estimation of the rocks' production rate are among the most important factors influencing the accurate planning procedure in the production area, enhancing the productivity. Therefore, numerous studies have been conducted on the rocks' properties in terms of cutting operations and cutting machines used in this industry [1-2].

In a research carried out by Tumac et al., the performance of chain saw machines was evaluated and examined using factors such as shore hardness and other characteristics of construction rocks. This study was conducted on six different construction rocks from six quarry mines in the west of Turkey based on some physical and mechanical properties of

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rocks, the results of which show the highest significance of Shore scleroscope hardness index with the areal net cutting rate (ANCR) compared to other physical and mechanical properties of samples under study [3]. 14 different quarries in Iran were investigated by Mikaeil et al. for predicting performance of the circular saw machine using the imperialist competitive algorithm and fuzzy clustering technique. In comparison to the two methods, it was found that the applicability of ICA model for predicting the sawability of the dimension stone was more reliable than the FCM [4]. The sawability performance of large diameter circular saws was predicted by Tumac. For this propose, he used the artificial neural network as an optimization method, physical and mechanical properties of eleven stones as input parameters and their associated areal slab production rate as targets. The results showed that ANN could be introduced as a reliable optimization algorithm for the prediction of the sawability performance [5]. The performance of the diamond wire saw was evaluated by Mikaeil et al. based on the wear rate of the diamond wire saw and some stone properties, including the uniaxial compressive strength, Schimazek F-abrasivity factor, Shore hardness, and Young's modulus. The harmony search algorithm was considered as a suitable method to evaluate the clustering efficacy. The results obtained indicated that the harmony search algorithm could be used for classifying the performance of the diamond wire saw [6]. In a research conducted by Korman et al., the relationship between the cutting special energy and cutting rate was studied. By conducting a linear simulation, their research showed that the cutting special energy had a direct relationship with the reduction of saw’s speed, and was increased and decreased with the increase and decrease in speed, respectively. It is worth noting that, the cutting force and abrasion of the cutting machine had a significant role in determination of its optimal speed [7]. A new rock classification was developed by Almasi et al. for ranking the sawability of hard dimension stones using the multiple curvilinear regression analysis. Some rock properties, including the toughness, abrasiveness, and hardness of rock were used in their study [8]. The optimization investigation of the cutting direction in granite quarries in Iran was carried out by Yarahmadi et al. using experimental studies. Based on their results, some recommendations were made for the diamond beads production. It was found that there was a strong relationship between the quartz content and the cutting rate, while no logical relationship was observed between the rock’s equivalent hardness and the cutting rate [9]. The cutting rate for building stone was investigated and predicted by Almasi et al. using the M5P tree algorithm. In their study, a logical relationship was obtained between the hard rock sawability and the some physical and mechanical rock properties [10]. In the study of Mikaeil et al., the wear rate of diamond wire saw was investigated based upon 38 different rock samples in some famous quarries located in Turkey. The artificial intelligence techniques were considered as the investigation methods [11]. Two intelligent approaches were developed by Dormishi et al., namely Hybrid ANFIS-DE and Hybrid ANFIS- PSO algorithms for the performance evaluation of the gang saw machine based on the maximum energy consumption. 120 samples were tested on 12 carbonate rocks. Finally, it was found that the Hybrid ANFIS- PSO algorithm had higher performance capacity in predicting the maximum energy consumption compared to Hybrid ANFIS-DE algorithm [12]. A comprehensive study was carried out by Romoli on the cutting force monitoring of chain saw machines at different rake angles. The results indicated that the application of a negative value of the rake angle γ, a reduced clearance angle α, could be tolerated considering the higher resistance section of the carbide inserts, therefore globally empowering the instrument [13].

As mentioned above, considering the significance of predicting the dimensional stones production rate in increasing the productivity of rock factories and mines, the present study aims to predict the production rate for the chain saw machine. Thus, in this research, 7 carbonate rock samples are selected for experimental and field tests, and after conducting the required experiments, a set of data on the rocks under study is collected. Then, the modeling is performed based on the multilayer perceptron. In this modeling, some of the rock properties, including uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) Test, Schmidt Hammer (Sch), and equivalent quartz content (Qs) are considered as input data, and the production rate is considered as the output data. It is worth mentioning that the artificial neural network has certain benefits in terms of performance capacity in predicting unpredicted and uncertain conditions in quarries. This achievement means that a reliable system of modeling technique for predicting many issues is guaranteed, so that more problems of rock mechanics can be solve.

2. Field and Laboratory Studies

In this study of datasets, 7 carbonate rock samples were collected and 98 laboratory tests were conducted. Samples were prepared from different quarries including Dehbid quarry, and rock blocks with the approximate dimensions of 30 × 30 × 30 cm were collected from Shayan quarry. Figure 1 shows a view of Dehbid marble quarry and Figure 2 indicates the chain saw machine used in this study. In the next step, for the determination of physical and mechanical properties, rock samples were sent to the laboratory, and based on ISRM international standard, some of the physical and mechanical properties were determined for samples, including the special mass, water absorption, porosity, Schmidt hardness, grain size, uniaxial compressive strength, Brazilian tensile strength, and Los Angeles abrasion [14]. Basic descriptive statistics of the physical and mechanical properties for this study are shown in Table 1.

Table 1. Basic descriptive statistics of the physical and mechanical properties

Statistical Values	Uniaxial Compressive Strength (Mpa)	Los Angeles abrasion (LAA) Test	Equivalent Quartz Content	Schmidt Hammer	Production rate
Maximum	111	3.5	2.3	77	4.95
Minimum	90	2	0.8	68	1.4
Average	108.5	2.79	1.45	72.43	3.23
St. deviation	7.47	0.54	0.66	2.98	0.84
Variance	55.8	0.29	0.44	8.88	0.71

Figure 1. A view of the Dehbid 's Marble Quarry

Figure 2. Chain Saw Machine

3. Artificial Neural Network (ANN)

Computational intelligence is one of the most practical computing techniques in different science areas. The artificial neural network is one of the most prominent elements of the computing intelligence which has a special place in different industrial and engineering areas due to having a high ability in solving complicated problems. In fact, the artificial neural network is an interception of the biology and computer science [15-19]. In neural networks, the accuracy of results is highly dependent on the method and amount of training data. There are various methods for training neural networks, among which the back-propagation (BP) algorithm is one of the best-known training algorithms. Thus, in this study, this algorithm is used for training the multi-layer feed-forward neural network. The multi-layer feed-forward back-propagation neural network or the multilayer perceptron which is highly popular among users and researchers has three general layers, including the input, the hidden and the output layers. In recent years, different researches have been conducted in various areas using this technique.

An evaluation was carried out by Sonmez et al. for predicting the elastic modulus of intact rocks based on a large database, including the elastic modulus of intact rocks and other rock properties. Finally, they proposed a new empirical equation using the artificial neural network [20]. The blast-induced ground vibration and frequency were investigated and forecasted by Khandelwal and Singh using artificial neural networks and some statistical techniques. 154

experimental and monitored blast records were collected from coal mines in India. The obtained results showed that this artificial neural networks had better performance compared to other techniques [21]. The missing hydrometric data were investigated and predicted by Bahrami et al. using the artificial neural network method and nonlinear regression method. Based on some performance indices, the results showed that ANN could be applied as an appropriate tool for predicting the missing data [22]. Based on intact rocks' behavior and some carbonate rocks' properties, the relationship between slake durability cycles on the prediction of uniaxial compressive strength and modulus of elasticity was evaluated by Yagiz et al. using artificial neural network and nonlinear regression techniques. The results showed the superiority of the ANN model, and also the slake durability cycles were a suitable input variable to estimate UCS and E of carbonate rocks [23].

As mentioned, considering the significance of artificial neural networks, in this research, the modeling is performed based on the multilayer perceptron, and the network's performance is controlled based on the performance indices, including value account for (VAF), root mean square error (RMSE), and coefficient of determination (R^2) according to Equations (1)-(3), respectively.

$$VAF = \left[1 - \frac{\mathrm{var}(x_i - y_i)}{\mathrm{var}(x_i)}\right] \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \tag{2}$$

$$R^2 = \frac{[\sum_{i=1}^{n}(x_i - x_{mean})^2] - [\sum_{i=1}^{n}(x_i - y_i)^2]}{[\sum_{i=1}^{n}(x_i - x_{mean})^2]} \tag{3}$$

Where n shows the number of datasets, and x_i and y_i are the measured and estimated production rates, respectively. It is worth noting that for obtaining the proper performance index, the VAF value must reach 100%, and R^2 and RMSE values must be close to 0 and 1, respectively.

4. Modelling and Discussion

This section aims to provide an optimal model for predicting the production rate in the chain saw machine based on the multilayer perceptron (MLP). For modelling in this research, after conducting the experimental tests, a set of data including 98 experimental tests on 7 rock samples is collected, among which 74 test samples (75%) are selected as training data and the rest, 24 data, (25%) are selected as the test data. Additionally, as mentioned above, four parameters, including the uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) Test, equivalent quartz content (Qs), and Schmidt Hammer (Sch) are considered as the input data and the production rate is the output parameter of the artificial neural model. One of the fastest back-propagation algorithms for training the artificial network is Levenberg–Marquardt (LM) learning algorithm [24]. Thus, Levenberg–Marquardt (LM) learning algorithm is used as the algorithm of artificial network training in the modelling. Also, the tansig and purelin are considered as transfer functions of the hidden layers and output, respectively. Another important section of simulation is the selection of input, output and hidden layer's neurons. Considering the number of input data and output layers, the numbers of input and output neurons are N_0=1 and N_i=4, respectively. For the neurons in the hidden layer, different experimental relations are provided based on Table 2. According to this table, the number of hidden layer's neurons for the dataset is considered in a range of 1 to 10.

Table 2. The equations for determining the number of neurons in the hidden layer [20]

Researchers	Equations
Hecht-Nielsen [25]	$\leq 2 \times N_i + 1$
Kaastra and Boyd [26] Kannellopoulas and Wilkinson [27]	$2N_i$
Ripley [28]	$(N_i + N_0)/2$
Paola [29]	$\frac{2 + N_0 \times N_i + 0.5N_0 \times (N_0^2 + N_i) - 3}{N_i + N_0}$
Wang [30]	$2N_i/3$
Masters [31]	$\sqrt{N_i + N_0}$

N_i: Number of input neurons, N_0: Number of output neurons

After determining the initial structure of the neural network, the type of training algorithm and number of neurons in the input and output layers, simulation is done for different numbers of neurons proposed in the hidden layer based on the algorithm's performance indices. The modelling results in Table 3 are shown for models with neurons 1 to 10.

Table 3. Effects of the neuron of hidden layer on the statistical functions performance in MLP network

Model No.	Neuron of Hidden Layer	The Results of Network for R^2		The Results of Network for RMSE		The Results of Network for VAF	
		Training	Testing	Training	Testing	Training	Testing
1	1	0.69	0.74	0.25	0.27	55.31	49.93
2	2	0.73	0.71	0.24	0.25	66.07	67.22
3	3	0.73	0.81	0.23	0.22	67.01	62.07
4	4	0.71	0.79	0.25	0.22	58.83	57.5
5	5	0.75	0.67	0.24	0.26	66.93	44.43
6	6	0.74	0.66	0.24	0.25	64.8	56.46
7	7	0.76	0.58	0.24	0.25	68.47	49.75
8	8	0.74	0.73	0.23	0.27	64.02	60.17
9	9	0.72	0.78	0.24	0.25	60.8	70.1
10	10	0.73	0.75	0.25	0.23	62.7	69.91

In the next step, each model is ranked based on a simple ranking method [32]. Table 4 shows the ranking of each model for 10 simulations.

Table 4. Ranking of each model using MLP network

Model No.	Neuron of Hidden Layer	The Results of Network for R^2		The Results of Network for RMSE		The Results of Network for VAF		Total Rank
		Training	Testing	Training	Testing	Training	Testing	
1	1	4	6	8	6	1	3	28
2	2	7	4	9	8	7	8	43
3	3	7	10	10	10	9	7	53
4	4	5	9	8	10	2	5	39
5	5	9	3	9	7	8	1	37
6	6	8	2	9	8	6	4	37
7	7	10	1	9	8	10	2	40
8	8	8	5	10	6	5	6	40
9	9	6	8	9	8	3	10	44
10	10	7	7	8	9	4	9	44

According to the ranking results in Table 4, the most appropriate model for predicting the production rate based on the rank obtained from the neural network's performance indices is the model No. 3. Therefore, the structure of the optimization model for predicting the production rate has 4 input neurons, 3 hidden layer neurons and 1 output neuron. Figures 3 and 4 show the diagrams of the coefficient of determination (R^2) for model No. 3's training and testing with values of 0.73 and 0.81, respectively. They also show the proper accuracy of this modelling.

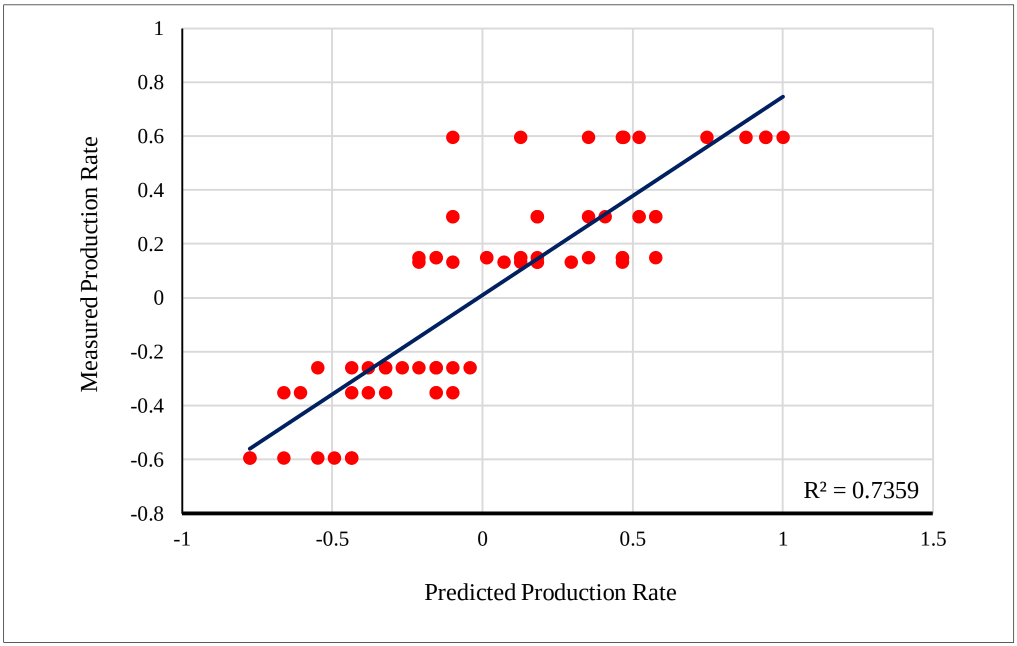

Figure 3. R^2 of the predicted and measured production rate values for training data

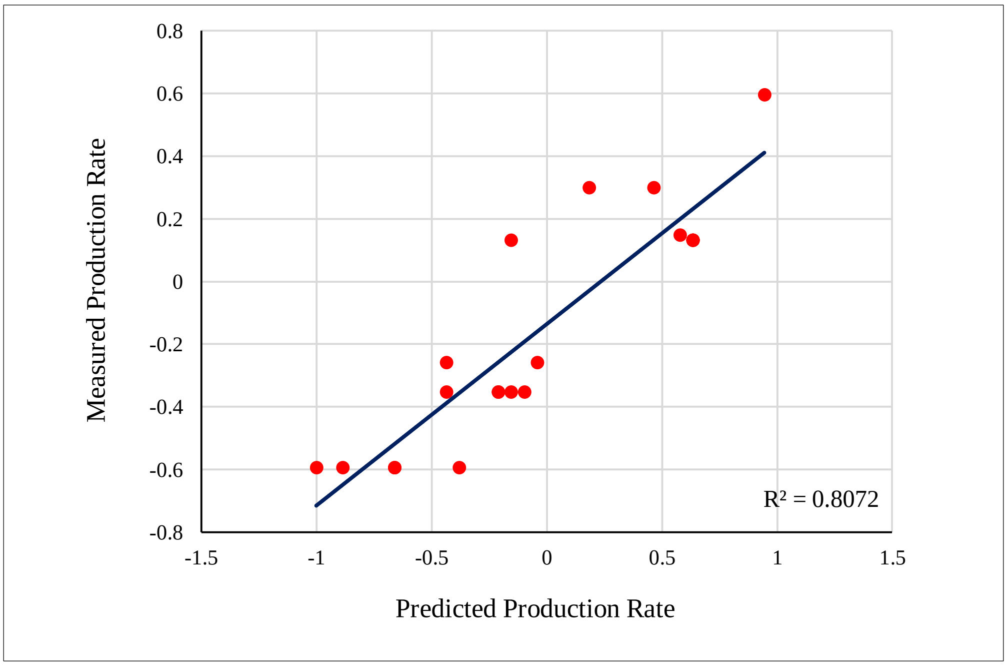

Figure 4. R^2 of the predicted and measured production rate values for testing data

Also, the best training performance based on the mean square error for model No. 3 is obtained in the sixth epoch, and the algorithm is stopped in this step. Figure 5 shows the basic form of the model No. 3 of MLP with a 4×3×1 structure, including 4 input neurons, 3 neurons in the hidden layer and 1 output neuron. Figure 6 shows the best training performance based on the mean square error for model No. 3 with the mean square error equal to 0.0529.

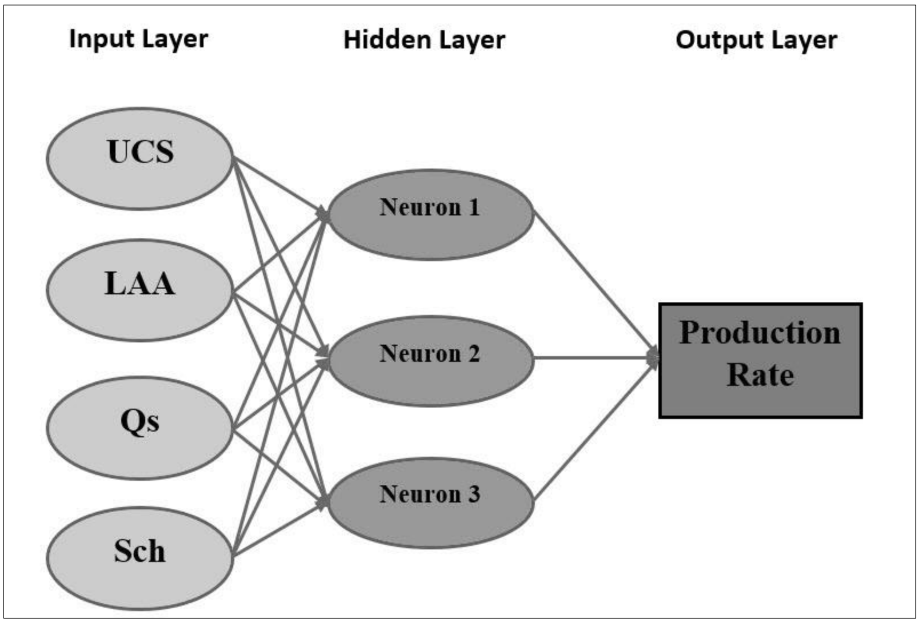

Figure 5. A basic form of the developed model of MLP

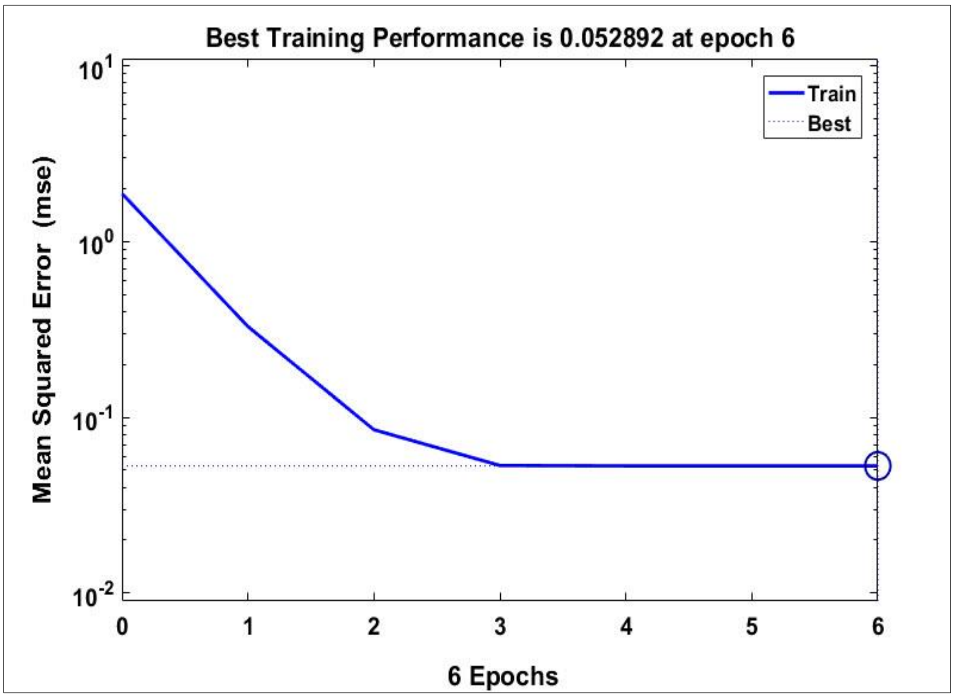

Figure 6. MSE values for training steps

As mentioned before, dimensional stones as one of the most important building materials have a significant role in the construction industry. Furthermore, determination of an appropriate model for the prediction and evaluation of the production rate of chain saw machines enhances productivity and efficiency in mines using this type of cutting machine. Overall, 10 models were simulated, among which model No. 3 with the performance indices of R^2=0.73, RMSE=0.23 and VAF=67.01 for train data and R^2=0.81, RMSE=0.22 and VAF=62.07 for test data obtained the highest rank. The algorithm's performance indices in this model show the high ability of MLP neural networks in the simulation in order to provide a model for the accurate prediction of the chain saw machine's production rate.

5. Conclusion

The production rate is one of the most important influential parameters in the process of increasing or decreasing the productivity of rock factories and mines. Due to the significance of this problem, this study aims to provide an optimal model based on the artificial neural networks in order to predict the carbonate rocks' production rate during the cutting process using the chain saw machine. For this purpose, by collecting 98 test samples on 7 different carbonate rock samples, four parameters, including the uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) Test, equivalent quartz content (Qs), and Schmidt Hammer (Sch) were considered as input data and the production rate was considered as the output data. Next, for determining the most appropriate number of neurons in the hidden layer, the required analyses were conducted for 10 models, and based on a simple ranking method and performance indices of each model, model No. 3 out of 10 models was selected as the most appropriate model with the rank of 55. This model has the coefficient of determination (R^2) equal to 0.73 and 0.81 for the training and test data, respectively, and also RMSE is equal to 0.23 and 0.22 for training and test data, respectively. Therefore, the artificial neural network model proposed for predicting the production rate of carbonate rock samples in the chain saw machine has a 4x3x1 structure, and is composed of 4 input neurons, 3 hidden layer neurons and 1 output neuron.

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