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Performance evaluation of chain saw machines for dimensional stones using feasibility of neural network models

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Abstract

Prediction of the production rate of the cutting dimensional stone process is crucial, especially when chain saw machines are used. The cutting dimensional rock process is generally a complex issue with numerous effective factors including variable and unreliable conditions of the rocks and cutting machines. The Group Method of Data Handling (GMDH) type of neural network and Radial Basis Function (RBF) neural network, as two kinds of the soft computing method, are powerful tools for identifying and assessing the unpredicted and uncertain conditions. Hence, this work aims to develop prediction models for estimating the production rate of chain saw machines using the RBF neural network and GMDH type of neural network, and then to compare the results obtained from the developed models based on the performance indices including value account for, root mean square error, and coefficient of determination. For this purpose, the parameters of 98 laboratory tests on 7 carbonate rocks are accurately investigated, and the production rate of each test is measured. Some operational characteristics of the machines, i.e. arm angle, chain speed, and machine speed, and also the three important physical and mechanical characteristics including uniaxial compressive strength, Los Angeles abrasion test, and Schmidt hammer (Sch) are considered as the input data, and another operational characteristic of the machines, i.e. production rate, is considered as the output dataset. The results obtained prove that the developed GMDH model is able to provide highly promising results in order to predict the production rate of chain saw machines based on the performance indices.

1. Introduction

Construction rocks are one of the most important materials used in the construction industry that have gained a special position in the construction industry sector due to the increasing development of this industry all over the world. In terms of the construction rock resources and reservoirs in the world, Iran is one of the most important countries in this area. Therefore, creating appropriate conditions to increase the productivity in production and extraction of construction rocks is inevitable and very important. In other words, the lack of technical knowledge and appropriate technology in the areas of extracting and processing can impose irreparable damages on this industry. The construction rock extraction methods generally include wire cutting, parallel holes, wedge, application of expandable materials, water jet, explosive materials, hydro mechanical method, heat cutting machine, and chain saw machine [1-6]. Among the present methods, the chain saw machine method, of diamond cutting type, is one of the most popular and common methods. A chain saw machine is a flexible machine that has a high ability and power and a hydraulic control system for cutting different types of construction rocks in vertical and

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horizontal dimensions. Another advantage of such cutting machines is that in the open-pit and underground mines, they can extract large high-quality blocks through vertical and horizontal cuts. It is worth mentioning that the larger the mine and the length of working face, the more is the efficiency and productivity in using this method and the less is the energy consumption and waste of time. The correct choice of machine in terms of structure, operational parameters of cutting elements, physical and mechanical properties, and rock mass density are parameters influencing the efficiency and productivity of a chain saw machine in the construction rock mines. Unlike the high ability of this method in extracting construction rocks, extensive studies have not been carried out in this area. The cutting performance of chain saw machines in Basaranlar travertine quarry mine in Turkey has been evaluated by Copur et al. (2006) [7]. The results obtained have led to the conclusion that in extracting travertine, a combination of two methods of chain saw machine and diamond cutting machine have improved the cutting performance up to 20% [7]. The field and experimental studies (linear cutting test) have been conducted by Copur et al. (2011) on construction rocks including two types of travertine and three types of marble in order to predict the performance of chain saw machines. Their research works have shown that in choosing the chain saw machines, out of the physical and mechanical properties, the two parameters uniaxial compressive strength and Brazilian tensile strength are the most important and effective parameters. Finally, the predicted results have shown a high correlation coefficient [8]. The performance of chain saw machines has been studied by Tumac et al. (2013) using the parameters such as shore hardness and other physical and mechanical properties of the construction rocks. In this work, six different construction rock samples extracted from six quarry mines in the west Turkey were analyzed. In addition, the dependence between the surface areal net cutting rate (ANCR) and any of the mechanical parameters of the rock was analyzed. The results obtained from this research work showed that compared with the other physical and mechanical properties of the rocks under study, the Shore sclera scope hardness index had the highest correlation with ANCR [9]. The performance of chain saw machines has been estimated by Tumac (2014) according to shore sclera scope hardness. In this work, two empirical models developed previously were improved for estimating the areal net cutting rate (ANCR) of chain saw machines. The results obtained showed that the cutting force and the normal force had a strong and weak relationship with Shore hardness values, respectively [10].Enhancing the performance of chain saw machines for extracting construction rocks has been studied by Hekimoglu. The results obtained from this work have led to the reduction of tool wear and increase in the performance of chain saw machines. The chain saw cutting process was simulated by the linear cutting machine. The research results showed that the special cutting energy was reduced by reduction in the cutting speed. In the meantime, the optimal saw speed depends on the cutting force and cutting tool wear [11]. The cutting force monitoring of chain saw machines with various rake angles has been carried out by Romoli (2018). The results obtained indicated that the use of a negative value of the rake angle γ led to the tolerance of a reduced clearance angle α, providing a higher resistance section of the carbide inserts, and therefore, globally strengthening the tool [12].

As mentioned earlier, enhancing the productivity of the construction rock industry is very important at the level of extraction. The high ability in accurately studying and predicting the production rate of construction rocks is one of the most important factors involved in increasing the productivity of quarries. Accordingly, the present work aimed to investigate and predict the construction rock production rate using chain saw machines according to the artificial neural networks. Thus Radial Basis Function (RBF) neural network and Group Method of Data Handling (GMDH)-type neural network were used as the most practical methods of artificial neural networks for a highly accurate modeling. In addition, in this modeling, 98 data was collected from the field study results on 7 carbonate rock samples as datasets. In this work, three operational parameters of machines including Arm Angle (AA), Chain Speed (CS), and Machine Speed (MS), and three parameters of physical and mechanical properties of rocks under study including Uniaxial Compressive Strength (UCS), Los Angeles Abrasion (LAA) test, and Schmidt hammer (Sch) were considered as the input parameters, and the production rate parameter was considered as the output parameter. Finally, simulations were performed to indicate the effectiveness of neural networks modeling. As a result, a comparison was made between the two modeling, and a sensitive analysis was performed among the inputs and the predicted production rate.

2. Materials and method

The carbonate rock mines studied in this work include the Dehbid and Shayan marble mines. Figure 1 shows a view of the under studied Dehbid mine. Overall, from different workshops in the Dehbid mine, six samples, and from the Shayan mine, rock blocks in approximately 30*30*30 cm dimensions were extracted for conducting physical and mechanical experiments. These samples were sent to the laboratory and their physical and mechanical parameters including special mass, water absorption, porosity, Schmidt's hardness, grain size, uniaxial compressive strength, Brazilian tensile strength, and Los Angeles abrasion were determined for the samples under study based on the ISRM international standards [13]. The results obtained from the experimental studies are shown in Table 1.

The characteristics of the chain saw machine (Figure 2) used in the mines under study are shown in Table 2. This table also shows the sample machine used in this work.

Figure 1. Dehbid marble mine.

Figure 2. The chain saw machine used in this work.

Table 1. Operational characteristics of the machine, and the physical and mechanical properties of rock samples under study.

Sample No.	UCS (Mpa)	Los (n)	Sch (n)	Arm angle	Chain speed (m/s)	Machine speed (cm/min)	Production rate (m2/h)	Sample No.	UCS (Mpa)	Los (n)	Sch (n)	Arm angle	Chain speed (m/s)	Machine speed (cm/min)	Production rate (m2/h)
1	92	3.4	68	65	7.5	8	3.8	50	90	3.1	72	75	7.5	8	4
2	92	3.4	68	70	7.5	8	4.5	51	90	3.1	72	75	8	8	4.2
3	92	3.4	68	75	7.5	8	4.85	52	90	3.1	72	75	8.5	8	4.2
4	92	3.4	68	80	7.5	8	4.01	53	90	3.1	72	75	7.5	6.5	2.9
5	92	3.4	68	85	7.5	8	4	54	90	3.1	72	75	7.5	7	3.2
6	92	3.4	68	75	6	8	3.4	55	90	3.1	72	75	7.5	7.5	3.4
7	92	3.4	68	75	7	8	4.1	56	90	3.1	72	75	7.5	8	4
8	92	3.4	68	75	7.5	8	4.85	57	109	2.4	76	65	7.5	8	2.6
9	92	3.4	68	75	8	8	4.85	58	109	2.4	76	70	7.5	8	2.8
10	92	3.4	68	75	8.5	8	4.85	59	109	2.4	76	75	7.5	8	2.9
11	92	3.4	68	75	7.5	6.5	3	60	109	2.4	76	80	7.5	8	2.6
12	92	3.4	68	75	7.5	7	4	61	109	2.4	76	85	7.5	8	2.4
13	92	3.4	68	75	7.5	7.5	4.73	62	109	2.4	76	75	6	8	2.4
14	92	3.4	68	75	7.5	8	4.95	63	109	2.4	76	75	7	8	2.7
15	99	2.8	70	65	7.5	8	3.5	64	109	2.4	76	75	7.5	8	3
16	99	2.8	70	70	7.5	8	4	65	109	2.4	76	75	8	8	3.1
17	99	2.8	70	75	7.5	8	4.1	66	109	2.4	76	75	8.5	8	3.1
18	99	2.8	70	80	7.5	8	3.8	67	109	2.4	76	75	7.5	6.5	2.2
19	99	2.8	70	85	7.5	8	3.5	68	109	2.4	76	75	7.5	7	2.5
20	99	2.8	70	75	6	8	3	69	109	2.4	76	75	7.5	7.5	2.9
21	99	2.8	70	75	7	8	3.5	70	109	2.4	76	75	7.5	8	2.9
22	99	2.8	70	75	7.5	8	4.2	71	105	2	73	65	7.5	8	2.8
23	99	2.8	70	75	8	8	4.2	72	105	2	73	70	7.5	8	3
24	99	2.8	70	75	8.5	8	4.2	73	105	2	73	75	7.5	8	3
25	99	2.8	70	75	7.5	6.5	3	74	105	2	73	80	7.5	8	2.9
26	99	2.8	70	75	7.5	7	3.5	75	105	2	73	85	7.5	8	2.4
27	99	2.8	70	75	7.5	7.5	3.9	76	105	2	73	75	6	8	2
28	99	2.8	70	75	7.5	8	4.1	77	105	2	73	75	7	8	2.4
29	100	3.5	71	65	7.5	8	3.7	78	105	2	73	75	7.5	8	2.9
30	100	3.5	71	70	7.5	8	4.3	79	105	2	73	75	8	8	2.9
31	100	3.5	71	75	7.5	8	4.3	80	105	2	73	75	8.5	8	2.9
32	100	3.5	71	80	7.5	8	4.3	81	105	2	73	75	7.5	6.5	2.1
33	100	3.5	71	85	7.5	8	3.3	82	105	2	73	75	7.5	7	2.5
34	100	3.5	71	75	6	8	2.8	83	105	2	73	75	7.5	7.5	2.6
35	100	3.5	71	75	7	8	2.9	84	105	2	73	75	7.5	8	2.8
36	100	3.5	71	75	7.5	8	3.5	85	111	2.3	77	65	7.5	8	1.8
37	100	3.5	71	75	8	8	3.5	86	111	2.3	77	70	7.5	8	1.8
38	100	3.5	71	75	8.5	8	3.5	87	111	2.3	77	75	7.5	8	2.4
39	100	3.5	71	75	7.5	6.5	3	88	111	2.3	77	80	7.5	8	2
40	100	3.5	71	75	7.5	7	3.4	89	111	2.3	77	85	7.5	8	2
41	100	3.5	71	75	7.5	7.5	4	90	111	2.3	77	75	6	8	1.6
42	100	3.5	71	75	7.5	8	4.3	91	111	2.3	77	75	7	8	2
43	90	3.1	72	65	7.5	8	3.2	92	111	2.3	77	75	7.5	8	2.3
44	90	3.1	72	70	7.5	8	3.5	93	111	2.3	77	75	8	8	2.4
45	90	3.1	72	75	7.5	8	3.6	94	111	2.3	77	75	8.5	8	2.4
46	90	3.1	72	80	7.5	8	3.8	95	111	2.3	77	75	7.5	6.5	1.4
47	90	3.1	72	85	7.5	8	2.9	96	111	2.3	77	75	7.5	7	1.8
48	90	3.1	72	75	6	8	2.8	97	111	2.3	77	75	7.5	7.5	2.2
49	90	3.1	72	75	7	8	3.4	98	111	2.3	77	75	7.5	8	2.5

Table 2. Characteristics of the chain saw machine used in this work.

Manufacturer	Model	Blade length (m)	Useful cutting length (m)	Electrical power (KW)	Machine weight with rail (kg)	Machine motion speed (cm/min)	Saw speed (m/s)	Cutting thickness (Mm)	Arm rotation (valve)	Hydraulic tank volume (L)
Fantini	70RA/PA	7.2	6.3	50	10500	0-13	0.1-0.7	38	360	300

3. Methodology

3.1. Radial basis function (RBF) neural networks

Artificial neural networks are one of the soft computing techniques that within less than a decade have gained a significant role in the information analysis and process of problems lacking an available solution or could not be easily solved [14-16]. Among the different methods, the RBF neural networks is one of the most practical artificial neural networks that has a higher speed compared with many artificial neural networks. The RBF neural networks are one of the forward neural networks with applications such as classification and mapping between the input and output vectors [17-19]. These neural networks, like the multi-layer perceptron neural networks, have the three input, middle, and output layers. In this network, the input layer is only used for the data entry and does not have any role in data processing. The middle layer, also called the hidden layer, determines the non-linear mapping between the input and output data, and the number of neurons in this layer is obtained based on a trial-and-error method. At the end, there is the output layer, the input of which is the output of the hidden layer, which is a simple linear weight sum. Figure 3 shows a basic form of the RBF neural networks.

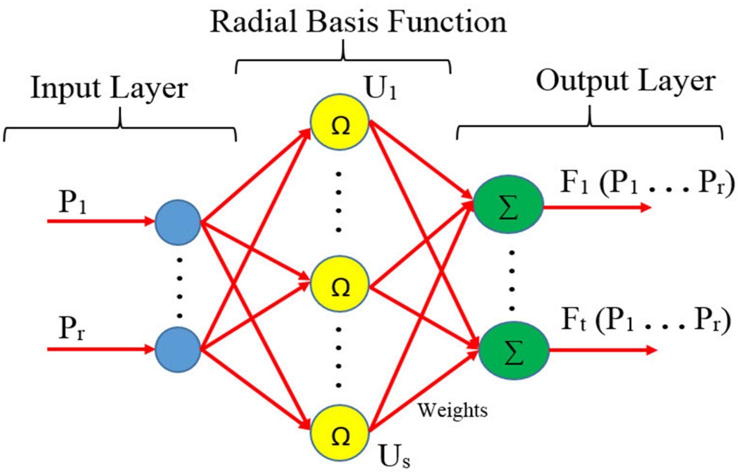

Figure 3. A Basic form of RBF [20, 21].

3.2. Group method of data handling (GMDH)-type neural networks

One of the most important areas of soft computing in the recent decades has been artificial neural networks, which has attracted the attention of numerous researchers in different scientific fields. On the other hand, artificial neural networks can be considered as one of the intersections of the computer and biological sciences. Human brain as one of the most complicated body organs has many wonderful abilities, which despite various accurate studies, still many unknown aspects have remained. In the meantime, learning is one of the most obvious abilities of the human brain. Artificial neural networks by simulating a part of brain performance has a very good ability in solving problems about learning, pattern recognition, control systems, and image processing [22-32]. Many models for artificial neural networks have been proposed by the researchers, one of which is GMDH. This method was provided by Ivakhnenko in 1968 based on the self-organizing and one-way algorithms that have several layers and neurons, and are one of the linear regression and modeling methods. In fact, the GMDH network includes a set of neurons formed by a combination of different pairs through a second-degree polynomial. The GMDH neural network introduced by Ivakhnenko is also known as a polynomial neural network whose main basis is formed by a second-degree polynomial model and the least squares error algorithm [33].

By integrating the quadratic polynomials obtained from all neurons, the algorithm shows an approximate function (proper mapping) with output for a set of inputs like X=(xi1, xi2, xi3, ..., Xim) with a minimum possible error in comparison with the output y according to Eq. (1).

$$\hat{y} = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots\ldots\ldots x_{im}) \quad i = (1,2,3,\ldots\ldots.,m) \tag{1}$$

Eq. (2) shows the general form of the GMDH basic neural network mapping for the input data based on the output data. This equation is also known as the Ivakhnenko equation, in which for an output like y, a number of data for x1, x2, x3, ..., Xm values is introduced with m.

Figure 4 shows a set of n observations,where n and m indicate the total number of observations and number of variables, respectively. Also, nt shows the number of observations in the training set.

$$y = a + \sum_{i=1}^{m} b_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} x_i x_j + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} d_{ijk} x_i x_j x_k + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m}\sum_{l=1}^{m} e_{ijkl} x_i x_j x_k x_l, \ldots \tag{2}$$

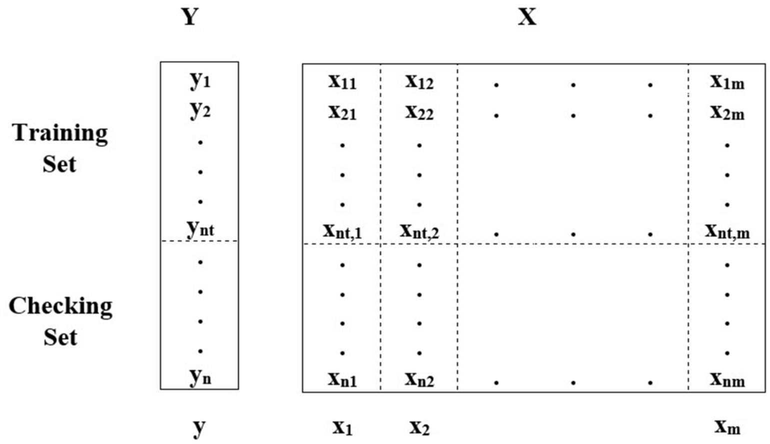

Figure 4. Input to the GMDH algorithm [34].

In fact, this algorithm has several different layers, which in the first time step, when the input data enter the algorithm and is given to the first layer in the form of a combination of data, data in the first layer is transferred to the next one after being processed. This process is defined for n layers, and when the algorithm in each layer reaches an acceptable convergence, the algorithm working process is stopped. In fact, by creating the initial answers and improving them, and then choosing the most appropriate answer, this algorithm performs like evolutionary algorithms and follows a recursive system. One of the main advantages of this method compared to the other neural network methods is determination of a mathematical model for the problem under study based on polynomials [34, 35]. Furthermore, another advantage of this technique is its appropriate and desired ability in the convergence of neural networks in different problems. The GMDH-type neural network has been used and developed by many researchers. Eight natural soil samples have been investigated by Hassanlourad et al. for predictingthe dry unit weight of compacted soils using the GMDH-type neural network. They carried out a comparison between the predicted and experimentally measured values. The results obtained showed that this approach could be applied for evaluating dry unit weight withhighly acceptable degrees of accuracy [36]. The group method of data handling–type neural network algorithm has been considered byZhao et al.for maintainingthe useful life estimation of equipment [37]. The settlement and bearing capacity of foundation based on the moisture content (ω), plasticity index, and corrected SPT blow counts (N60)have been evaluated by Ziaie Moayed et al. However,the GMDH-type neural network and genetic algorithm were considered as analysis approaches for the prediction of pressure-meter modulus and (E_M) and limit pressure (P_L).The results obtained demonstrated thatthe GMDH-type neural network had a higher capability in the prediction of pressure-meter modulus and limit pressure of clayey soils compared tothe other methods [38]. The shear strength parameters including C and φhave been estimated by Mola-Abasi and Eslami. For this purpose, they evaluated a database containing 50 datasets from CPTu data and used the GMDH-type neural network and genetic algorithm. Finally, the results obtained indicated that the GMDH-type neural network could provide a higher performance capacity in predicting the shear strength parameters compared to the other available correlations [39]. For prediction of theelasticity modulus of clayey deposits from a database including 131 plate load tests (PLT) and standard penetration tests (SPTs), the GMDH-type neural networkhas been used by Naeini et al. They proposed a new equation to predict theelasticity modulus with an appropriate accuracy [40].

According to the high ability of this algorithm in solving complex and ambiguous problems on one hand and existence of different influential parameters and lack of certainty in the process of cutting dimensional rocks on the other hand, in this work, the GMDH-type neural network was used to predict the rock production rate for chain saw machines.

4. Modeling and discussion

In this work, in order to predictthe production rate in the chain saw machine, the linear regression prediction methods, i.e. the GMDH-typeand RBF neural network, were used. Moreover, for the performance evaluation of simulations, three performance indices were used based on Eqs. (3)-

(5) including value account for (VAF), root mean square error (RMSE), and coefficient of determination (R^2).

$$VAF = \left[1 - \frac{\operatorname{var}(x_i - y_i)}{\operatorname{var}(x_i)}\right] \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (4)$$

$$R^2 = \frac{[\sum_{i=1}^{n}(x_i - x_{mean})^2] - [\sum_{i=1}^{n}(x_i - y_i)^2]}{[\sum_{i=1}^{n}(x_i - x_{mean})^2]} \quad (5)$$

where n shows the number of datasets, and x_i and y_i are the measured and estimated production rates, respectively.

The significant point in the analysis of the values for performance indices is that the closer the VAF and RSME values to 100 and 0, respectively, the more accurate and correct is the algorithm performance. Also this is the case for R^2 when its value is close to the unity [41-43].

4.1. Prediction of production rate using RBF neural network

As mentioned earlier, in a simulation conducted in this work, 98 data were collected as the datasets from the experimental results obtained from 7 carbonate rock samples. Then according to the suggestion proposed in the Looney's research works, the value of 75% for data was considered as the training data and the rest were the testing data [44]. In this work, six parameters including three operational parameters of the chain saw machine, and three physical and mechanical parameters of rocks including uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) test, and Schmidt hammer (Sch) were considered as the input data, and the parameter production rate was considered as the output data. Figure 5 shows the structure ofthe RBF neural network model based upon the input and output parameters. Then for the modeling, the algorithm control parameters were adjusted according to the views of the experts and past studies. The important issue is that some of these control parameters must be adjusted experimentally and through trial-and-error. Therefore, according to the experts, the numberof the two parameters spread (controlling the dispersion in functions) and neurons was considered as 5, 0, 1, and 1.5, and 30, 20, and 10, respectively, and totally, 9 models were constructed for predicting the production rate. The results obtained from this modeling were determined based on the algorithm performance indices, as seen in Eqs. (3)-(5) and Table 3.

After the determination of each performance index for each model, a simple ranking method was used for ranking each model [45]. The results obtained from this ranking are provided in Table 4.

According to the results of ranking models in Table 4, the most appropriate model for the prediction of production rate is model No. 8. This model has coefficients of determination (R^2) equal to 0.97 and 0.66 for the training and testing data, respectively. Figures 6 and 7 show the R^2 values for the training and testing data, respectively.

Additionally, Figures 8 and 9 show a comparison between the predicted results for the production rate and its measured values for the training and testing data. The procedure of this comparison in these figures indicates a good and accurate prediction.

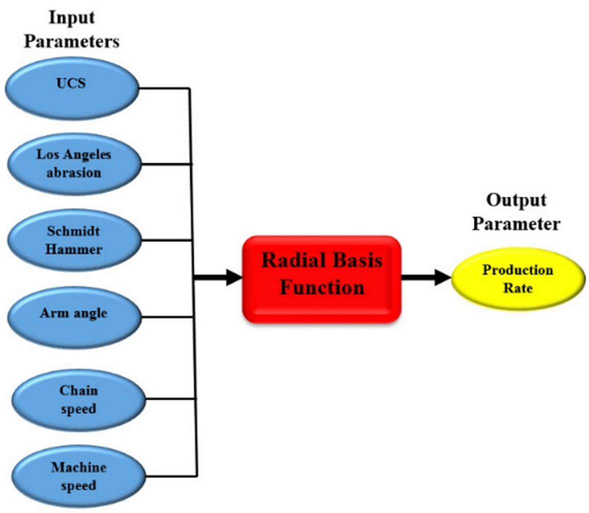

Figure 5. A structure of RBF model.

Table 3. Effects of spread and number of neurons on the statistical function performance in RBF network.

Model No.	Layer size	Spread	Number of neurons	Results of network for R^2		Results of network for RMSE		Results of network for VAF	
				Training	Testing	Training	Testing	Training	Testing
1	3	0.5	10	0.55	0.59	0.55	0.55	19.85	11.26
2	3	0.5	20	0.83	0.39	0.34	0.8	79.9	8.39
3	3	0.5	30	0.89	0.43	0.26	0.89	88.72	32.39
4	3	1	10	0.65	0.6	0.5	0.52	45.84	33.61
5	3	1	20	0.81	0.75	0.36	0.51	75.87	70.77
6	3	1	30	0.86	0.53	0.3	0.71	84.9	51.92
7	3	1.5	10	0.55	0.66	0.53	0.58	17.08	32.42
8	3	1.5	20	0.97	0.66	0.16	0.73	96.44	65.94
9	3	1.5	30	0.89	0.62	0.27	0.63	87.97	60.6

Table 4. Ranking of each model using RBF network.

Model No.	Layer size	Spread	Number of neurons	Results of network for R^2		Results of network for RMSE		Results of network for VAF		Total rank
				Training	Testing	Training	Testing	Training	Testing	
1	3	0.5	10	3	5	1	7	2	2	20
2	3	0.5	20	6	2	5	2	5	1	21
3	3	0.5	30	8	3	8	1	8	3	27
4	3	1	10	4	6	3	8	3	5	29
5	3	1	20	5	9	4	9	4	9	40
6	3	1	30	7	4	6	4	6	6	39
7	3	1.5	10	3	8	2	6	1	4	24
8	3	1.5	20	9	8	9	3	9	8	46
9	3	1.5	30	8	7	7	5	7	7	41

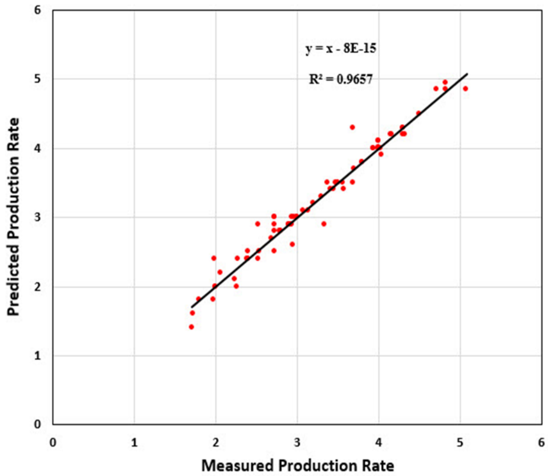

Figure 6. R^2 between measured and predicted production rates for training datasets for RBF model.

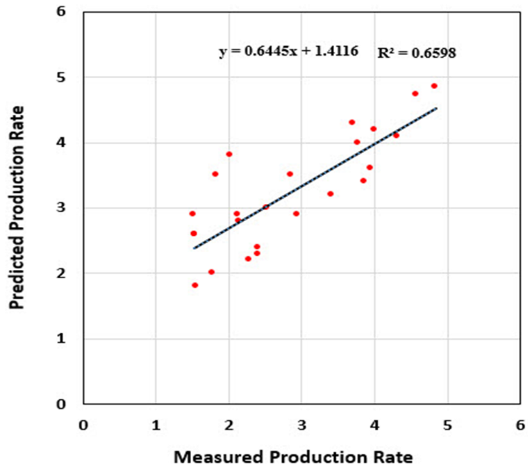

Figure 7. R^2 between measured and predicted production rates for testing datasets for RBF model.

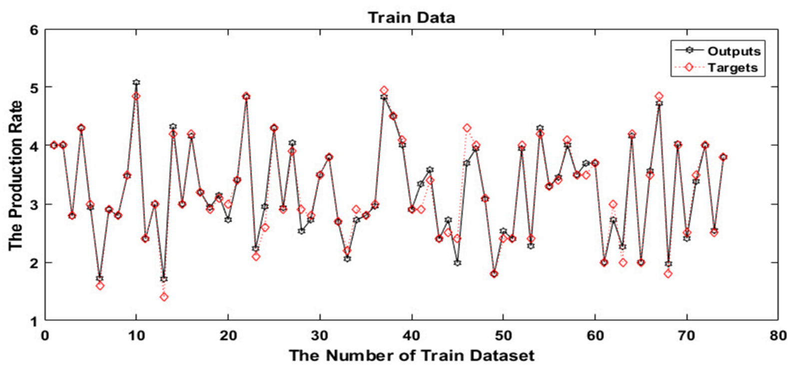

Figure 8. Comparison of predicted and measured RBF for training datasets for RBF model.

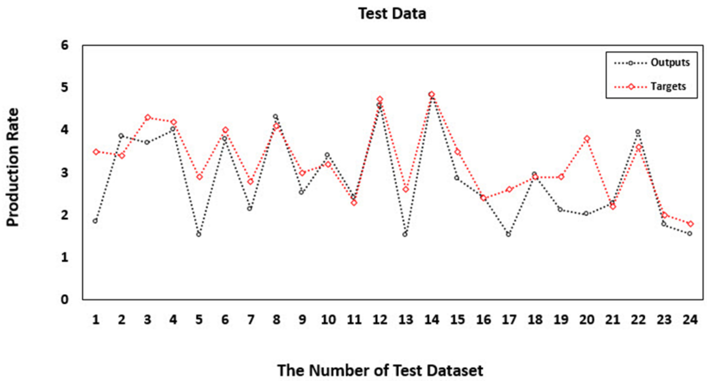

Figure 9. Comparison of predicted and measured RBF for testing datasets for RBF model.

4.2. Prediction of production rate using GMDH neural network

As mentioned earlier, a database of 98 laboratory tests were conducted on 7 different varieties of carbonate rocks extracted from Iranian quarries. Then the three operational properties of the machine, i.e. arm angle (AA), chain speed (CS), and machine speed (MS),and three important physical and mechanical properties including uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) test, and Schmidt hammer (Sch) were considered as the input data, and another operational property of the machine, i.e. the production rate, was considered as an the output dataset. There are some ideas about the percent of data for training. According to thework of Looney, 75% of all datasetsshould be considered for trainingpurposes[44], while this percent has been suggested by Swingler as 80% of the whole datasets [46]. Hence, in this work, 80% of dataset was used randomly for the training dataset and the remaining 20% was considered as the testing data in each simulation.

In the next simulation step,the structure of a neural network must be formed. For modeling the GMDH-type neural network, like other artificial neural networks, the neural network structure must be defined. Therefore, the number of layers and neurons must be determined in each layer. Although the exact number of layers and neurons in each layer for the best model cannot be determined at the beginning of modeling, based on the number of datasets, an acceptable range can be determined for them. Thus in this work, according to the number of datasets and using the perspectives of experts in the neural network modeling, different numbers of layers were considered including 2, 3, and 4 layers, and the modeling was done for each layer with different numbers of neurons such as 5, 10, 20, 30, 40, and 50. In fact, for determining the most appropriate numbers of layers and neurons in the hidden layer, 18 models were created, and the performance of each model was calculated based on the performance indices in accordance with Eqs. (3)-(5). Table 5 shows 18 models created and the performance indices for each one. It is worth mentioning that in choosing the number of layers and neurons in each layer, there is no specified relation for their determination and this choice has an experimental process, which is generally based upon issues such as the number of samples under study, complexity of the problem, and perspectives of experts in neural network problems, and then the best model is determined through trial-and-error.

As mentioned earlier, the modeling was done for three different types of layers and six states with different neurons, and the performance indices were determined for each model. In the next step, according to the results obtained (Table 5) and a simple ranking method, a rank was considered for each model [45]. The results of ranking for each model are shown in Table 6.

According to the results obtained (Table 4), the rank of each model was determined. The best model based on the obtained rank is model No. 18, which has the score 108. In this model, the performance index values include coefficient of determination (R^2) of training = 0.91 and testing = 0.92, RMSE of training = 0.252, and testing = 0.245; and also VAF of training = 90.30 and testing = 92.06. Figures 10 and 11 show the diagrams of coefficient of determination (R^2) for the training and testing datasets.

Figures 12 and 13 make a comparison between the measured values and the values predicted from the production rate value, respectively, for training and testing the datasets for model No. 18.

According to Figure 12, the data measured for 78 experimental samples shows that the predicted values appropriately match together in terms of the training data. For example, data Nos. 2, 7, and 8 were completely predicted. Data Nos. 10 and 74 had a partial difference, and although some data such as Nos. 18 and 76 had much difference between the measured and predicted values of the production rate, their difference was generally acceptable and the performance of the total set was highly acceptable. Furthermore, in Figure 13, a comparison was made between the results measured and predicted from the production rate for the testing data, indicating the high ability and productivity of this algorithm in predicting the testing data. For instance, 11 out of 20 data were tested in the algorithm; for example,data Nos. 3, 2, 1, 15, 11, 10, 4,and 19 fully match with the predicted and measured data.

Table 5. Effects of layer size and number of neurons in each layer on performance indices in GMDH.

Model No.	Layer size	Number of neurons in each layer	Results of network for R^2		Results of network for RMSE		Results of network for VAF	
			Training	Testing	Training	Testing	Training	Testing
1	2	5	0.79	0.85	0.362	0.382	75.74	82.63
2	2	10	0.81	0.86	0.32	0.521	76.53	52.84
3	2	20	0.75	0.8	0.373	0.545	74.28	35.17
4	2	30	0.76	0.68	0.393	0.448	71.72	49.65
5	2	40	0.83	0.89	0.341	0.35	80.25	85.38
6	2	50	0.85	0.71	0.343	0.41	81.35	70.67
7	3	5	0.83	0.69	0.34	0.48	80.5	69.34
8	3	10	0.78	0.59	0.385	0.562	73.45	52
9	3	20	0.86	0.58	0.373	0.35	84.36	49.23
10	3	30	0.87	0.66	0.295	0.446	85.94	62.62
11	3	40	0.81	0.74	0.35	0.491	77.25	70.54
12	3	50	0.82	0.73	0.369	0.347	79.12	67.65
13	4	5	0.84	0.79	0.325	0.373	81.21	73.84
14	4	10	0.86	0.82	0.305	0.395	84.26	82.15
15	4	20	0.78	0.83	0.374	0.373	74.43	78.6
16	4	30	0.85	0.85	0.301	0.383	82.6	81.9
17	4	40	0.82	0.76	0.344	0.515	76.61	75.55
18	4	50	0.91	0.92	0.252	0.245	90.30	92.06

Table 6. Ranking of each model using GMDH.

Model No.	Layer size	Number of neurons in each layer	Results of network for R^2		Results of network for RMSE		Results of network for VAF		Total rank
			Training	Testing	Training	Testing	Training	Testing	
1	2	5	10	15	8	14	5	16	68
2	2	10	11	16	14	5	6	5	57
3	2	20	7	12	6	4	3	1	33
4	2	30	8	5	3	9	1	3	29
5	2	40	13	17	11	16	10	17	84
6	2	50	15	7	10	11	13	10	66
7	3	5	13	6	12	8	11	8	58
8	3	10	9	3	4	3	2	4	25
9	3	20	16	2	6	16	16	2	58
10	3	30	17	4	17	10	17	6	71
11	3	40	11	9	9	7	8	9	53
12	3	50	12	8	7	17	9	7	60
13	4	5	14	11	13	15	12	11	76
14	4	10	16	13	15	12	15	15	86
15	4	20	9	14	5	15	4	13	60
16	4	30	15	15	16	13	14	14	87
17	4	40	12	10	9	6	7	12	56
18	4	50	18	18	18	18	18	18	108

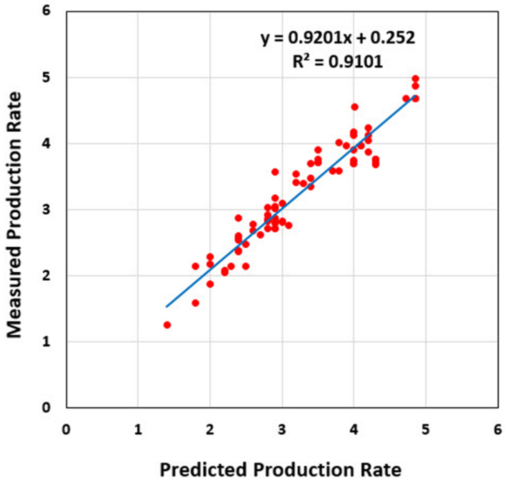

Figure 10. R^2 between measured and predicted production rates for training datasets for GMDH model.

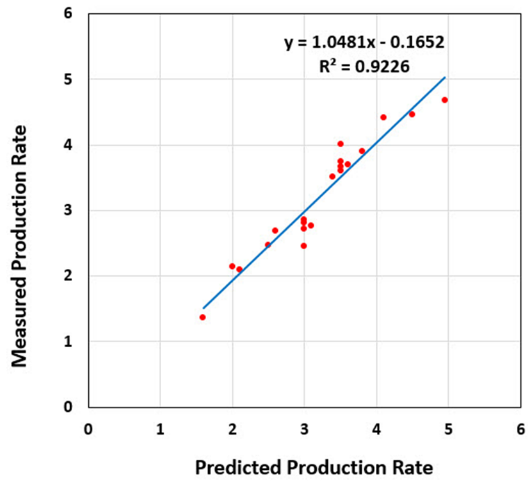

Figure 11. R^2 between measured and predicted production rates for testing datasets for GMDH model.

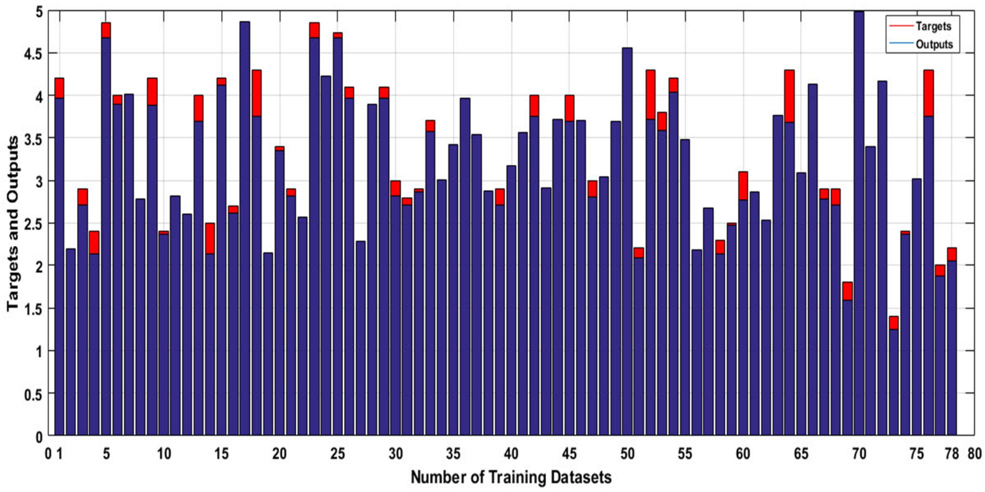

Figure 12. Graphical comparison between measured and predicted production rates for training datasets for GMDH model.

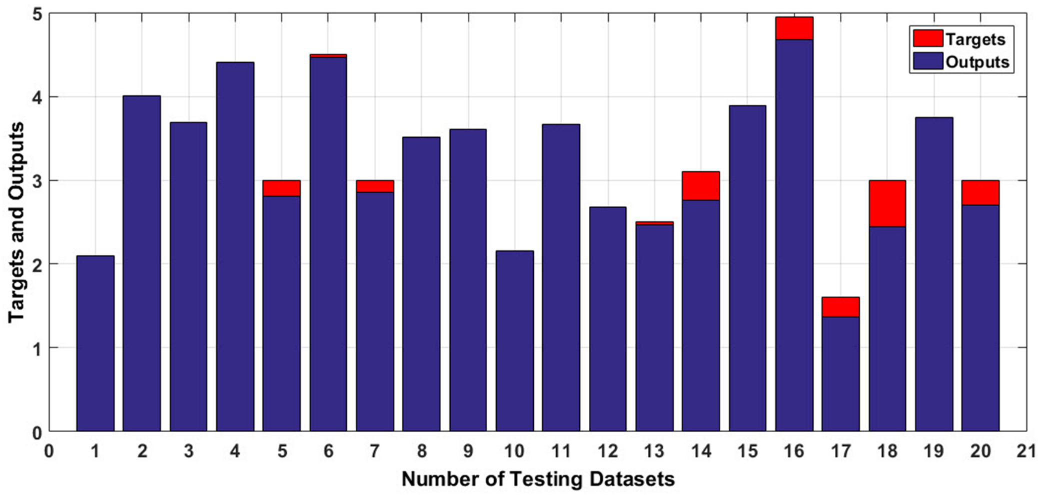

Figure 13. Graphical comparison between the measured and predicted production rates for testing datasetsin GMDH model.

4.3. Discussion

After the design and construction of the RBF and GMDH neural networks, and the most appropriate determination of simulation by any algorithm, in this section, the results obtained by the two methods were compared. The results obtained from the two modellings are shown in Table 7.

By observing and comparing the results of the best models from these methods, according to the performance index of networks indicating the amount of optimization and efficiency of the model, it is obvious that although the RBF neural network has an acceptable performance, the GMDH neural network performance is better than that for the RBF neural network. In the next step, for the optimized model from GMDH neural network (model No. 18), a sensitivity analysis was performed for the predicted inputs and outputs. This sensitivity analysis was conducted among three operational properties of the machine, i.e. arm angle (AA), chain speed (CS), and machine speed (MS),and three important physical and mechanical properties including uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) test, and Schmidt hammer (Sch) and predicted production rate and measured production rate.

In the process of sensitivity analysis, each input data was determined for a range of data, then by fixing the other 5 input data and changing one of them to the desired range, the sensitivity analysis was conducted for each input data, respectively. Figures 14 and 15 make the sensitivity analysis for each input data based upon the measured and predicted production rate, respectively.

The sensitivity analysis was done for the production rate measured and predicted from the optimized model (model No. 18), GMDH. Based on the results obtained, for the physical and mechanical input data, Schmidt hammer, uniaxial compressive strength, and Los Angeles abrasion data have the highest to the lowest effect on the measured and predicted production rate process, respectively. Consequently, based upon the results of sensitivity analysis, it can be concluded that the machine operational analysis including arm angle, chain speed, and machine speed have the highest to the lowest effect on the measured and predicted production rate process, respectively.

Table 7. A comparison between the performance indices of the best models RBF and GMDH.

Method	R^2		RMSE		VAF	
	Training	Testing	Training	Testing	Training	Testing
RBF	0.97	0.66	0.16	0.73	96.44	65.94
GMDH	0.91	0.92	0.252	0.245	90.30	92.06

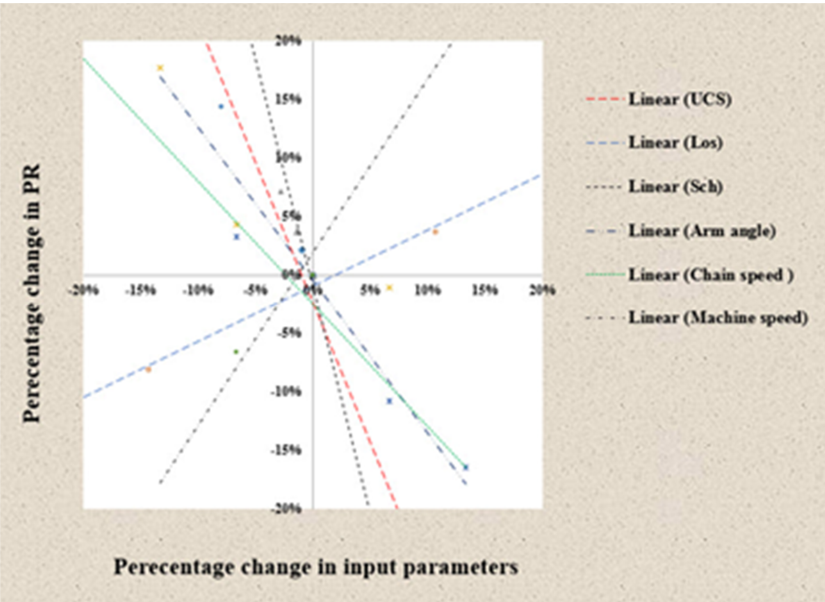

Figure 14. Sensitivity analysisbased upon predicted production rate.

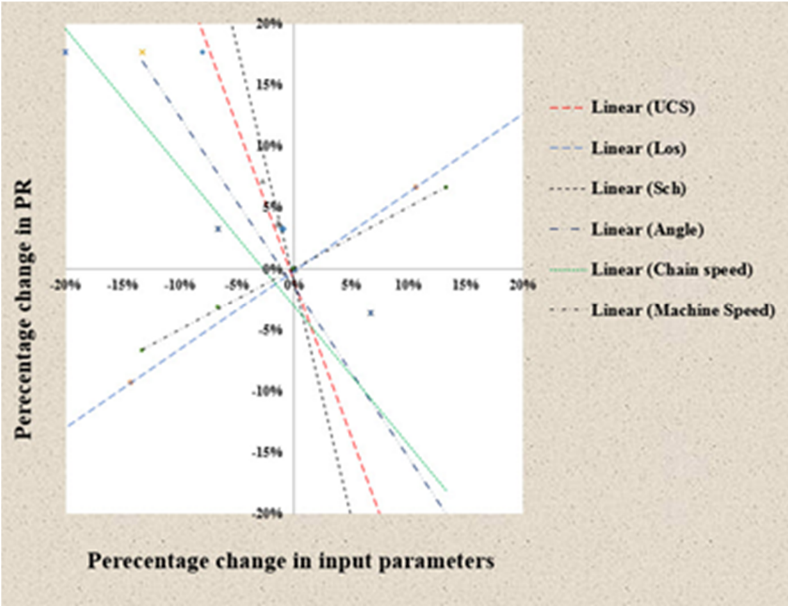

Figure 15. Sensitivity analysis based upon measured production rate.

5. Conclusions

Dimensional stone is one of the most important building materials, which has 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 leads to the increase in productivity and efficiency in mines using this type of cutting machine. The primary focus of this work was to develop a precise model for estimating the production rate. For this purpose, a database including 98 laboratory tests on 7 carbonate rock samples was collected.Some operational properties of the machine, i.e. arm angle (AA), chain speed (CS), and machine speed (MS),and three important physical and mechanical propertiesincluding uniaxial compressive strength (UCS), Los Angeles abrasion (LAA) test, and Schmidt hammer (Sch) were considered as the input data, and another operational property of the machine, i.e. the production rate,was considered as an output dataset. In this work, different models were developed using the most important soft computing techniques including the GMDH-type neural network and RBF neural network. However, three performance indices including VAF,RMSE, and R^2 were considered to evaluate the algorithm results.For modeling, 18and 9 models were constructed by the GMDH and RBF neural networks, respectively. A comparison was made among the 18 simulations based on the performance indices, and the 18thmodel of GMDH had the best performance to predict the production rate with coefficient of determination (R^2) of training = 0.91 and testing = 0.92. Also in RBF, the model No. 8 with the performance indices of R^2=0.97 and 0.66 for training and testing data obtained the highest rank. Finally, based on the performance indices, it was found that the GMDH algorithm could provide a higher performance capability for estimating the production rate of carbonate rocks compared to the RBF method, althoughthe RBF approach in this work is applicable to predict the production rate. In the future research works, prediction of the production rate for chain saw machines can also be investigated and improved using other kinds of artificial neural networks such as the Hopfield network and multi-layer perceptron (MLP) neural network.

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ارزیابی عملکرد ماشین برش اره زنجیری برای سنگ‌های کربناته با استفاده از امکان‌سنجی مدل‌های شبکه‌های عصبی

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چکیده:

پیش‌بینی نرخ تولید فرآیند برش سنگ ساختمانی و به خصوص زمان استفاده از ماشین برش اره زنجیری بسیار سخت است. فرآیند برش سنگ‌های ساختمانی عموماً یک موضوع پیچیده به همراه فاکتورهای مؤثر متعدد شامل شرایط مختلف و غیرقابل اطمینان سنگ‌ها و ماشین‌های برش است. روش گروهی مدیریت داده‌ها (GMDH) از نوع شبکه عصبی و شبکه عصبی مصنوعی شعاعی (RBF) به عنوان نوعی از روش محاسباتی نرم، ابزاری قدرتمند برای تعیین و ارزیابی شرایط پیش‌بینی نشده و غیرقطعی هستند. از این‌رو، در این پژوهش هدف توسعه مدل‌های پیش‌بینی برای تخمین نرخ تولید ماشین برش اره زنجیری با استفاده از روش شبکه عصبی مصنوعی RBF و روش شبکه عصبی GMDH است و سپس مقایسه نتایج به دست آمده از مدل‌های توسعه‌یافته بر مبنای شاخص‌های عملکرد شامل VAF، RMSE و ضریب همبستگی (R^2) است. برای این هدف، پارامترهای ۹۸ تست آزمایشگاهی روی هفت نوع سنگ کربناته به طور دقیق بررسی شده است و نرخ تولید هر تست اندازه‌گیری شده است. برخی مشخصات عملیاتی ماشین از جمله زاویه اره (AA)، سرعت زنجیر (CS) و سرعت ماشین (MS) و سه مشخصه مهم فیزیکی و مکانیکی سنگ شامل مقاومت فشاری تک‌محوره (UCS)، تست سایش لس‌آنجلس (LAA) و تست سختی چکش اشمیت به عنوان داده‌های ورودی و نرخ تولید ماشین به عنوان مجموعه اطلاعات خروجی در نظر گرفته شده است. نتایج به دست آمده ثابت می‌کند مدل توسعه‌یافته GMDH برای مهیا کردن نتایج با اطمینان بالاتر برای پیش‌بینی نرخ تولید ماشین برش اره زنجیری بر اساس شاخص‌های عملکرد تواناتر است.

کلمات کلیدی: سنگ ساختمانی، ماشین برش اره زنجیری، نرخ تولید، GMDH، سنگ‌های کربناته.