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Estimation of the Ampere Consumption of Dimension Stone Sawing Machine Using the Artificial Neural Networks

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Abstract
Nowadays, estimating the ampere consumption and achievement of the optimum condition from the perspective of energy consumption is one of the most important steps in reducing the production costs. In this research, we tried to develop an accurate model for estimating the ampere consumption using the artificial neural networks (ANN).In the first step, experimental studies were carried out on 7 carbonate rock samples in different conditions at particular feed rates (100, 200, 300 and 400) and depth of cut (15, 22, 30 and 35mm) using a fully instrumented laboratory rig that is able to change the machine parameters and to measure the ampere consumption. In the next step, a retro-propagation neural network was designed for modelling the sawing process to predict the ampere consumption. The input network consists of two parts: machine, work piece characteristics and the output of neural network was ampere consumption. This research evaluated the competencies of neural networks to estimate the ampere consumption in sawing process. The correlation coefficient between measured and predicted data in training and testing data is 0.95 and 0.97, respectively. The Root Mean Square Error (RMSE) for train and test data is 1.2 and 0.7, respectively. The results of this study show that the ANNs can be used to estimate the ampere consumption with high ability and low error for industrial applications. Moreover, the cost of sawing machine ampere consumption can be accurately estimated using this neural model from some important physical and mechanical properties of rock.
Keywords: *Ampere consumption, machine characteristic, neural network, rock characteristic.*

1. Introduction

Nowadays, Iran is known as one of the global big holdersbiggest sources of the dimension stones in the world. In spite of the huge capacity of the reserves of building stones, diversity of their mines and high level of their potential, the building stones have not gained attained the appropriate stage position in the global market and export concept yet. It is so clear that the stone sawing industry plays an important role in the domestic economy of the country. The Its current capacity and its potential currently available in Iran make makes it reasonably achievable profitable just with providing a few principal and appropriate series of programming and political backgrounds. The first step to achieve this goal is the to have a precise knowledge of about the sawing process and the influential parameters on it. The appropriate knowledge of stone sawing process, its executive capability assessment and the prediction of cost factors in the stone sawing industry can result in improvements with in form of higher production rate and lesser costs. According to these concepts, Iran can enter the worldwide competing markets with by increasing of the production and the quality with through reduction reducing the of operational consuming costs, Iran can enter the worldwide competing markets. In this research, we tried to assess and show the competence of an ANN model in the prediction ofpredicting the electric current consumption (Ampere) in the sawing process. The stone sawing process is an abrasive process. That is, the in which sawing of the stone is made carried out by abrasion and friction caused by passing of the diamond segments on the surface of a piece of rock named work piece. In overall, the sawing process of shearing diamond can be identified by two steps:; firstly first, the movement of diamond segment on the shearing surface, and subsequently, causes the production of rock swarf in accordance to the penetration of diamond segment into the stone. Diamond segment produces a stone splinter and a new surface for the next diamond segment with through scratching and splitting of the sheared surface produces stone splinter and a new surface for the next diamond segment. Likewise to the other machinery process, there are two groups of distinct effective factors in sawing process operation:

1) Work piece (dimension stone) characteristics such as uniaxial compressive strength; , Young’s modulus; , Indirect Brazilian tensile strength; , impact strength; , shear strength; , bending strength; , hardness; , abrasivity; , density,; grain size; , and quartz content.

2) Sawing characteristics (machine, sawing tools, sawing type and way): The sawing characteristics include work piece feed rate, peripheral velocity, sawing depth, disc, segments, and type and way of sawing.

Recently, numerous studies with experimental tests have been carried out so far in order to investigate the sawing process and its relationship with work piece characteristics and sawing characteristics. Especially, among these studies, several empirical models and classification systems were investigated to prediction predict of the stone sawing capabilities were investigated based on the its mechanical and physical properties of the stone.

Wei et al. [1] evaluated and classified the sawability of granites by means of the fuzzy ranking system. In this study,They used the wear wearing performance of the diamond blade saw and the cutting force were used as the sawability criteria. Kahraman et al. [2] predicted the sawability of carbonate rocks using multiple curvilinear regression analysis. Gunaydin et al. [3] investigated the relationship between the sawability of carbonate rocks and brittleness indexes using regression analysis. Ersoy and Atici [4] experimentally studied the performance of circular diamond saws in terms of specific cutting energy in cutting different types of rocks. Kahraman et al. [5] studied shear strength parameters as predictors in an ANN based prediction model to predict the sawability of carbonate rocks. Kahraman et al. [6] developed a new classification system based on P-wave velocity of dimension stones in cutting with gang saws. The results showed that the classification and estimation of slab production efficiency of the dimension stones can be made by ultrasonic measurements.Tutmez et al. [7] developed a new fuzzy classification to investigate the performance of large diameter circular saw into three main categories based on the rock properties such as uniaxial compressive strength, tensile strength, Schmidt hammer value, point load strength, impact strength, Los Angeles abrasion loss and P-wave velocity. Mikaeil et al. [8] developed statistical model to predict the production rate of carbonate rock based on uniaxial compressive strength and equal quartz content. Atici and Ersoy [9] correlated the specific energy of cutting saws with rock brittleness and destruction energy.Yousefi et al. [10] studied the factors affecting on the sawability of the dimension stone. Mikaeil et al.[11]developed sawability classification system to assess the sawability of carbonate rock based on some important mechanical properties such as uniaxial compressive strength, Brazilian tensile strength, Schmidt hammer value and Los Angeles abrasion loss. Yurdakul and Akdas [12] developed predicted models to predict the specific cutting energy based on the operational variables of block cutters and rock properties. Uniaxial compressive strength, bending strength, Brazilian tensile strength, point load strength, Shore hardness test, Schmidt hammer hardness test, seismic velocity, water absorption at atmospheric pressure, apparent density, open porosity, saw blade diameter, and depth of cut values were used as input parameters in the analysis for the prediction of specific cutting energy. Ataei et al. [13] presented a new classification system to evaluate and ranking the sawability of carbonate rock based on the uniaxial compressive strength, Young's modulus, Mohs hardness, and a new abrasivity index using Fuzzy analytical hierarchy process approach. Sengun and Altindag [14] investigated the relationship between the specific energy of circular saw and carbonate rock properties such as bulk density, apparent porosity, uniaxial compressive strength, Brazilian tensile strength, flexural strength, Schmidt rebound hardness, Shore hardness, point load strength index, Los Angeles abrasion values, and P-wave velocity using simple regression. Mikaeil et al. [15, 16] classified and ranked the sawability of some famous carbonate rocks using fuzzy approaches (FDAHP and FAHP) and multi-criteria decision-making techniques (TOPSIS). Mikaeil et al. [17, 18] predicted the specific ampere draw and production rate in dimension stone sawing process based on rock brittleness indexes using regression analysis. Aydinet al. [19] developed predictive models to evaluate the specific energy of circular diamond saw blade using statistical analyses based on physical, mechanical and mineralogical properties in granitic rocks sawing. Engin et al. [20] investigated the relationships between specific energy values and rock properties such as Shore hardness, abrasion resistance, uniaxial compression and tensile strength, brittleness and modulus of elasticity. Yurdakul et al. [21] applied the adaptive hybrid intelligence (AHI) techniques to predict the specific cutting energy based on 40 different dimension stones in nineteen different dimension stone processing plants. The feed rate, depth of cut, uniaxial compressive strength, bending strength and point load strength of the rock were used as the input parameters in the development of the specific cutting energy prediction models. Jain and Rathore [22] developed ANN models to predict the cutting performance of diamond wire saw machine from shear strength parameter cohesion and machine parameters peripheral speed and thrust. Aydin et al. [23] applied the ANN and regression analysis to predict the performance of diamond saw blade (specific energy) with respect to peripheral speed, traverse speed and cutting depth in hard dimension stone sawing. The compared results showed that the ANN model is more reliable than the regression model for the prediction of the specific energy. Yurdakul[24] investigated the effect of the cutting mode, cutting depth, and feed rate on the level of consumed power, during granite cutting using circular saw blades. Tumac [25] applied ANN to predict the sawability performance of large diameter circular saw based on mechanical and physical properties such as uniaxial compressive strength, Brazilian tensile strength, Cerchar abrasivity index, porosity, and density.

2. Materials and methods

The ANN was used as a tool to estimate the performance of diamond circular saw in terms of ampere consumption. A data base is generated by collecting block samples from different dimension stone processing plants and performing laboratory tests on them. In the first step, experimental studies were carried out on 7 carbonate rock samples in different conditions at particular feed rates and depth of cuts cut using a fully instrumented laboratory rig. In the next step, a back retro-propagation neural network was designed for modelling the sawing process for predicting the ampere consumption.

2.1. Artificial neural networks

Nowadays, the using of ANNs are increasingly used in solving engineering problems increasingly develops. The design and implementation of incredible operation of human brain in an artificial system is always tempting and desirable for researchers. Numerous researchers worked in this area, and regardless of their huge efforts and results, it is a principle that the human brain performance is achievable [5, 22, 23, 25]. ANNs are comparative systems that change their structures based on the internal and external date which stream in the system during the training phase of the systems. In the other wordwords, ANN belongs to that group of artificial dynamic systems which transfer the cryptographic rule inside the data into the network by the process on the empirical data. In training phase, the network tries to find the best linking factors (weight) between the input and output data of the network (finding a mapping with the best overlapping with the training data).

The first and most important step in designing of a neural network model is the determination of input factors, i.e. the effective (influential) parameters on the process which is under study. The effective parameters in the stone sawing process can be distinguished mainly by three different setsets [4]: (a) work piece parameters; , (b) the sawing process parameters (including operational parameters and sawing pattern properties), and (c) performance parameters (such as operator's expertise and work environmental properties). Among all of these parameters, operational parameters and sawing pattern parameters are the controllable or dependent factors, and the parameters related to the stone properties are not controllable and are regarded as dependent factors. Each of these parameters has its own influence on the performance and production characteristics of the sawing process. Under the same condition of work environment (the same condition of machine, swing instrument and operator's expertise), the rock characteristics and operational parameters are the most important factors. In this study, two sets of input parameters were used for to model the stone sawing process modelling. The first set is related to stone properties (including four important parameters) and the second set one is related to stone sawing operational properties. These two sets of input parameters were depicted in Figure 1.

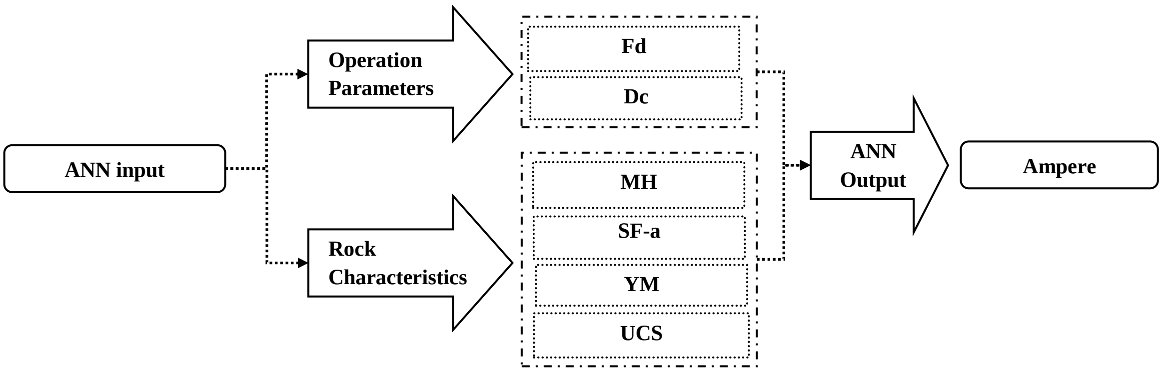

Fig.1.Inputs and outputs of neural network model

According to Figure 1, two parameters of sawing depth and feed rate were chosen as the parameters which are more important and effective in production rate. These two parameters are representative parameters for operational properties. Four parameters of uniaxial compressive strength, elasticity modulus, Mohs hardness, and Schimazek's abrasiveness factor were chosen as the most important physical properties of the rock. These six important parameters are briefly described as follows.

A) Uniaxial compressive strength

influence on the sawing rate and depreciation. Various methods have been introduced so far to assess and evaluate the stone abrasion [13]. The Schimazek's abrasiveness factor abrasion index has more privilege amongst the results of these efforts since it considers the tensile strength, grain size, and the quartz content. This index has a high capability in the evaluation of stone sawing process because it considers the microscopic texture.

C) Mohs hardness

Hardness is another important rock factor and has an effective influence on the overall hardness of the stone and finally on its sawing capability. The Mohs hardness (MH) is used as a usual index to study the hardness of stone. This index is determined by the study of thin section and the investigation of mineralogical combination of the stone. In this study, one of the main reasons of choosing this hardness index is its well-known concept,the familiarity of the researchers in this

The uniaxial compressive strength (UCS) can be regarded as the representative parameters for various mechanical and physical properties such as rock strength, texture, density, weathering degree, rock quality and rock matrix [13]. These parameters are the result of a simple and well-known test and provide the information about weathering which cannot be determined quantitatively.

B) Schimazek's abrasiveness factor

Abrasion is one of the most important parameters of rocks from the sawing process point of view. This parameter has an extensive area, and its high precision due to application of thin sections.

D) Elasticity modulus

In the rock failure process and rock swarf formation during the sawing process, the rock behaviour is controlled by its maximum compressive strength. In spite of the fact that the elasticity modulus (YM) is under the influence of some rock properties, it has influential effect on the rock behaviour under sawing process. Therefore, it was chosen as one of the influential parameters in the rock behaviour under sawing process.

E) Feed rate

In general, the operational parameters include the feed rate work piece, cutting depth, and the peripheral speed. The peripheral speed, in addition to the forces applied on the disc, determines the feed rate of the work piece. The best disc performance is obtained in an optimised condition. Very high feed rates cause high abrasion, energy consumption, excessive vibration and declining of sawing process.

F) Cutting depth

Cutting depth is the parameter of the disc penetration into the rock during sawing process. Cutting depth and feed rate are two main and effective factors in the sawing process. By multiplying these two parameters, the production rate of the sawing process could be determined. Increasing the cutting depth higher than a threshold raises the abrasion, energy consumption, vibration (of work piece and the disc), buckling and destroys the disc sooner than its normal life span.

3.1 Laboratory study

In order to design and present a neural network model to predict the electric current consumption (Ampere), a set of experimental tests were carried out on several building stone samples at different operational conditions.

2.1.1 Sawing machine characteristic

The sawing device were designed and made in such a way that the machinery parameters, including cutting depth and feed rate can change only by simple and few change in machine configuration. Different parts of the machine include the machine basement (two guiding rails for the movement of sawing table), (frame), upper part (the place for the main machine axis) and (frame) lower part (the place for collecting mud, water, and rock splinter) (Figure 2).

Fig. 2.Schematic view of sawing tool

The moving table of the machine has a flat surface on which the stone sample is fixed. This moving table moves on the machine rails by wheels and chain mechanism connecting to a hydraulic motor. The application of hydraulic system allows to control and adjust the speed of moving table to be equal to the feed rate. The transmission of force to the main axe is supplied by poley and belt. The shear disk is tightened between two iron-cast washers by bolt and nut mechanism. The whole narrow passageway is fixed on the steal bearing that can rotate about 8 degrees. The main spindle motor with a power of 7.5 KW is fastened over the bearing. The vertical movement is supplied by a hydraulic motor, as well. This mechanism is based on bolt and nut and has the adjustability of grooving of 0.01 mm precision. The start moving of the motors (horizontal movement) and passageway (vertical movement) is processed by hydraulic unit. This special system allows the control of different feed rates. The electric circuit of the machine was designed in such a way that it makes possible to operate under three different types of movement, i.e. manual, semi-automatic and fully-automatic. The feed rate is measured by an electronic counter. The intensity of electric current consumption (Ampere) in different machinery conditions is measured and recorded by a precise Ammeter. These different machinery conditions include four different feed rates (100, 200, 300, and 400 centimetres per minute) and four different depths of cut (15, 22, 30, and 35 millimetres). In all of these tests, the direction of sawing (work piece movement) is in the same direction with the disc rotation and the cooling fluid is water.

2.1.2 Sawing device characteristics

In sawing tests, a metallic soft cutting disc was used. The disc diameter and thickness are 41 centimetres and 2.7 millimetres, respectively. 28 diamond segments of $3\times10\times40$ mm^3 dimension were soldered on the disc perimeter. Artificial diamond segments have the shape of octahedral cubic with a mesh of 30/40 and a weight percentage of 25 to 30 distributed on the metal board.

2.1.3 Work piece (stone) characteristic

The laboratory study was carried out on seven building stones. For this purpose, the rock blocks were produced and transferred to the rock mechanics laboratory. All tests were performed under the standards of International Society of Rock Mechanics (ISRM). In addition, to wholly understand the mineralogical properties of rocks and their texture, one thin section was produced from each rock sample. A sample of rock thin section is depicted in Figure 3.

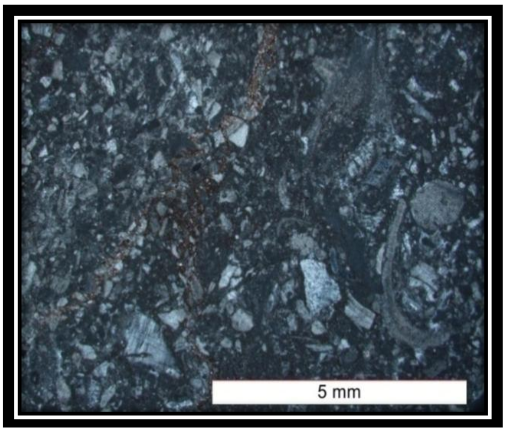

Fig.3.The microphotograph of the Anarak marble rock sample

Based on the examination of these thin sections, the type, the percentage of each mineral and the equivalent quartz content were measured to determine the sawability (abrasion) and hardness. The mechanical, physical, and sawability index are summarised in Table 1.

Table 1. Physical and mechanical characteristics of studied rocks

Rock sample		Type	mine	UCS	BTS	EQc	Gs	SF-a	YM	MH
				MPa	MPa	%	Mm	N/mm	GPa	n
A_1	Cream Harsin	Marble	Zolfaghar	71.5	6.8	3.6	0.55	0.135	32.5	3.5
A_2	Pink Anarak	Marble	Golsang	74.5	7.1	3.4	0.45	0.109	33.6	3.2
A_3	Red	Travertine	Azarshahr	53	4.3	2.8	1.01	0.122	20.7	2.9
A_4	Hajiabad	Travertine	Hajiabad	61.5	5.6	2.6	0.85	0.124	21	2.9
A_5	Darebokhari	Travertine	Darebokhari	63	5.4	2.7	0.87	0.127	23.5	2.95
A_6	Salsali	Marble	Salsali	68	6.3	3.2	0.52	0.105	31.6	3.1
A_7	Pink	Marble	Haftoman	74.5	7.2	4	0.6	0.173	35.5	3.6

NX core sample with a length to diameter ratio of 2.5:1, loading rate of 1 MPa/s in UCS test. SF-a) is defined as:

$$SF_a = \frac{EQC \times Gs \times BTS}{100}$$

YM: The tangent Young's modulus at a stress level equal to 50% of the ultimate uniaxial compressive strength. BTS isindirect Brazilian tensile strength. EQC is the equivalent quartz content percentage, Gs is the median grain size.

Totally, 130 tests are carried out, and in each test, the rock piece with a length of 30 centimetres and different thicknesses of 15, 22, 30, and 35 millimetres were fastened to the machine table, and then the sawing process was performed. The results of these tests were employed to train and evaluate the neural network performance.

2.2 Training of neural network

Training process of neural network can be considered as a function of optimization in which it is tried to determine the network parameters in such a way that the error between the network output and the target function tends to its minimum value. Accordingly, various function optimization techniques can be chosen directly for network training. Amongst the optimization methods, those methods which are based on the gradient (such as back propagation method) are the most common methods used by researchers.

Retro-propagation neural network technique has a main disadvantage over fitting phenomenon. This happens when the error on the training set is driven to a very small value, but when new data are presented to the network, the error is large. This problem occurs mostly in case of large networks with only few available data. Early stopping and automated Bayesian regularization methods are most common to avoid over fitting. In this study we used automated Bayesian regularization method in MATLAB toolbox [26].

In neural network training, the target function is an error function defined as follows [27-29]:

$$mse = \frac{\sum (y_p - y_{NN})^2}{n} \tag{1}$$

Where y_{nn}, y_p, and n are the network output, the real output (which is the favourable network output), and the total number of training parameters, respectively.

2.3 Sawing process simulation by neural network

In this study, estimating by neural network simulation was carried out using MATLAB R2009A software code. The input estimating vector of the network was chosen following equation (2). The number of training data and test data were 82 and 30 cases, respectively, that were selected from 112 experimental data. The structure of ANN is shown in figure 4. This network has three layers including input layer with 6 inputs, hidden layer with 10 neurons and output layer with 1 neuron. The training algorithm was Bayesian regularization.

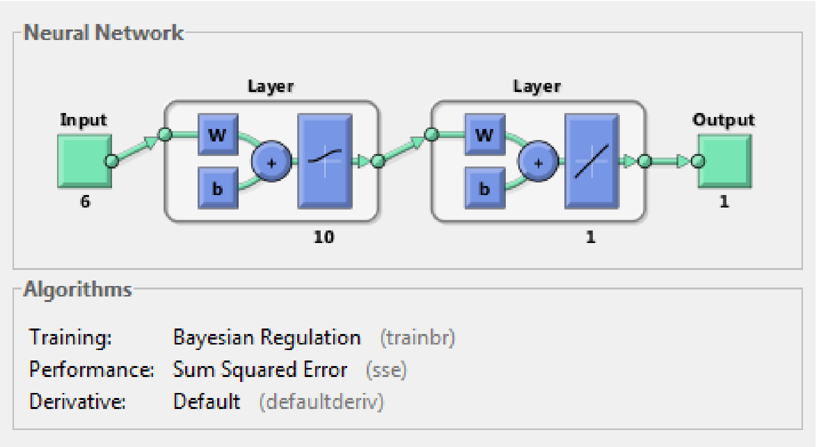

Fig. 4: The structure of ANN

The results of predicted electric current consumption (Ampere) versus measured values for training and testing data is depicted in Figures 5, 6. The correlation coefficient between measured and predicted data in training and testing data is 0.95 and 0.97, respectively. The average relative error between measured and predicated data in training and testing data is 5.5% and 4.67%, respectively. The Root Mean Square Error (RMSE) for train and test data is 1.2 and 0.7, respectively. As shown in Figures 5 and 6, the network output converged to the real data of the consuming electric current (Ampere) with a reasonable error.

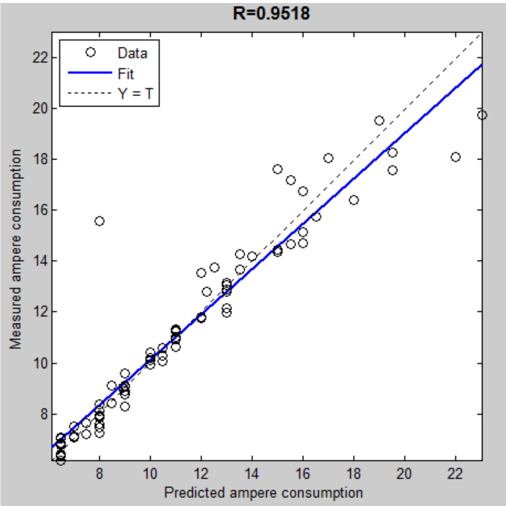

Fig. 5. The predicted ampere consumption versus experimental values for the training data

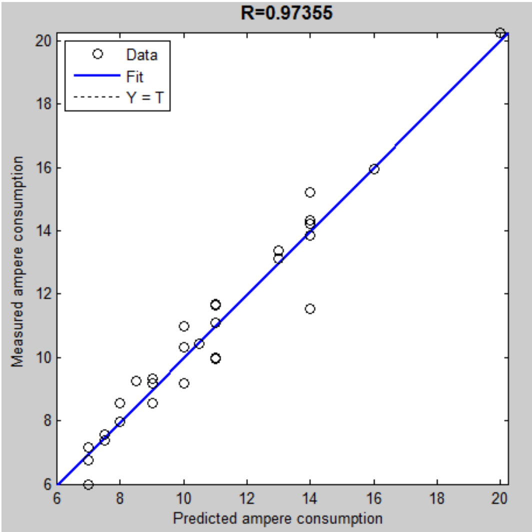

Fig. 6.The predicted ampere consumption versus experimental values for the training data

3. Conclusions

Nowadays, two important factors in competition in the world markets are price and quality. Factors such as labour expenses, machine and maintenance costs of sawing tools and the rate of energy consumption influence the final price. The better and more precise estimation of each factor can help the industry managers to better design and produce. It is obvious that the precise prediction of each factor requires the precise knowledge of influencing factors and employing the best methods for finding the relationship between the factors. In recent years, it has been observed and found that there is a continues motion and transformation from the pure theoretical studies to experimental and application-based studies especially in the fields of data processing, prediction and simulation of the process, and a simple solution has not been found yet. Neural network is amongst these practical simulation methods for anticipating the complex process. Neural networks are considered as multi-purpose nonlinear estimators with appropriate precision which play a remarkable role in nonlinear and even dynamic problems. In this study, the predicting simulation of the consuming electric current in sawing process of carbonate building stone was carried out using a designed feed-forward neural network. Four stone properties and two parameters of sawing machinery process were chosen and considered. The results of this study show that the neural network simulation can be employed as a practical method of low cost and error, as well as high capabilities in predicting the consumption electric current even in the industry. The correlation coefficient between measured and predicted data in training and testing data is 0.95 and 0.97, respectively. The Root Mean Square Error (RMSE) for train and test data is 1.2 and 0.7, respectively. Therefore, the expenses of consuming electric current can be easily predicted and considered by the managers of this part of the industry based on the characteristics of stone and sawing machinery.

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References

[1] Wei, X., Wang, C.Y., & Zhou, Z.H. (2003). Study on the fuzzy ranking of granite sawability. Journal of Materials Processing Technology, 139, 277–80.

[2]Kahraman, S., Fener, M., &Gunaydin, O. (2004).Predicting the sawability of carbonate rocks using multiple curvilinear regression analysis. International Journal of Rock Mechanics & Mining Sciences, 41, 1123–1131.

[3] Gunaydin, O., Kahraman, S., &Fener, M. (2004). Sawability prediction of carbonate rocks from brittleness indexes. The Journal of the Southern African Institute of Mining and Metallurgy, 104, 239–244.

[4] Ersoy A., & Atici U. (2004). Performance characteristics of circular diamond saws in cutting different types of rocks. Diamond and Related Materials, 13, 22–37.

[5] Kahraman, S., Altun, H., Tezekici, B.S., &Fener, M. (2005). Sawability prediction of carbonate rocks

from shear strength parameters using artificial neural networks. International Journal of Rock Mechanics & Mining Sciences, 43(1), 157–164.

[6] Kahraman, S., Ulker, U., &Delibalta, S. (2007). A quality classification of building stones from P-wave velocity and its application to stone cutting with gang saws. The Journal of the Southern African Institute of Mining and Metallurgy, 107, 427–430.

[7] Tutmez, B., Kahraman, S., &Gunaydin, O. (2007). Multifactorial fuzzy approach to the sawability classification of building stones. Construction and Building Materials, 21, 1672–1679.

[8] Mikaeil, R., Ataei, M., &Hoseinie, S. H. (2008). Predicting the production rate of diamond wire saws in carbonate rocks cutting, Industrial Diamond Review, 3, 28-34.

[9] Atici, U., &Ersoy, A. (2009). Correlation of specific energy of cutting saws and drilling bits with rock brittleness and destruction energy.journal of materials processing technology, 209, 2602–2612.

[10] Yousefi, R., Mikaeil, R., &Ataei, M. (2010). Study of Factors Affecting on the Sawability of the Ornamental Stone.Proceedings of the 8th International Scientific Conference SGEM. Bulgaria.

[11] Mikaeil, R., Yousefi, R., Ataei, M., &AbasianFarani, R. (2011). Development of a New Classification System for Assessing of Carbonate Rock Sawability, Archives of Mining Sciences, 56(1), 57–68.

[12] Yurdakul, M., & Akdas, H. (2012). Prediction of specific cutting energy for large diameter circular saws during natural stone cutting. International Journal of Rock Mechanics & Mining Sciences, 53, 38–44.

[13] Ataei, M., Mikaeil, R., Hoseinie, S. H., & Hosseini, S. M. (2012). Fuzzy analytical hierarchy process approach for ranking the sawability of carbonate rock. International Journal of Rock Mechanics & Mining Sciences, 50, 83–93.

[14] Sengun, N., & Altindag R. (2013). Prediction of specific energy of carbonate rock in industrial stones cutting process. Arab J Geosci, 6:1183–1190.

[15] Mikaeil, R., Yousefi, R., &Ataei, M. (2011). Sawability Ranking of Carbonate Rock Using Fuzzy Analytical Hierarchy Process and TOPSIS Approaches. ScientiaIranica, Transactions B: Mechanical Engineering, 18, 1106–1115.

[16] Mikaeil, R., Ozcelik, Y., Ataei, M., &Yousefi, R. (2013). Ranking the sawability of ornamental stone using Fuzzy Delphi and multi-criteria decision-making techniques. International Journal of Rock Mechanics & Mining Sciences, 58, 118–126.

[17] Mikaeil, R., Ozcelik, Y., Ataei, M., &Yousefi, R. (2011). Correlation of Specific Ampere Draw with Rock Brittleness Indexes in Rock Sawing Process. Archives of Mining Sciences, 56(4), 741–752.

[18] Mikaeil, R., Ataei, M., &Yousefi, R. (2013). Correlation of production rate of ornamental stone with rock brittleness indexes. Arabian Journal of Geosciences, 6, 115-121.

[19] Aydin, G., Karakurt, I., & Aydiner K. (2013). Development of Predictive Models for the Specific Energy of Circular Diamond Sawblades in the Sawing of Granitic Rocks.Rock Mech Rock Eng. 46:767–783.

[20] Engin, I.C., Bayram, F., &Yasitli, N.E. (2013). Experimental and Statistical Evaluation of Cutting Methods in Relation to Specific Energy and Rock Properties.Rock Mech Rock Eng. 46:755–766.

[21] Yurdakul, M., Gopalakrishnan, K., & Akdas, H. (2014). Prediction of specific cutting energy in natural stone cutting processes using the neuro-fuzzy methodology. International Journal of Rock Mechanics & Mining Sciences, 67, 127–135.

[22] Jain, S. C., & Rathore, S. S. (2015). Prediction of Cutting Performance of Diamond Wire Saw Machine in Quarrying of Marble: A Neural Network Approach. Rock Mech Rock Eng, 44:367–371.

[23] Aydin, G., Karakurt, I., & Hamzacebi, C. (2015). Performance Prediction of Diamond Saw blades Using Artificial Neural Network and Regression Analysis. Arab J Sci Eng, 40:2003–2012.

[24] Yurdakul, M. (2015). Effect of cutting parameters on consumed power in industrial granite cutting processes performed with the multi-disc block cutter. International Journal of Rock Mechanics & Mining Sciences, 76, 104–111

[25] Tumac, D. (2016). Artificial neural network application to predict the sawability performance of large diameter circular saws, Measurement. 80, 12–20.

[26]Jr, E. P. A., & Bartolac, T. J. (1993).Parallel Neural Network Training. In Proc. AAAI Spring Symposium on Innovative Applications of Massive Parallelism, Stanford Univ.

[27]Hagan, M.T., Menhaj, M. B. (1994). Training Feed forward Networks with the Marquardt Algorithm. IEEE Trans. on Neural Networks, 5(6), 989 – 993.

[28]Levenberg, K. (1944). A Method for the solution of certain nonlinear problems in least squares.Applied Mathematics, 2, 164 – 168.

[29]Marquardt, D.W.(1963). An Algorithm for least squares estimation of nonlinear parameters. SIAM J, 11, 431 – 441.