Modeling of Breakdown Voltage by Artificial Neural Network

B. Monchusi, S. Letlotla
Centre for Mining Innovation
CSIR
Johannesburg, South Africa
bmonchusi@csir.co.za, SLetlotl@csir.co.za

H. Ilgner, J. McGill
Centre for Mining Innovation
CSIR
Johannesburg, South Africa
HIlgner@csir.co.za, JMcGill@csir.co.za

Abstract—**The paper presents a model to determine the breakdown voltage of rocks under AC excitation conditions by employing the Artificial Neural Network (ANN) method. A relationship between the input parameters and the breakdown voltage is demonstrated. The inputs to the neural network are the starting temperature, input current and power. The output of the ANN is the breakdown voltage. A Multi-layer Feedforward Neural Network (MFNN) employing back propagation algorithm is used for learning and to train the ANN. The ANN is designed, trained and tested with Matlab software.**

Keywords-breakdown voltage; ANN; rock breaking; multi-layer feedforward neural network.

I. Introduction

Rock breaking is a process that has been in existence for more than a billion years. The natural form of rock breaking is the faulting of the earth's crust, weathering, volcanic activities and breaking caused by lightning. The knowledge of breaking rocks has evolved over time from the use of compressive forces and mechanical forces, to tensile stresses caused by electrical energy. Of these technologies, studies have not yet proved which one is the best criterion for rock breaking [1].

Alternative methods to rock breaking are important to research technological advances in the South African mining industry. In developing these methods, internal and external electrical energy conversion mechanisms can be applied. To generate stresses which will create fractures in the rock, electrical energy can be transmitted into the rock and the electric power be converted into electrothermal, electromagnetic, or electromechanical forces which breaks the rock [2].

The breakdown voltage is influenced by a large number of external factors such as temperature; humidity; duration of test; whether AC, DC, or impulse voltage is applied; pressure applied to the contact and shape of the electrodes; discharges in the surrounding medium and discharges in cavities. The fundamental mechanisms of breakdown in solids are understood much less clearly than those in gases; nevertheless, several distinct mechanisms have been identified and treated theoretically [3].

Padhy et al showed that the breakdown voltage of white minilex paper in the presence of voids can be modeled under AC and DC conditions using neural networks in [5]. The values of the mean square error and the mean absolute error showed the effectiveness of the multilayer feedforward neural network in predicting the breakdown voltage.

The break down voltages in N_2+SF_6 gas mixtures were predicted using four different multi-layer feedforward back propagated Artificial Neural Network (ANN) in [7]. A 5% average relative error on predicted breakdown voltages was found for training and testing the ANN.

The paper presents a model to determine the breakdown voltage of rocks by employing the ANN method under AC conditions. With the help of neural networks a relationship between the input parameters and breakdown voltage is established. A multi-layer feedforward ANN is employed for the prediction of the breakdown voltage. The ANN that is designed consists of one input layer with three neurons, one output layer and one hidden layer.

The input variables used are input currents, starting temperatures and input powers. These values are obtained from results of previous tests done using the CSIR in-house, high-voltage, AC-based test rig (60 kHz). The tests were conducted using rock samples which were 10-15cm by 1cm thick from narrow reefs. The output variable is the breakdown voltage. The sigmoid function is employed as the activation function for all the neurons except for those in the input layer. The ANN is trained using the back propagation method. The design, training and testing of the ANN is done with the Matlab software.

II. Rock Properties

A. *Resistivity*

The negative temperature coefficient of resistivity is a characteristic of all insulators [2]. In an alternating electric field, a dielectric material is characterized by its dielectric loss, which is the fraction of electric energy lost in the form of heat. The amount of heat generated in high resistive material by the AC conduction is a function of the electric field, frequency and dissipation factor. The electrical resistivity of metallic ores is sensitive to the frequency and power levels used. Many rocks

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can be classified as semi-conductors because they become conductive at some critical voltage level [2]. Rocks which have very high resistivity would require hundreds of thousands of volts of direct current to fracture or break [8]. When using AC, the voltage is slowly ramped up until the rock breaks because of the thermal stresses. The amount of heat generated under AC conditions can be calculated as follows:

$$Q = (\frac{5}{9})\varepsilon' \tan\delta f E 10 - 12 \qquad \text{Watt} \qquad (1)$$

where E is the volts per cm, f is the frequency, ε' is the relative dielectric constant and *tan δ* is the dissipation factor.

III. BREAKDOWN VOLTAGE PROCESS

The breakdown voltage of any insulator is that amount of minimum voltage above which the insulator starts behaving like a conductor. Thus the purpose of an insulator is defeated and hence it is of great importance to calculate the breakdown voltage of any insulator. Breakdown voltage is a characteristic of an insulator that defines the maximum voltage difference that can be applied across the material before the insulator collapses and conducts. In solid insulating materials, this usually creates a weakened path within the material by creating permanent molecular or physical changes by the sudden current. In rarefied gases found in certain types of lamps, breakdown voltage is sometimes called the "striking voltage" [5]. Rock electrical properties are highly variable. Even very accurate measurements of rocks in the laboratory do not reflect their electrical properties in situ, so the measurements are made purely to get an indication of the bulk electrical regime of the sampled rocks (Grant and West, 1965).

A test rig consisting of a variable voltage supply of 0-500 kV at a frequency of 60 kHz was designed and built to break rocks using electricity at CSIR, see Fig. 1. The rock samples tested were air dried and polished with a fine grid wet sand paper until shiny. One rock sample was tested for each rock type. The voltage was transmitted into the rock samples with thermosyphon-cooled electrodes. The electrodes were placed on top of the sample so as to make contact with the sample. A medical gel was applied on the probes to improve electrical contact with the rock samples.

Figure 1. CSIR in-house, high-voltage, AC-based test rig (60 kHz).

The voltage transmitted generated heat in local spots of the rock, resulting in a localized drop in the electrical resistance, due to the rock having a negative temperature coefficient. As the resistance dropped, the resulting current from the applied voltage increased. Soon a conducting channel was formed and thermal runaway occurred along this path. If the resistive heating rate is much faster than its conduction rate into the surrounding rock, tensile stress builds up inside the rock due to local thermal expansion. Once this stress exceeds the tensile strength of the rock, a break occurs and the current flow stops [2].

IV. ARTIFICIAL NEURAL NETWORK

Artificial neural networks are computational networks which attempt to simulate the networks of nerve cells (neurons) of the biological (human or animal) central nervous system. The perceptron is the neural computational model. The ANN has a function f(x) which shows the relation between the inputs, weights, bias and the activation function. The activation function relates the output of a neuron to its input based on the neuron's input activity level. Some of the commonly used functions include: the threshold, piece-wise linear, sigmoid, tangent hyperbolic, and the Gaussian [5].

A. Learning

The ANN has an attractive feature of learning. It uses a set of observations to solve the task at hand by learning from its environment and additionally improves performance through learning. Depending on the algorithm, the ANN can be categorized into: fixed weight, supervised and unsupervised. Fixed weight ANNs do not need any learning. Unsupervised ANNs are trained (weights are adjusted) based on input data only. The networks learn to adapt using experience gained from previous input. Supervised ANNs are the most commonly used ANNs. In these networks, the system makes use of both input and output data. The weights and biases are updated for every set of input/output data. The Multi-Layer Feedforward Neural Network (MFNN) falls into this category [5].

The learning process of the MFNN network involves using the input-output data to determine the weights and biases. One of the techniques used to obtain these parameters is the back-propagation algorithm. In this method, the weights and biases are adjusted iteratively to achieve a minimum mean square error between the network output and target value. MFNNs are the most widely used ANNs in applications. They have been used mainly for pattern recognition, control and classification [9].

The ANN can be applied using the following process: feature extraction, collecting training data, selection of ANN, training and testing of ANN. There are two different ways in which the algorithm can be implemented: incremental mode and batch mode. In the incremental mode the weights and biases are updated after each input is applied to the network. In the batch mode the weight and the biases of the network are updated only after the entire training set has been applied to the network [9]. The batch mode is used in this paper.

V. DEVELOPMENT OF THE NEURAL NETWORK FOR BREAKDOWN VOLTAGE

The purpose of the ANN developed is to estimate the breakdown voltage from the input current, the starting temperature and input power of the rock sample, which are obtained from previous experiments results.

A. *Input Selection*

The inputs to the neural network ANN are input currents, starting temperatures and input powers, totaling to 13 sets. The output of the neural network model consists of one neuron representing the breakdown voltage for a specific operating condition. In this work, the frequency at which the input and output values were obtained is 60 kHz. The reason for this frequency is that the AC test-rig that was used for electric rock breaking, where the input current, starting temperature, input power and breakdown voltage were measured, operates at a frequency of 60 kHz. The chosen input data were divided into two groups, the training group, corresponding to 62% of the patterns, and the test group, corresponding to 38% of patterns; so that the generalization capacity of network could be checked after the training phase. The output of the neural network model consists of one neuron representing the breakdown voltage for a specific operating condition.

B. *Selection of ANN*

The ANN used is the multi-layer feedforward type, with one hidden layer represented in Fig. 2. The number of units in the hidden layer is determined experimentally, from studying the network behavior during the training process taking into consideration some factors like convergence rate and error criteria.

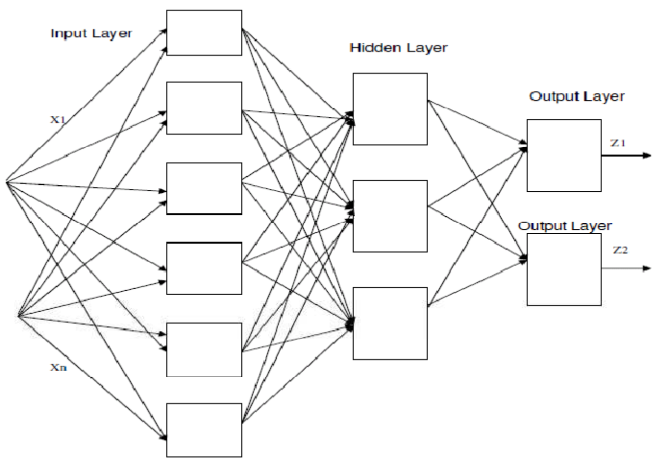

Figure 2. Multi-layer feedforward ANN

In this regard, different configurations are tested and the best suitable configuration is selected based on the accuracy level required. The sigmoid function is used for the units for all the neurons except for those in the input layer. The neural network is trained offline. In the future the ANN will be trained online and will have a feedback loop to determine the breakdown strength and the appropriate excitation voltage.

C. *ANN parameters*

The learning rate, η and the momentum factor, α have a very significant effect on the learning speed of the Back Propagation Algorithm (BPA). The BPA provides an approximation to the trajectory in the weight space computed by the method of steepest descent. If the value of η is made very small, this results in slow rate of learning, while too large, in order to speed up the rate of learning, the MFNN may become unstable (oscillatory). A simple method of increasing the rate of learning without making the MFNN unstable is by adding the momentum factor α. Preferably the values of η and α should lie between 0 and 1 [5].

D. *Evaluation Criterion*

The Mean Square Error (MSE) E_{tr} for the training patterns after the mth iteration is defined as:

$$E_{tr}(m) = \left(\sum_{p=1}^{p}\left(V_{b1p} - V_{b2p}(m)\right)^2\right) * (1/p) \quad (2)$$

where, V_{b1p} is the experimental value of the breakdown voltage taken for training purpose, $V_{b2p}(m)$ is the modeled value of the breakdown voltage after mth iteration and P is the number of training patterns. The training is stopped when the least value of E_{tr} has been obtained and this value does not change with the number of iterations [5].

E. *Mean Absolute Error*

The Mean Absolute Error (MAE) E_{ts} is a good performance measure for judging the accuracy of the ANN System. The E_{tr} tells how well the network has been adopted to fit the training data only, even if the data is contaminated. On the other hand, the E_{ts} indicates how well a trained network behaves on a new data set not included in the training set. The E_{ts} for the test data expressed in percentage is given by:

$$E_{ts} = \left(\frac{1}{s}\right) * \left(\sum_{s=1}^{s}\frac{|V_{b4s} - V_{b3s}|}{V_{b3s}}\right) * 100 \quad (3)$$

where,V_{b3s} is the experimental value of the breakdown voltage taken for testing purpose, V_{b4s} is the modeled value of the breakdown voltage after the testing input data is passed through the trained network and S is the number of testing patterns [5].

VI. SIMULATION RESULTS

A. *Simulations, training and testing*

The MATLAB software tool is used to create, train and test the neural networks. The training algorithm used is the back-propagation algorithm because it is the most useful supervised learning method for feedforward networks. The initial weights as well as the initial biases employed are random values between -1 and 1. To generate the ANNs training and validation data sets, the MATLAB/ SIMULINK software tool is used. The input data for ANN is shown in Table I. Few measurements were recorded because the aim of the tests done was to prove the concept that AC can break rocks and the consistency of the AC test-rig in breaking rocks.

TABLE I. DATA TO TRAIN NEURAL NETWORK FOR BREAKDOWN VOLTAGE OF ROCKS

Sample No.	Input current in (A)	Starting temperature (°C)	Input Power (W)	Voltage (V)
80	0.257	23.8	100.78	17.19
	0.726	29	711.76	16.82
	0.977	30	1340.98	21.43
	0.964	33	1512.16	39.72
92	0.123	25	72.35	98.77
	0.692	25.4	814.12	78.34
114	0.273	23.2	214.12	144.36
	0.712	25.6	837.65	1139.7
124	0.588	26	1406.59	322.26
	0.767	27.4	2556.67	442.78
	0.835	28.4	3110.78	495.18
152	0.362	28.2	569.97	74.8

The input currents and powers are the amounts of currents and powers that were transmitted from the test rig into the rock samples. The starting temperature is the temperature measured on the rock samples when the current was transmitted through the rock.

The ANN was tested under three conditions:

- Keeping the number of hidden neurons and learning rate factor constant and varying the momentum factor.
- Keeping the momentum factor and learning rate factor constant and varying the number of hidden neurons.
- Keeping the number of hidden neurons and momentum factor constant and varying the learning rate factor.

B. Results

The results for training and testing data sets under AC condition to find the breakdown voltage of rocks are shown below. Tables II to IV show the error between the measured values and the predicted values so that the generalization capacity of the network can be checked after training and testing phase.

TABLE II. MEAN SQUARE ERROR BY KEEPING THE NUMBER OF HIDDEN NEURONS AND LEARNING RATE FACTOR CONSTANT AND VARYING THE MOMENTUM FACTOR

No.	Nh (No. of hidden neurons)	α (Momentum factor)	Eta (Learning rate factor)	MSE (Mean square error)
1	3	0.4	0.4	1.3327 x 10-4
2	3	0.5	0.4	9.7399x 10-5
3	3	0.6	0.4	6.2360 x 10-5
4	3	0.65	0.4	4.5838 x 10-5
5	3	0.7	0.4	3.1158 x 10-5

TABLE III. MEAN SQUARE ERROR BY KEEPING THE MOMENTUM FACTOR AND LEARNING RATE FACTOR CONSTANT AND VARYING THE NUMBER OF HIDDEN NEURONS

No.	Nh (No. of hidden neurons)	α (Momentum factor)	Eta (Learning rate factor)	MSE (Mean square error)
1	4	0.7	0.4	1.3952 x 10-5
2	5	0.7	0.4	7.1961 x 10-6
3	6	0.7	0.4	3.8085 x 10-6

TABLE IV. MEAN SQUARE ERROR BY KEEPING THE NUMBER OF HIDDEN NEURONS AND MOMENTUM FACTOR CONSTANT AND VARYING THE LEARNING RATE FACTOR

No.	Nh (No. of hidden neurons)	α (Momentum factor)	Eta (Learning rate factor)	MSE (Mean square error)
1	6	0.7	0.5	1.9527 x 10-6
2	6	0.7	0.6	1.1361 x 10-6
3	6	0.7	0.65	8.9679 x 10-7
4	6	0.7	0.7	7.2089 x 10-7

The mean absolute error of all three conditions is 0.78%. This indicates that the measure of error between the measured values of the breakdown voltage and those predicted by the ANN is low. Fig. 3 shows the variation between the number of iterations and the mean square error. The above results show that the proposed ANN model is effective and can perform good prediction with the least error. The mean square root error is in the range of 10^{-4} to 10^{-7} indicating that the overall error of the network considering all training cases are low.

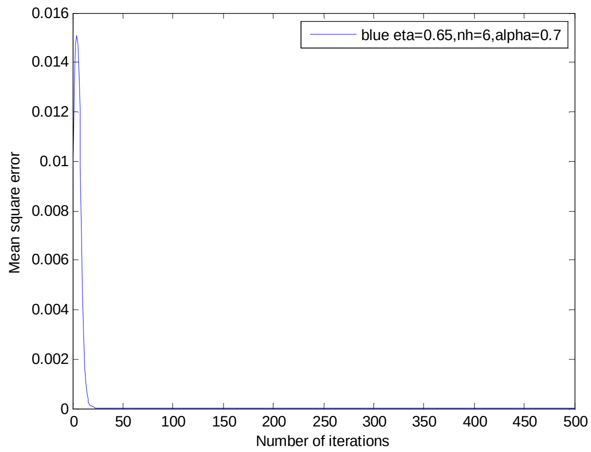

Figure 3. Variation between the number of iterations and the mean square error

VII. CONCLUSION

The ANN is designed, trained and tested to estimate the breakdown voltage of rocks using the input current, starting temperature and input power which are obtained from previous experiments. Matlab software is employed in the design, training and testing of the ANNs .The values of mean square error and the mean absolute error show the effectiveness of MFNN in predicting the breakdown voltage. The overall training error is low with the mean square error ranging from 10^{-4} to 10^{-7}. The Mean absolute error is 0.78 %. The results suggest that this neural network can be an important tool for estimating the breakdown voltage of rocks, which in turn will help in developing alternative rock breaking methods for the South African mining industry.

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