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Artificial Neural Networks Approach for Electrochemical Resistivity of Highly Organic Soil

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The resistivity of highly organic soils was measured using electrochemical resistivity reactor. Artificial neural networks (ANNs) were developed for the prediction of the resistivity at the different organic content, porosity, water content, and temperature. The results of study revealed that the resistivity of the highly organic soil decreased as the water content or temperature increased. The study showed that the resistivity of highly organic soil was also affected by degree of humification. As the degree of peat humification increased, the resistivity decreased. It was also concluded that the constructed ANNs models exhibited high performance for predicting of the resistivity of the highly organic soils.

Keywords: Organic soil, Resistivity, Artificial neural networks

1. INTRODUCTION

Soil resistivity is important to understand the mechanism of electrokinetics [1,2]. Application of direct current through a soil specimen induces three mechanisms including redox at the electrodes [3-4], water decomposition [5-7], and ion migration [8-11]. Electrical conductivity phenomena arise from the movement of ions or electrons through a conducting system under the influence of an electric field [12].

Resistivity of a soil depends on the surface conductivity of the colloids (i.e. clay or/and humus), presence of ions, porosity, moisture content, and temperature; and is determined according to the Ohm's law. Resistance is that property of a conductor which opposes electrical current when a voltage is applied across the two ends[19-20]. The resistivity measured in Ohm-m, and can be derived from the resistance, length, and cross sectional area of the conductor. The mathematical equation that describes this relationship is (Eq. 1):

$$\rho = \frac{E}{I}\frac{A}{L} \qquad (1)$$

Where:

ρ= resistivity of soil, (Ω-m)
E = applied voltage across the sample (V)
A= cross section area (m^2)
I= current (Amp)
L= Length of the sample (m)

An artificial neural networks (ANNs) is a mathematical model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. The basic architecture consists of three types of neuron layers: input, hidden, and output layers. The neurons interact with each other via weighted connections. In the input layer, data are presented to the neural network. The output layer holds the response of the networks to the input. The hidden layers enable these networks to represent and compute complicated associations between inputs and outputs [13].

The capture of the complex relationships between variations in organic content, water content, porosity, and temperature as inputs and resistivity of organic soil as an output provide an excellent context for using ANNs as a reliable data-modeling tool in this study.

2. MATERIALS AND METHODS

2.1. Materials

Peat samples were selected using Von Post humification scale from Kg. Jawa Klang, Selangor, Malaysia.

Table 1. Physicochemical properties of representative samples

Parameter	H2 peat	H7 peat	Clay
Squeezed pore fluid	Yellowish	dark	-
Soil pH	4.5	6.50	5.1
Organic content, %	94	85	16
CEC, meq/100 g soil	43	89	12

Clay soil samples from a layer of the soil on the surface were also collected from the same area. Some holes were dug up to collect the respective pore peat fluids. Table 1 shows the basic properties of the representative samples.

2.2. Resistivity reactor

The resistivity reactor used in this study is presented in Figure 1.

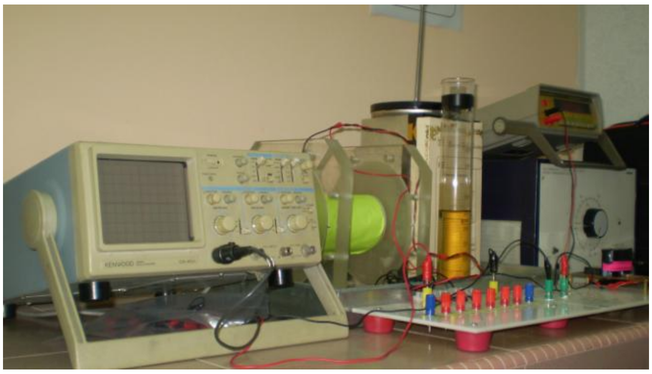

Figure 1. Resistivity reactor

Since the peat is a non-homogeneous material, the soil cell was designed bigger than those were used by some researchers for mineral soils [12]. The resistivity reactor consisted of an acrylic cylinder which was 170 mm in length, 3600 mm^2 in area, where the soil was molded, connected at both ends to titanium electrodes. The electrodes had a central pin that went out of the cylinder and were connected to a power supply. An digital multimeter and oscilloscope allowed the signal current and voltages to be viewed, respectively.

2.3. Procedures of Resistivity Test

In order to make a wider difference between the degrees of humification of two representative samples, the H7 peat was mixed in 10% fraction passing a No. 100 sieve of the peat. The peat specimens were prepared by mixing the last representative peat samples with different amount of the clay soil and peat pore fluid to bring the soils to the desired specimens in a process of trial and error. After sample preparation, the organic content and water content of the specimens were measured again and the last measured values were recorded as the soil properties. The temperature of each specimen was adjusted using an incubator. Each specimen was then gently placed in the resistivity reactor and the titanium electrodes were inserted into the soil at the both ends of the resistivity reactor. In order to increase the degree of accuracy, different constant electrical potentials of 40, 70, and 90 V were applied across the specimen. The currents were recorded to calculate the average resistivity of the soil.

At the end of testing the current was terminated and the resistivity setup was dismantled. The porosity of each sample was calculated using bulk density, moisture content, and specific gravity.

2.4. ANNs Model of Resistivity

Five variables were selected to be the resistivity model inputs. These inputs were organic content, degree of decomposition, porosity, water content, and temperature. The backpropagation learning algorithm was used in training stage.

The number of hidden layer was one. The optimum number of neurons in the hidden layer was determined by varying their number starting with a minimum of two then increasing the network size in steps by adding one neuron each time. A variety of different functions were investigated to achieve best performance in training and testing. Learning rate and training goal were selected as 0.01 for the training process to search the effective ANN structure. The maximum number of epochs (One pass through the set of training patterns together with the associated updating of the weights is called a cycle or an epoch) was chosen as 500.

The performance of the trained network was controlled using the regression analysis. The coefficient of determination (R^2) between the output and targets was used to evaluate the performance of the ANN models. The performance of the model was also controlled using the root mean square error (RMSE) and variance account for (VAF). (Equations 2 and 3).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left((x)_i - (x_p)_i\right)^2} \qquad (2)$$

$$VAF = \left[1 - \frac{\operatorname{var}(x - x_p)}{\operatorname{var}(x)}\right] \times 100 \qquad (3)$$

Where:

x = Measured value

x_p = Predicted value

N = Number of samples

80% of resistivity tests were used to train the ANNs. Once the optimal ANNs were designed the ANNs structures were used to predict the values of electrical resistivities separately. 20% of the resistivity tests which were not included in training phase were randomly selected from the same testing program for testing phase. Finally, the ANNs results were compared with experimental results for testing samples. In both models, the network training was accomplished with the neural network toolbox [13].

3. RESULTS AND DISCUSSION

3.1. Resistivity of the Samples

The resistivity of the specimens was affected by water content and temperature as depicted in Tables 2 and 3(see appendix).

The results of the study showed that the resistivity of the peat decreased as the water content or the temperature increased. Despite the fact that the water content of the very slightly humified peat was higher than the water content of the highly humified peat, interestingly, the resistivity of the highly humified peat was lower than the very slightly humified peat, indicating a higher degree of peat humification resulted in a lower peat resistivity.

The study also showed that the resistivity of both very slightly humified and highly humified peat increased as the organic content increased.

The porosity of the peats is also important factor in the resistivity of the peat. Peat is a high porosity material.

Since the peat tends to have high water content due to the high organic matter and cells of the plant remains, most of the void could be peat water. Therefore, as the porosity of the peat increased, the potential for the presence of peat water increased and resulted in the lower resistivity in the peat environment [14-16].

The humification processes of peat are chemical, biological, and enzymes [17]. The bacteria, soil micro flora, and fungi are responsible for the breakdown of the plants.

The higher degree of humification results in the higher contribution of humus to the soil surface charge[18]. Therefore, two conditions would affect the soil matrix due to humification processes: (i) the changes in soil particle size and tends to the finer particles and (ii) the complex mechanisms of humification that increase the surface charge of the fine particles. In order to bring the representative peat to the highly humified peat, the sieving process has been used.

However, since the humification processes could increase the quantity of the humus particles, thus, the higher degree of humification would decrease the resistivity.

Since the average temperature in Malaysia ranges from 23 to 32 ˚C, the temperatures were adjusted in such ranges. The results showed that the effect of the temperature on the soil resistivity was around 20%.

3.2. Modeling of Resistivity

It was observed that the ANNs of the resistivity with a model having 1 hidden layer, 6 neurons, 300 epoches, a tan-sigmoid transfer function in the neurons of hidden layer, and a pure linear transfer function in the neuron of the output layer showed a high prediction performance.

The measured versus predicted resistivity of the peats for training and testing data sets were compared in Figures 2 and 3, respectively. The target T values show the real resistivity of the samples, while the output A values show the predicted resistivity values. The R^2, RMSE, and the VAF of the training and testing data were 0.99, 1.19, and 98.50 %; and 0.989, 1.64, and 97.65%, respectively.

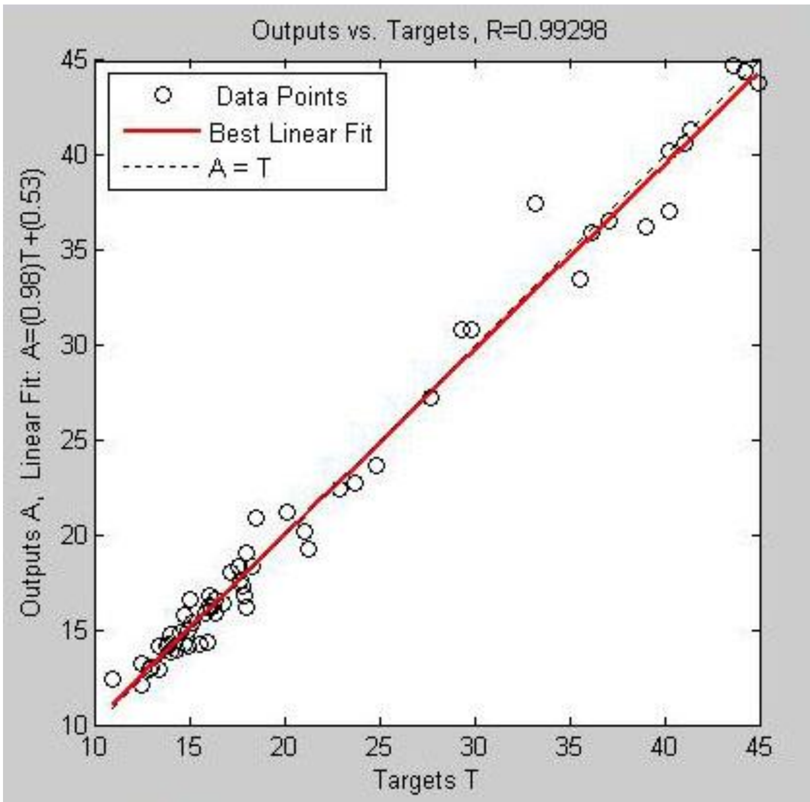

Figure 2. Training Resistivity Data Set

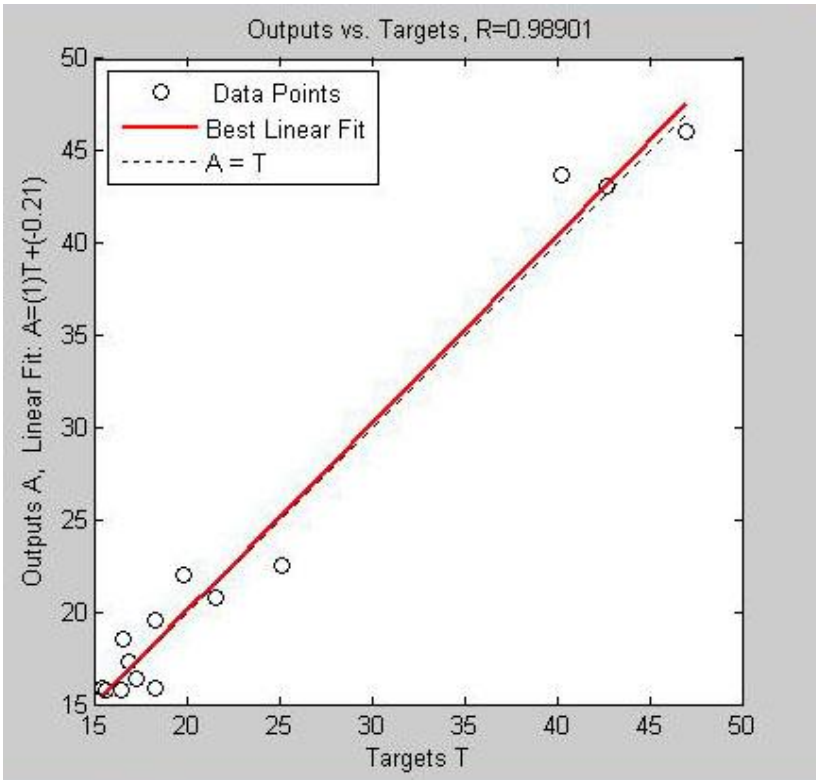

Figure 3. Testing Resistivity Data Set

It was concluded that the constructed neural network models for predicting the resistivity of the soil from determined organic content, prosity, degree of decomposition, water content, and the temperature exhibited high prediction results.

4. CONCLUSIONS

The resistivity of the highly organic soil was affected by the organic content, porosity, water content, and temperature. The resistivity of the highly organic soil decreased as the water content or temperature increased as the organic content increased. As the degree of peat humification increased, the resistivity decreased. The higher degree of humification could decrease the resistivity due to changes in quality and quantity of surface charges. Since the highly organic soil tends to have high water content due to the high organic matter and cells of the plant remains, the most volume of the void occupied with peat water. Therefore, as the porosity of the highly organic soil increased, the potential for the presence of peat water increased and resulted in the lower resistivity in the peat environment. It was also concluded that the constructed ANNs models showed high performance for predicting of the resistivity of the highly organic soils.

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APPENDIX

Table 2. Resistivity of the sample made up of the very slightly humified peat

Organic Content %	Porosity %	Water Content %	Temperature C°	Resistivity Ω-m
94	90	806	23	44.2373
			30	40.2853
			33.5	35.5126
	91	827	22	40.18
			27.5	33.2156
			34	29.7643
	92	899	22.5	39.0626
			27	29.336
			33	27.6983
62	90	542	24.5	46.9426
			28	44.9266
			32	40.2166
	91	605	23	43.63
			27.5	41.3303
			33	37.0356
	91	628	23.5	42.6643
			27	41.011
			33	36.1113
51	73	150	22.5	24.767
			28	21.2503
			33.5	17.832
	74	155	23	19.7723
			27	17.939
			32	15.9933

	75	165	23	18.455
			27.5	17.0753
			32	14.9576
31	83	241	23.5	18.1896
			28	16.3086
			31	14.857
	84	250	23	17.9203
			27.5	16.0533
			33	13.8916
	85	268	22	17.213
			28	15.763
			33.5	13.3583

Table 3. Resistivity of the sample made up of the highly humified peat

Organic Content %	Porosity %	Water Content %	Temperature C°	Resistivity Ω-m
85	80	285	21	25.053
			28	22.82
			33	20.9616
	83	343	22.5	23.638
			27	20.0963
			33	17.5773
	86	445	22.5	21.4616
			28	18.2366
			33.5	15.953
53	80	212	22	18.2536
			27.5	15.9286
			33	13.948
	82	242	23.5	16.764

			28	15.0946
			33	13.8133
	82	254	23	17.6863
			26.5	15.5916
			34	13.7593
42	76	161	23	17.5606
			27	16.712
			33.5	15.526
	81	213	23	16.357
			27.5	14.676
			33	12.9163
	85	300	23	14.9043
			28.5	12.3696
			33	10.8253
30	70	110	22	16.4903
			27	14.6783
			32	13.3266
	73	127	23	16.296
			27	14.4466
			33.5	12.8516
	75	136	23	15.3823
			27.5	14.2676
			33	12.414