DEVELOPMENT OF THE METHOD ON THE PREDICTION OF SOIL PLAT PENETRATION RESISTANCE

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During operation, the lug wheels penetrate the soil and form certain angle to the soil surface at varying penetration depths. In order to determine the soil reaction force against plate penetration given to the soil, penetrometer was mounted on the plate. Plate sizes used in this experiment were 5x5 cm^2, 5x10 cm^2, 5x15 cm^2 and 5x20 cm^2. The measurement was carried out at varying angles and depths i.e. 90°, 75°, 60°, 45°, 30° and 4 cm, 8 cm, 12 cm and 16 cm, respectively. The objective of this research was to develop the method on the prediction of soil plat penetration resistance at varying depths and angles. Prediction method was developed using linear or polynomial regression method which compared with Artificial Neural Network (ANN). The research showed that ANN generated better prediction value which indicated by lower error magnitude compared with regression method i.e. 9.9% and 19.7%, respectively.

penetrometer; plate; force; regression; ANN

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INTRODUCTION

Soil resistance is the physical and dynamic force called soil strength. The strength of the soil is the ability of the soil to resist forces that work to avoid deformation. Measurement and prediction of the soil reaction force is essential in designing a lugged wheel for hand tractors. Particularly in deep muddy fields, the design of the lugged wheels used is strongly influenced by soil strength to produce traction for the tractor to operate.

The measurement of soil reaction force against penetration given by lugged wheel (P) is conducted by using plat penetrometer. Penetration force given by penetrometer indicates soil plat penetration resistance acting during operation (Hermawan et al., 2000). In this experiment, the measurement was conducted at different penetration angles and different depths accordingly. This was done as lugs formed varying penetration angles to the soil surface at different penetration depths (sinkage) during operation (Hermawan et al., 1998). Mathematic calculation was done to determine soil reaction force acting due to changes of penetration angles and depths of each plat. The magnitude of P could be determined based on the magnitude of plate size, sinkage and penetration angle which then computed using two different methods i.e. regression mathematical modelling and Artificial Neural Network (ANN).

The used of artificial neural networks to predict the skidder pull-load relationship using field data has been done. Brons et al. (1993) combined neural network techniques with classical methods of image processing to determine a relationship between human judgments on the quality of pot plants and physical measurements. Y a n g (1993) used a neural network with machine vision to classify apple surfaces with an average accuracy of 96.6%. G o o d a c r e et al. (1993) used neural networks with a pyrolysis mass spectrometer to assess the adulteration of virgin olive oils by other seed oils. S a t o et al. 1993) trained a neural network to differentiate between operator voice and tractor noise at 2500 rev/min engine speed (T o h m a z , H a s s a n , 1995). A literature search indicated soil plat penetration resistance prediction using linear method and neural networks method was not available.

The objective of this research was to find the best method between linear method and neural networks method to compute P magnitude which indicated by the lowest error of P generated from actual measurement and prediction of those two methods.

MATERIALS AND METHODS

The measurement of soil plate penetration resistance was conducted at soil bin test in Field Laboratory of Siswadhi Soepardjo Leuwikopo, Bogor. Soil plate penetration resistance was carried out using penetrometer with lug plate on the top side. The lug plate consisted of four different sizes i.e. 5 cm x 5 cm, 10 cm x 5 cm, 15 cm x 5 cm and 20 cm x 5 cm. The use of various plate sizes is intended to derive a soil reaction force against the plate due to plate size differences in determining the width and wheel length of the lug wheels designed to produce optimum lift and pull forces. The penetration angle (θ) was set with cantilever mounted on penetrometer. Soil was taken from paddy wet land area, dried and sieved with 2 mm size. Soil and water were then placed into soil bin and mixed to produce a condition similar with paddy wet land area with 25 cm depth. Plat was mounted on penetrometer and set the penetration angle at 30°, 45°, 60°, 75° and 90° at 4 cm, 8 cm, 12 cm and 16 cm of penetration depths (R i z a l d i et al., 2014a). The depth of plate presses up to 16 cm is intended to determine the soil's capability when accepting the force of pressure by the plate so that it can be used to determine the lugged wheel operating parameters that are operated at a depth of 15 cm. This is to avoid the body of the tractor does not touch the ground when operated on land with a depth of soil> 30 cm. Penetrometer was equipped with ring transducer and strain gauge connected by bridge box which already connected to strain amplifier. Calibration was carried out first prior measurement. 1 unit of data logger, bridge box and strain amplifier was used during experiment. All signals were recorded in voltage unit in data logger. The data was then processed using calibration result to generate P value. The measurement procedure is shown in Fig. 1.

Data generated by penetrometer at each depth was recorded in data logger and stored in computer. This was done at each plate size and penetration angle. Data was then processed to obtain mathematic equation of soil plate penetration resistance as shown in Eq. 1.

$$P = \frac{F}{A} \tag{1}$$

P is soil penetration resistance (Pa), F is soil reaction force (kg), and A is plate surface area (cm^2) with width and length comparison 1:1, 2:1, 3:1 and 4:1. Penetration force generated by penetrometer is still in kilogram (kg) unit thus it is divided with each plate surface area to obtain Pascal (Pa) unit.

Method to determine the soil plate penetration resistance

The influence of plate size (A) and penetration depth (z). This experiment used four different sizes of plates i.e. A_1 = 25 cm^2, A_2 = 50 cm^2, A_3 = 75 cm^2 and A_4 = 100 cm^2. By using soil plate penetration resistance at 90° for each plate size, the magnitude of ln(P) and ln(z) could be obtained accordingly. The result was then plotted to generate correlation between ln(z) and ln(P) at each plate size and created the trend line to obtain R^2 closed to 1. The equation which generated from the second-order polynomial trend line had higher R^2 value compared with linear regression type. The next step was to convert the equation into $Y = fx^2 + gx + h$ and the value of f, g and h from the polynomial equation formed from each plate size was tabulated into one table. The value of f and g was then plotted into each plate size to obtain the correlation between plate size and f, g and h value. Plot between f and g was then formed into linear equation $Y_1 = f_1x + f_2$, $Y_2 = g_1x + g_2$ and $Y3 = i_1x + i_2$. Therefore, P_1 could be developed:

$$\ln P_1 = \left(\left(f_1 A + f_2\right)\left(\ln z\right)^2\right) + \left(\left(g_1 A + g_2\right)\left(\ln z\right)\right) + \\ + \left(i_1 A + i_2\right) \tag{2}$$

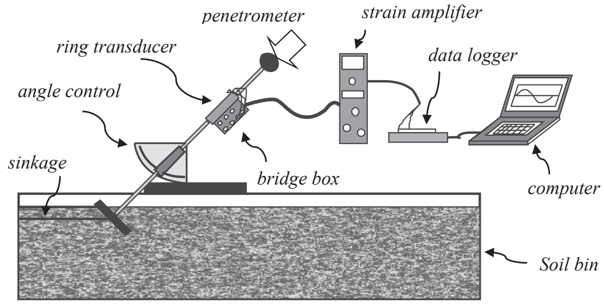

Fig. 1 The measurement of soil plate penetration resistance

$$P_1 = e^{\ln P} \quad (3)$$

The Influence of Penetration Angle (θ) The equation was influenced by penetration angle acting on the soil which given at 90°, 75°, 60°, 45° and 30°. Plate penetration force data at 25 cm^2 of plate size were collected at each penetration angle. After collecting data completed, a correlation between P at 90° and 75° of penetration angle was developed as well as P at 90° and 60° and so on for each penetration angle at each depth. By employing linear regression, a formula of $Y_1 = fx + h_2$ was developed. After f and h value were obtained, f value was then plotted on radian value of each penetration angle to develop second-order polynomial regression type with $Y_2 = fx^2+gx+h_1$. With same procedure, a computation was done for plate size of 50 cm^2, 75 cm^2 and 100 cm^2. The average of f, g, h_1 and h_2 was computed. The formula of plate penetration force at each penetration angle is as follow:

$$P = \left(\left(\left(rataan(f) \times rad^2\right) + \left(rataan(g) \times rad\right) + \right.\right. \\ \left. + rataan(h_1)\right) \times P_1\Big) + rataan(h_2) \quad (4)$$

P is penetration force at each angle (Pa) and P_1 is penetration force at 90° of penetration angle in accordance with plate size at each depth (Rizaldi et al., 2014b).

Artificial Neural Networks (ANN) Method. Back propagation is one of several learning algorithms used in ANN and widely used in various fields of application such as pattern recognition, forecasting and optimization. This could be due to that this method uses supervised learning method where pattern of input and target is given in a pair set. Initial weights are trained in forward propagation to generate error at the output layer. This error moves backward to generate expected weight to reduce error therefore the network can compute satisfactory output target. The aim of this model is to obtain the balance performance of the network ability to recognize pattern given during training and network ability to generate satisfactory response with different input data set (Rudiyanto et al., 2003).

RESULT

Measurement of soil resistance

Agricultural soil type used in this research was ultisol with texture wet silt clay loam containing 9.85% of sand, 51.62% of dust, 38.53% of clay, 55.78% of moisture content, 1.32 gr/cm^3 of dry bulk density and 2.051 gr/cm^3 of wet bulk density. Based on the measurement result as seen in Table 1 to 4, soil reaction force was higher along with deeper penetration of the plate into soil.

The next step is to develop correlation graph between ln(P) and ln(z). The magnitude of f, g and h was obtained by generating second-order polynomial trend line as seen in Fig. 2.

Fig. 2 shows polynomial equation which generated from correlation between ln(P) and ln(z) at each plat size. Based on the equation, the magnitude of f, g and h was generated as shown in Table 5.

Based on Table 5, a trend line which developed from the correlation between A and f, A and g, A and h were generated in linear regression type (Fig. 3).

Now, the magnitude of f_1, f_2, g_1, g_2 and h_1, h_2 could be computed and in turn the magnitude of P_1 at certain A and z could be calculated with this following equation:

$$\ln P_1 = (0.0013A + 0.22)(\ln z)^2 + (-0.007A \\ -0.437)(\ln z) + (-0.0028A + 11.6) \quad (5)$$

$$P_1 = e^{\ln P} \quad (6)$$

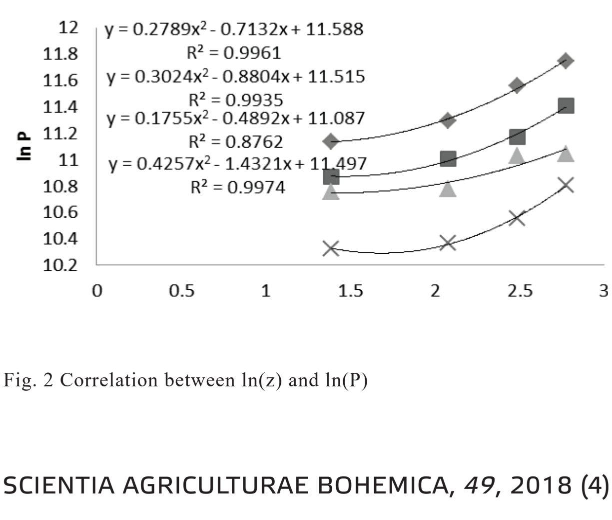

Fig. 2 Correlation between ln(z) and ln(P)

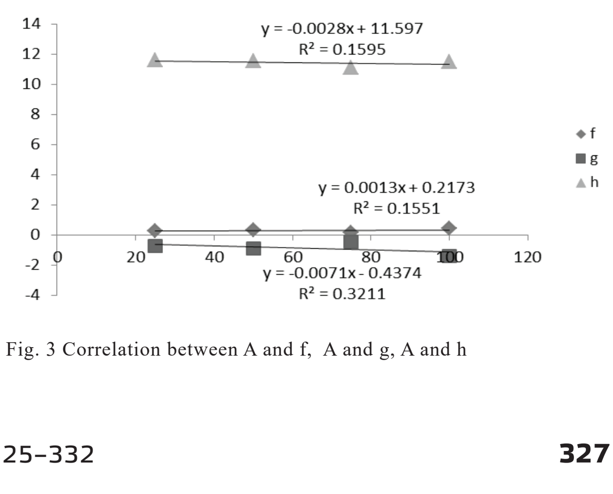

Fig. 3 Correlation between A and f, A and g, A and h

Table 1 Soil plate penetration resistance with 5x5 cm^2 of plat size

Sinkage (cm)	P (Pa) with penetration angle				
	90°	75°	60°	45°	30°
4	68728.70	57740.91	60907.37	54670.74	31830.6
8	80485.75	71608.28	63212.21	60044.77	56446.04
12	104860.50	78038.46	73335.44	62778.95	60816.00
16	125972.50	116328.70	74150.88	65706.67	65370.67

Table 3 Soil plate penetration resistance with 5x15 cm^2 of plat size

Sinkage (cm)	P (Pa) with penetration angle				
	90°	75°	60°	45°	30°
4	46875.93	37258.34	35295.72	28034.39	26226.67
8	48059.13	41885.05	36671.16	32800.28	31920.98
12	61622.60	49673.96	42685.10	34208.14	34048.00
16	62660.73	62310.32	49483.04	39038.55	36255.58

Table 3 Soil plate penetration resistance with 5x15 cm^2 of plat size

Sinkage (cm)	P (Pa) with penetration angle				
	90°	75°	60°	45°	30°
4	46875.93	37258.34	35295.72	28034.39	26226.67
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12	61622.60	49673.96	42685.10	34208.14	34048.00
16	62660.73	62310.32	49483.04	39038.55	36255.58

Table 4 Soil plate penetration resistance with 5x20 cm^2 of plat size

Sinkage (cm)	P (Pa) with penetration angle				
	90°	75°	60°	45°	30°
4	30564.70	24231.05	21375.79	19024.53	15833.75
8	31860.07	29581.26	27445.65	24446.95	18424.74
12	38241.86	37018.46	34619.30	28117.40	18880.84
16	49278.04	46639.16	43424.07	29365.12	20368.28

Table 5 The magnitude of *f*, *g* and *h*

A (cm^2)	f	g	h
25	0.2789	-0.7132	11.588
50	0.3024	-0.8804	11.515
75	0.1755	-0.4892	11.087
100	0.4257	-1.4321	11.497

Based on Equation 5 and 6, the magnitude of P_1 at each plate size could be predicted. The result is seen in Table 6.

In order to investigate how close prediction value represented actual value, correlation between actual and prediction value was developed as seen in Fig. 4.

Prediction of P value based on penetration angle

The magnitude of calculated P at each penetration angle could be generated by using the value of actual-

Table 6 The predicted P_1 at penetration angle 90°

Penetration depth (cm)	P_1 at each plat size			
	25 (cm^2)	50(cm^2)	75(cm^2)	100(cm^2)
4	69887.09	54232.08	42083.86	32656.89
8	83158.68	61693.72	45769.31	33955.32
12	102897.3	75440.16	55309.71	40550.87
16	125795.1	92052.18	67360.36	49291.8

Table 7 Predicted-P at 90° and actual-P at 75°, 60°, 45° and 30° at plat size of 25 cm^2

Penetration depth (cm)	P at penetration angle in radian unit (Pa)				
	1.570796	1.308997	1.047198	0.785398	0.5235988
4	68728.7	57740.91	60907.37	54670.74	31830.60
8	80485.75	71608.28	63212.21	60044.77	56446.035
12	104860.5	78038.46	73335.44	62778.95	60816.00
16	125972.5	116328.7	74150.88	65706.67	65370.67

Table 8 The magnitude of f and h_2 at each penetration angle (radian)

Radian	f	h_2
0.52	0.52	3646.80
0.79	0.19	43137.00
1.05	0.26	42900.00
1.31	0.99	-13389.00

P obtained from measurement test. Measurement data was a set of data at each plate size for each penetration angle. For plate size of 25 cm^2, it could be generated the correlation between calculated P at 90° and actual P at 75°, 60°, 45° and 30°. Penetration angle was converted into radian as seen in Table 7 and Fig. 5.

Based on Fig. 6, linear regression equation could be generated between predicted P at 90° (1.57 radian) and actual P at 75° (1.31 radian), 60° (1.05 radian), 45° (0.79 radian) and 30° (0.52 radian). Based on the equation, the magnitude of f and h_2 could be determined and tabulated in one table as seen in Table 8.

The next step was to create the correlation between f and penetration angle (radian) as seen in Fig. 6.

Based on Figure 6, polynomial trend was developed and some parameters value could be achieved i.e. f: 3.8854, g : -6.5589, h_1 : 2.9047 and h_2 was the average value as much as 21868.78. Using same procedure, calculation was carried out to determine the magnitude of the parameters with plate size area 50, 75 and 100 cm^2 (Table 9).

Therefore, the equation to calculate predicted P at each penetration angle at certain plate width (b) and zinkage (z) was as follow:

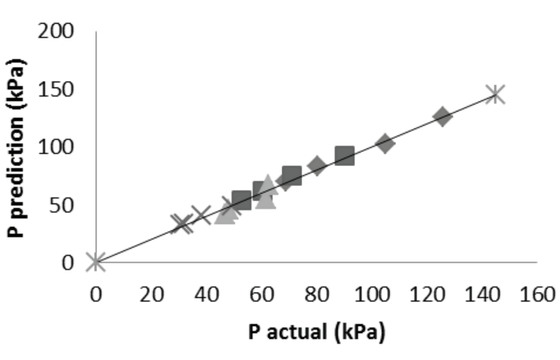

Fig. 4 Correlation between P resulted from actual and prediction

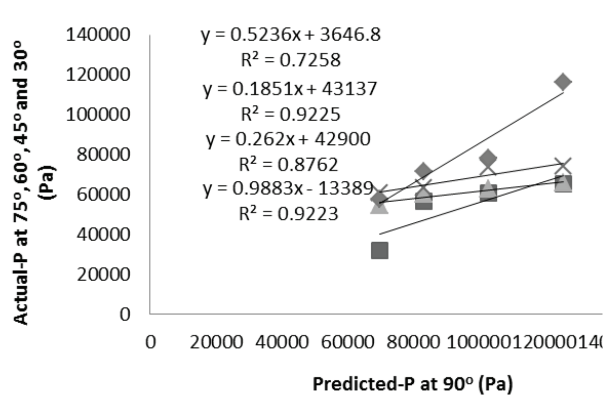

Fig. 5 Correlation between predicted-P at 90° and actual-P at 75°, 60°, 45° and 30°

Table 9 The magnitude of f, g, h_1 and h_2 at each plate size area

	Plate size area (cm^2)				
	25	50	75	100	Average
f	3.61	-6.09	2.70	21868.78	1.4499
g	1.41	-2.26	1.24	11759.83	-1.8886
h_1	1.60	-2.01	1.04	1102.08	0.97
h_2	-0.82	2.80	-1.10	951.88	8920.64

$$P = \left(\left(1.4499(rad)^2\right) + \left(-1.8886(rad)\right) + \right. \\ \left. + (0.97)\right)P_1 + 8920.64 \tag{7}$$

The magnitude of predicted P at each plate size and penetration angle could be determined using Equation 7. In order to investigate how close prediction value represented actual value, correlation between actual and prediction value was developed as seen in Fig. 7.

Prediction of P using ANN Method

The data of soil plate penetration resistance in soil bin obtained from measurement which arranged according to ANN standard method input data. File

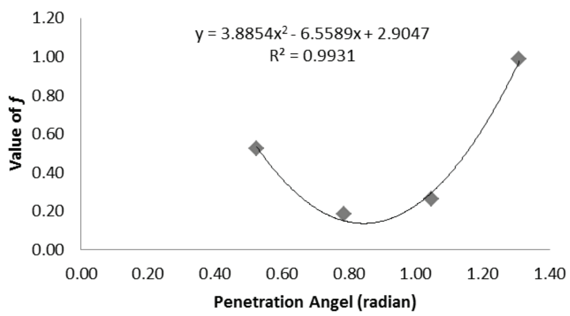

Fig. 6 Correlation between f and penetration angle (radian)

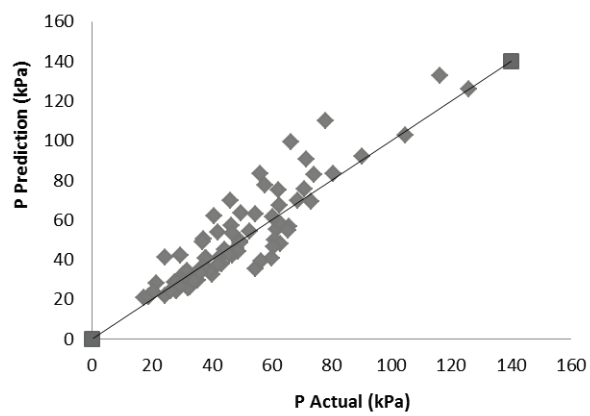

Fig. 7 Correlation between actual-P and predicted-P at plate size area 25, 50, 75 and 100 cm2 with regression method

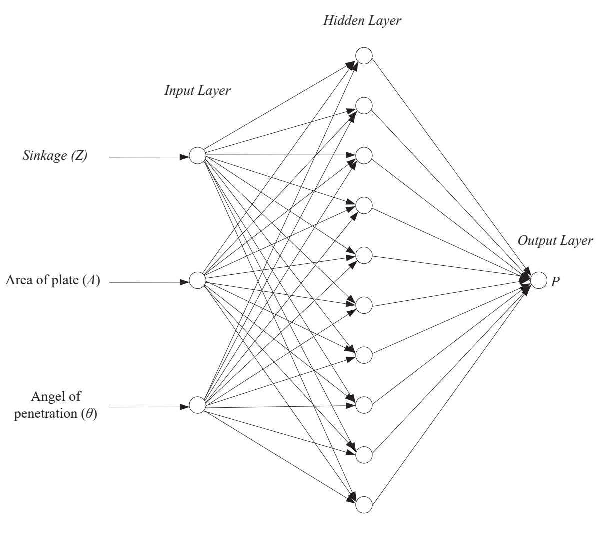

Fig. 8 Architecture of ANN

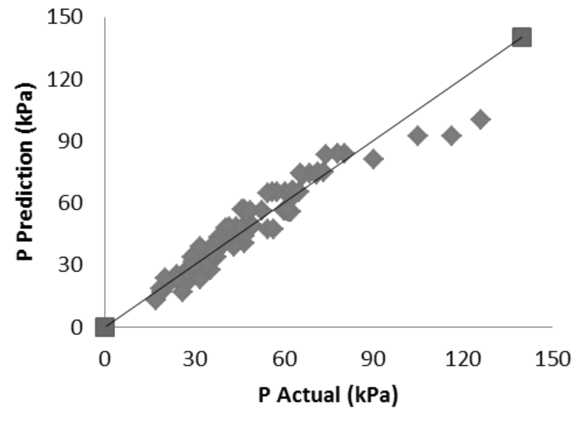

Fig. 9 Correlation between actual-P and predicted-P at 25, 50, 75 and 100 cm2 of plate size by ANN method

was then saved as and trained to predict P using ANN simulation program in which 60% of data is for training and 40% of data for testing. Some parameters used were: 10000 for iterations target; 0.9 for learning rate; 3 for input nodes, 10 for hidden layer nodes and 1 for output node as seen in Fig. 8.

The value of the soil resistance (P) is used as the target for the learning process (output layer). While the area of plate (A), sinkage (Z) and angle of penetration (θ) is an input parameter. There are 80 number of data sets used as targets, four variations of size A, four variations of depth Z and five variations of press angle θ. The input and target patterns are given as a pair of data and each variation of the input parameters is given the initial weights trained through the forward stage to obtain the desired output target. The targets obtained from the learning will result in the deviation value, then this drift is used as a backward step to obtain an appropriate weight value in order to minimize the deviation value so that the desired output target is reached.

DISCUSSION

Based on Fig. 7, it could be seen that predicted-P didn't give satisfactory result which indicated by error magnitude was 0.15409 and regression coefficient (R^2) was 0.766. Validation was carried out by creating correlation graph between actual and predicted value of P as seen in Fig. 9. In Fig. 9, it can be seen that regression coefficient (R^2) is 0.9067 and error is 0.099961 which indicate that predicted-P very closed to actual-P value. Compared with linear methods, it can be concluded that ANN method can give more accurate value of predicted-P. Because of the prediction of soil strength in high soil water levels is very difficult because soil strength is strongly influenced by water content. Therefore, the prediction of soil strength with the ANN method can be recommended. Tarawneh (2017) developed a back-propagation artificial neural network model to predict the ANN model output that is Standard Penetration Test (SPT) N60-value from Cone Penetration Test (CPT) data. It is concluded that back-propagation neural networks is a good tool to predict N60-value from CPT data with acceptable accuracy. Yaman et al. (2017) using artificial neural networks to predict the ingredients of self compacting concrete shows the accuracy of the output prediction looks very promising as the R2 values obtained between 0.63 and 1.0. Taghavifar, Mardani (2014) using artificial neural networks modeling to predict tire contact area and rolling resistance due to the complex and nonlinear interactions between soil and wheel provided the best accuracy with regression coefficients of 0.998 and 0.999 highly appropriate for soil–wheel interaction modeling. Ranasinghe et al. (2017) present the application of ANN for a priori prediction of the effectiveness of Rolling Dynamic Compaction (RDC). The predictions from the ANN models are in good agreement with the measured field data, as indicated by the model correlation coefficient of approximately 0.8.

CONCLUSIONS

Soil plat penetration resistance could be predicted by regression or ANN method. Regression method generated P prediction value with regression coefficient (R^2) 0.742 and accuracy 0.803 (80.3%). ANN method generated P prediction value with regression coefficient (R^2) 0.9067 and accuracy 0.9 (90%). Based on those results, ANN was concluded as the best method to predict soil plate penetration resistance.

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REFERENCES

Brons A, Rabatel G, Ros F,Sevila F, Touzet C. (1993): Plant Grading by Vision Using Neural Networks and Statistics. Computers and Electronics in Agriculture 9(1):25-39.

Goodacre R, Kell D B, Bianchi G. (1993): Rapid Assessment of the Adulteration of Virgin Olive Oils by Other Seed Oils Using Pyrolysis Mass Spectrometry and Artificial Neural Networks. Journal of Science. Food and Agriculture 63(3):297-307.

Hermawan W, Yamazaki M, Oida A. (1998): Experimental Analysis of Soil Reaction on a Lug of a Movable Lug Wheel. Journal of Terramechanics. 35(2):119-135. Doi: http://dx.doi.org/10.1016/S0022-4898(98)00017-2.

Hermawan W, Yamazaki M, Oida A. (2000): Theoretical Analysis of Soil Reaction on a Lug of the Movable Lug Cage Wheel. Journal of Terramechanics. 37(2):65-86. Doi: http://dx.doi.org/10.1016/S0022-4898(99)00014-2.

Ranasinghe R A T M, Jaksa M B, Kuo Y L, Nejad F P. (2017): Application of Artificial Neural Networks for Predicting the Impact of Rolling Dynamic Compaction Using Dynamic Cone Penetrometer Test Results. Journal of Rock Mechanics and Geotechnical Engineering. 9: 340-349. Doi: http://dx.doi.org/10.1016/j.jrmge.2016.11.011

Rudiyanto, Setiawan B I, Suroso. (2003). Backpropagation Neural Network. Institut Pertanian Bogor, Bogor.

Rizaldi T, Hermawan W, Mandang T, Pertiwi S. (2014a): Tractive Performance Testing of Lug Wheel in a Soil Bin. International Journal of Scientific & Engineering Research. 5(7):521-525. Doi:10.14299/000000.

Rizaldi T, Hermawan W, Mandang T, Pertiwi S. (2014b): Determining Parameters of Lug Wheels Design by Measurement of Soil Penetration Resistance in Paddy Field. Agritech. 34(4):473-481. ISSN: 0216-0455.

Sato K, Hoki M, Salokhe V M. (1993): Voice Recognition by Neural Network Under Tractor Noise. Transactions of the American Socie O, of Agricultural Engineers. 36(4):1223-1227.

Taghavifar H, Mardani A. (2014): Application of Artificial Neural Networks for The Prediction of Traction Performance Parameters. Journal of the Saudi Society of Agricultural Sciences 13: 35–43

Tarawneh B. (2017): Predicting Standard Penetration Test N-value from Cone Penetration Test Data Using Artificial Neural Networks. Geoscience Frontiers. 8:199-204. Doi: http://dx.doi.or8,5 Neural Networks. Computers and Electronics in Agriculture 9(l):1-12.

Tohmaz A S, Hassan A E. (1995): Application of Artificial Neural Networks to Skidder Traction Performance. Journal of Terramechanics. 32(3):105-114.

Yaman M A, Elaty M A, Taman M. (2017): Predicting The Ingredients of Self Compacting Concrete Using Artificial Neural Network. Alexandria Engineering Journal.56:523–532. Doi: http://dx.doi.org/10.1016/j.aej.2017.04.007

Yang Q. (1993): Classification of Apple Surface Features Using Machine Vision and Neural Networks. Computers and Electronics in Agriculture 9(l):1-12.

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