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Smart Computing Techniques for Predicting Soil Compaction Criteria under Realistic Field Conditions

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Abstract: The primary objective of this paper was to develop an artificial neural network (ANN) simulation environment and mathematical models for predicting with high accuracy soil compression parameters. The experiments were conducted at the College of Agriculture - University of Basra, located at Garmat Ali, the soil was silty clay loam. The factors that were investigated are moisture content (14 and 24%), tillage depths (0, 15, 30, 45, and 50 cm) forward speeds (0.57, 0.94, and 1.34 $m.s^{-1}$) and tire pressures (50, 100, and 150 kPa). ANN environment was developed with the back propagation algorithm using MATLAB software with various structures and training algorithms. Design Expert software utilized to evaluate the studied parameters and produce mathematical models. The results showed that all studied parameters had a significant effect on soil physical properties including bulk density and cone index. The effects of the studied factors on bulk density were depth > moisture content > forward speed, > tire pressure (6% 4%, 2.4%, 2%, respectively). Whereas, the order of the investigated factors based on their effects on cone index were depth > moisture content > tire pressure > forward speed (6%, 4%, 2.4% and 2%, respectively). The best model for predicting the bulk density under different field conditions was the 4-8-1 architecture. Levenberg-Marquardt (Trainlm) produced outstanding performance with an MSE of 0.00226 and R^2 of 0.986. Moreover, this performance was occurring at an epoch of 100. For predicting cone index, the best performance was achieved by Levenberg-Marquardt (trainlm) in 85 epochs, giving minimum MSE equal to 0.005112 and greater (R^2) equal to 0.967 during the training process. Thus, the optimal structure for predicting cone index was 4-7-1.

Keywords: ANN, Design-Expert software, Bulk density, Cone index.

Introduction

The sustainability of the agricultural systems depends mainly on preserving the soil and increasing its productivity. It can be achieved by avoiding improper practices that lead to soil degradation such as soil erosion or exposure to compaction and in this context. Soil compaction is described to indicate the shrinkage in the size of the pores between the soil aggregates (Pagliai *et al.,* 2003). Hence, bulk density increases, and in some cases the destruction of a large part of its construction.

Therefore, the problem of soil compaction is a source of concern for workers in the agricultural sector. Hence, researchers focused on studying soil compaction and tillage operations to reduce its damage (Canarache *et al.,* 2000; Arvidsson *et al.,* 2003; Défossez *et al*., 2003; Arvidsson & Keller, 2004; Filipovic *et al.,* 2006; Rücknagel *et al.,* 2007; Peng & Horn, 2008; Keller & Arvidson, 2016). The causes that lead to the compaction of soil are multiple and overlapping such as the high mechanical load, tire specifications, soil tillage and crop service within ranges of high soil moisture. Sivarajan *et al.* (2018) found a significant effect of the moisture content of the study area and indicated that the change in the moisture content from 18 to 24% led to an increase in the bulk density values from 0.95 to 1.01 $\text{Mg}.m^{-3}$. Dryer soils are less responsive to compaction as stress will spread and will be less able to distort the soil structure due to the ability of dry soils to distribute stress in the contact area between soil and tires (Batey, 2009). The important and fundamental factors to maintain soil productivity and reduce field soil compaction is the use of tires with a large contact area. Arvidsson *et al.* (2011) indicated that increasing the contact area between the tire and the field ground, is able to reduce the dry bulk density and increases the saturated hydraulic conductivity due to the high pressure dispersion generated under the double tires compared to the single tires, which is inversely proportional to the contact area. Also, Liu & Shalaby (2013) found that the tire pressure played a role in the compaction that the tire applied to the ground, as the soil pressure decreased by 15% under the center of the tire when the tire pressure was reduced from 690 kPa to 345 kPa. Marra *et al.* (2018) explained in a study of the impact or groove depths generated after the tractor has passed, where it is possible to express the soil pressure generated from different tires by scanning and analyzing images of the depths of the resulting cracks or grooves at the same number of times the tractor is passed. D'Acqui *et al.* (2020) showed that the main effect of passing agricultural machinery was not limited to dry bulk density in moist soil. Rather, machinery and tractors left a clear trace of irregular U-shaped grooves, as well as changing the type and size of the pores. Taghavifar & Mardani (2014) indicated that the use of soil penetration resistance as an indicator of soil compaction is directly affected by the forward speed of the tractor. It found the inverse proportion between penetration resistance and forward speed.

Intelligent computing technology has been used in various disciplines and fields of research in computational sciences with various software technologies such as statistics, machine learning, artificial neural networks (ANN), analysis of fuzzy data, and artificial intelligence - to solve many problems and manage technical processes in all kinds of medical and engineering sciences (Almalki *et al*., 2016; Kamilaris & Prenafeta-Boldú, 2018; Shafaei *et al.,* 2018; Almaliki *et al.,* 2019; Almaliki *et al.,* 2021; Monjezi, 2021; Monjezi & Hosseinzadeh, 2021).

Artificial Neural networks were used by Almaliki *et al.* (2019) to predict the tractive efficiency of the tractor during the tillage process and correlate this with a set of influencing factors such as soil penetration resistance, forward speed, and different tillage depths. These techniques gave high compatibility with the presented experimental data. For this reason, these models were considered in the study a fast, high-precision, and low-cost method. Santos *et al.* (2012) demonstrated the potential for using artificial neural networks to monitor and evaluate soil quality through some of its physical properties. ANN was also used to predict soil fragmentation during the tillage process. Also, it was linked with a set of outputs such as water movement in the soil, drainage rate, aggregate condition, size of aggregates, soil moisture content, forward velocity, different tillage methods, soil organic matter content and soil density (Taghavifar & Mardani, 2014). Also, developed several models from ANN to estimate soil erosion and to characterize sediment distribution patterns under field conditions (Krueger *et al.,* 2012).

Overall, there are no previous studies on the application of the artificial neural network simulation environment to predict soil compaction parameters based on realistic data resulting from changes in field conditions. Therefore, the essential objective of this research is to develop a valid ANN simulation environment and mathematical models for accurate prediction of the soil compaction parameters (bulk density and penetration resistance) under different operations conditions (soil moisture content, plowing depths, forward velocity, and tire pressure).

Materials & Methods

Field experiments

The experiments were conducted in one of the fields of the College of Agriculture, University of Basrah, Garmat Ali site, in silty clay soil. The experiment's field was divided into two equal parts, each of part is 1500 square meters (20 × 75 meters). All field operations (plowing, pulverization and leveling) were carried out to prepare the soil for cultivation. Before performing the experiment, samples and measurements were taken before and after the implementation of the initial characteristics, represented by the moisture content, bulk density, soil reality density, soil texture, saturated hydraulic conductivity, cohesion, soil penetration resistance, and mean weighted diameter. For more accuracy, measurements were performed with three replications for each site. Where random samples were taken from the soil of the field from five places, in which the field was divided in the form of a letter (x) and with depths from 0 - 30 cm. Table (1) shows some of the physical characteristics of the soil under study.

Field experiments tests

Soil penetration resistance was measured by a digital penetrometer. The measurement is made per 1 cm depth in the soil before and after the tractor wheels pass. The angle of inclination of the cone is 30 degrees and the area of its base is 1 cm^2. Soil penetration resistance was calculated for depths of 0-30 cm according to ASAE S313.2 standards (ASAE, 2009). The rate of readings for each experiment is calculated.

The soil bulk density was measured by Core Sample and reported in Black (1965) before and after soil compaction based on the following equation:

$$\boldsymbol{\rho_b} = \frac{\mathbf{M_S}}{\mathbf{V_t}} \qquad (1)$$

where

ρ_b= Soil bulk density $Mg.m^{-3}$

M_S= Dry soil weight Mg

V_t= Soil volume m^{-3}

The total porosity of the soil was calculated based on the value of the solid density and the bulk density of the soil using the following equation Black (1965).

$$T_p = (1 - \frac{\rho_b}{\rho_s}) * 100 \qquad (2)$$

where

T_p= Total porosity of the soil %

ρ_s= Solid density $Mg.m^{-3}$

Solid density was calculated according to the following equation:

$$\rho_s = \frac{M_S}{\frac{M_S - M_{SS}}{\rho_w}} \quad (3)$$

where

M_{SS}= Soil weight in water Mg

ρ_w= Density of water $Mg.m^{-3}$

Table (1): Physical characteristics of the soil understudy

Specification	Depth (0-30) cm	
Soil particles gm.kg^{-1}	Sand	**194.622**
	Silt	**509.453**
	Clay	**295.925**
Soil texture	**Silty clay loam**	
Bulk density (Mg.m^{-3})	**1.05**	
Solid Density (Mg.m^{-3})	**2.51**	
Porosity (%)	**0.576**	
Soil penetration (Mpa)	**0.823**	
aturated hydraulic conductivity (m.day^{-1})	**0.286**	
Mean weigh diameter (MWD)	Dry (mm)	**6.60**
	Wet (mm)	**0.206**
Cohesion (kN.m^{-2})	**4.01**	
Moisture content (%)	First site	**14**
	Second site	**24**

Tractors and equipment used in the experiment

Two CASE JX75T tractors were used to carry out the experiment. The first one was used for the purpose of demonstrating the effect of study factors on soil compaction, including three treatments of forward speeds, two levels of tire pressures and five levels of tillage depths. The second tractor was used to carry the subsoiler plow and the gearbox of it was placed in a neutral state. Both tractors are four-wheel drive. The horsepower of a tractor is 75hp (55kW), weight tractor is 2575 kg, a number of a cylinder is four, maximum torque is 242Nm, wheelbase is 2200mm, Ground clearance under rear axle is 555mm, type size tire of Front/Back is 16 - 7.5/ 30 – 16.9.

In this experiment, a mounted sub-soiler plow was used. The basis of the operation of this plow is to carry out a single plowing line. The purpose of its use is to load the tractor engine with different traction forces by using it at different plowing depths (0, 15, 30, 45, and 50) cm.

Experiments procedure

The research included an evaluation of the effect of four different factors on soil compaction parameters (soil bulk density and cone index). The studied factors are the moisture content, different plowing depths, and different tire pressures and forward speeds, as shown in table (2). The research included 90 treatments and three replications for each treatment, to be 270 experimental units and a length of 10 meters for the experimental unit. Experiments were carried out after determining the location of the experiment according to the moisture content

(14 or 24%). As well as determining the required tire pressure, choosing the front speed, and setting the plow at the required depth. The experiments were conducted using the RNAM system (RNAM, 1995). To find out the compaction of the soil, the soil density and cone index were measured directly after the tractor tire passed over the soil surface.

Table (2): Studied factor in an experiment

Moisture content %	Tire pressure kPa	Speed of tractor ms^{-1}	Plowing depth cm
14	50	0.57	0
24	100	0.94	15
	150	1.34	30
			45
			50

Mathematical models

Design-Expert software (version: 8.0.6.1) was used to evaluate, analyze, and produce mathematical models to predict soil compaction parameters (soil density and cone guide). A 270 experiments were conducted under realistic agricultural conditions. The study included four independent factors. Which includes two levels of moisture content (14 and 24%), three levels of tire pressure (50, 100, and 150 kPa), three front speeds (0.57, 0.94, and 1.34 ms^{-1}), and five plowing depths (0, 15, 30, 45, and 50 cm) to produce mathematical models with high accuracy and acceptability. The data were also analyzed using an ANOVA table to indicate the significance of the independent factors and their overlap on the compression criteria.

ANN Models

In this study, ANN models were used with a backpropagation algorithm that was developed to predict bulk density under different field conditions by using MATLAB (Demuth & Beale 1998). In general, the architectural structure of ANN consists of three layers: the input layer, the hidden layer, and the output layer. The data were divided randomly into three subgroups. The largest part of it was devoted to training the network 70%. As for the rest of the totals, 15% for validation of the model and 15% for testing the network. The network was tested using different algorithms to train the network and obtain the best performance of predicting depending on the statistical criteria (mean square error and coefficient of determination). The algorithms used are a graded origin with momentum (train-gdm), Bayesian regulation (train-br), Levenberg-Marquardt (train-lm) and Resilient (train-rp), and ratios graded with adaptive learning rate (train-gda). The number of hidden layers and the number of neurons within them were determined according to the trial and error method. As well as by comparing the network performance to choose the best execution.

The ANN architecture used in prediction models has four inputs and one output. These inputs were moisture content, plowing depth, forward speed, and tire pressure. The target of the model was bulk density as a criterion of soil compaction. Fig. (1) shows the schematic diagram of the ANN used to predict soil density. In this paper, the perceptual network was used. Triple layers consist of an input layer, one hidden mathematical pattern layer, and an output layer. In each stratum, a number of neurons that were connected to the neurons of neighboring neurons via some associations were considered. The effective input of each neuron in these networks was the result of multiplying the outputs of the previous neurons by the weights of those neurons. In order to increase the accuracy, performance, and speed of implementing ANN, the target input and output factors were normalized or scaled linearly and made their values between -1 and 1.

Various statistical parameters (Mean Square Error MSE and coefficient of determination R^2) were calculated to evaluate the performance of the developed ANN models. The MSE is used as a benchmark for comparing aspects of error in the different models. The R^2 is used to calculate standard error in estimation methods that illustrate the natural difference of the real data from the estimated data. The following are expressions of these statistical measures:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \quad (4)$$

$$R^2 = \frac{[\sum_{i=1}^{N}(\hat{x}_i-\bar{\hat{x}})(x_i-\bar{x})]^2}{\sum_{i=1}^{N}(\hat{x}_i-\bar{\hat{x}})^2 \times \sum_{i=1}^{N}(x_i-\bar{x})^2} \quad (5)$$

where:

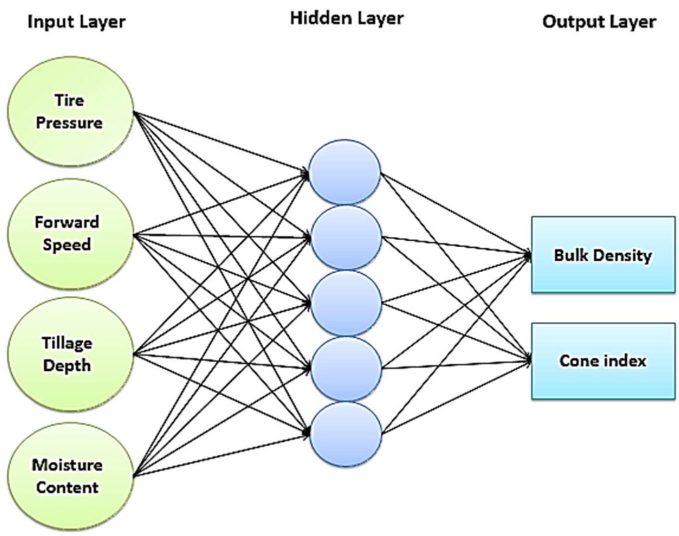
N: The number of test observation

x_i: The value of the variable being modeled (observed data)

$\hat{x}_i$: The value of variable modeled by the model (predicted)

$\bar{x}$: The mean value of the variable

Fig. (1): Three-layered artificial neural network architecture



Results & Discussion

Bulk density

Mathematical models

A total of 270 field experiments were conducted to obtain the best model for predicting bulk density under different field conditions (moisture content, tire pressure, forward speed and tillage depth. A collection of various polynomial models were analyzed using the Design-Expert software, to choose more valid and dependable models. In order to optimize and minimize the number of candidate regression factors, a stepwise regression algorithm was applied, as the most used variable selection technique (Montgomery & Runger, 2014).

ANOVA table was carried out to determine the significant effects of studied parameters on bulk density (Table 3). The results showed that all studied parameters had a significant effect on bulk density at probability value (equal to 0.0001). Moreover, the ANOVA table revealed a significant effect between interactions of these parameters on bulk density except for the interaction between forwarding speed and plowing depth where it was not significant.

Table (3) Analysis of variance for bulk density

Source	Sum of Square	df	F-Value	p-value Prob > F
Model	16.14	10	169.57	< 0.0001
A-Moisturecontent	5.76	1	605.58	< 0.0001
B-Tire pressure	0.97	1	101.49	< 0.0001
C-Tillage depth	7.64	1	802.40	< 0.0001
D-Speed	1.07	1	112.64	< 0.0001
AB	1.819E-4	1	0.019	0.0402
AC	0.079	1	8.26	0.0144
AD	6.977E-3	1	0.73	0.0327
BC	0.086	1	8.99	0.0030
BD	2.788E-4	1	0.029	0.0242
CD	2.047E-4	1	0.022	0.8835
Residual	2.46	259	000	000
Lackof fit	0.28	79	0.29	<0.0001
Pure error	2.18	180		
Cor Total	18.60	269		

Fig. (2) show that soil moisture content and drive tire pressure effected on bulk density. As the increase in moisture content from 14% to 24% led to an increase in the value of bulk density by 4%. This is due to the fact that increased moisture content increases the attraction of soil particles due to the increase in the surface tension between them and the overlap of their water membranes, thus increasing the bulk density and these results are compatible with results obtained by D'Acqui *et al.* (2020). The results also showed that the air pressure inside the tire affects the bulk density values. As the increase in tire pressure from 50 kPa to 150 kPa led to an increase of the bulk density by 2.3%, and the reason for this may be that the increase in tire pressure led to a decrease in the area of contact with the ground, which increased the compaction of the soil, thus increasing the values of bulk density and these results are in agreement with the findings of Antille *et al.* (2013). The results also showed the double interference of moisture content and tire pressure on the bulk density. The percentage of moisture content 14% and tire pressure 50 kPa gave the lowest value of bulk density, which amounted to 1.308 Mg .m^{-3}. In addition, the percentage of moisture content 24% and tire pressure 150 kPa gave the highest value of bulk density, amounting to 1.38 Mg.m^{-3}. It may be attributed to the ratio of moisture content 24% recorded the highest value of bulk density, while the large tire pressure reduced the contact area between the tire and the field soil, which increased the amount of pressure applied to the soil, and led to the compaction of the soil.

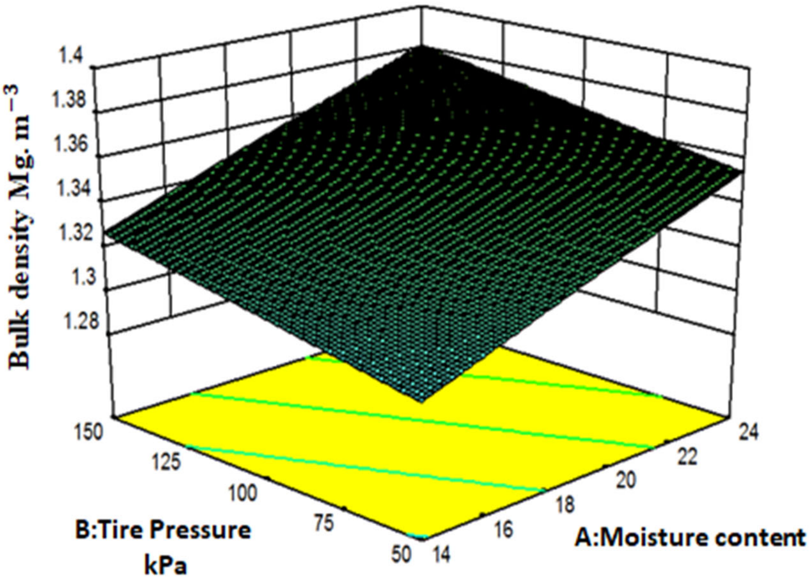


Fig. (2). The effect of soil moisture content and tire pressure on bulk density

Fig. (3) shows the dual effect of soil moisture and depth of tillage on bulk density. Bulk density increased by 5% when increasing the depth of tillage from 15 cm to 50 cm. The reason for this is that increasing the depth means more attachment of the plow to the soil, as well as more soil facing it. On the other hand, increasing the dynamic weight affecting the rear wheels to achieve adequate traction, thus increasing the pressure of the tractor tires on the field soil, which leads to compacting the soil. The results also showed the dual effect of both soil moisture and the depth of tillage, where the lowest value of bulk density was recorded at 14% moisture content, and the depth of plowing was 15 cm, and it was 1.275 Mg .m^{-3}. While the highest value of bulk density was recorded at 24% moisture content and a depth of 50 cm, reaching 1.418 Mg .m^{-3}. The reason for this is that both the soil moisture and the depth of tillage are directly proportional to the bulk density.

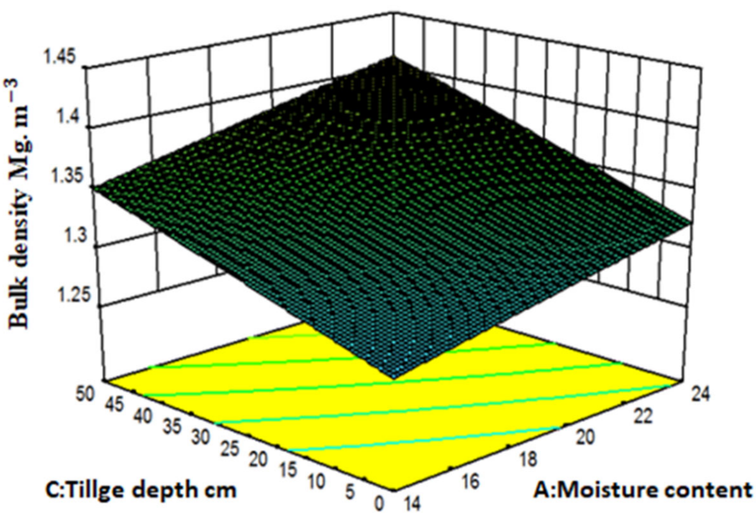


Fig. (3). The effect of soil moisture content and tillage depth on bulk density

Fig. (4) shows the combined effect of soil moisture and forward speed on bulk density. Increasing the practical forward speed of the tractor from 0.59 to 1.37 $m.s^{-1}$ led to a decrease in the bulk density value by 4%. This is due to the fact that the increase in speed means a reduction in the time of the tires staying over the field, which reduced the pressure of the tractor tires on the field soil and thus Soil bulk density decreased and these results are in agreement with the results obtained by Shahgholi & Abuali (2015).

The results showed that the lowest value of bulk density was recorded at 14% moisture content and forward speed 1.37 ms^{-1}, and it was 1.30 Mg $.m^{-3}$. Whereas, the highest value of bulk density was recorded at 24% moisture content and 50 cm depth, and it was 1.382 Mg $.m^{-3}$. The reason for this is attributed to the fact that the velocity of 1.37 ms^{-1} recorded the highest value of the bulk density while the low soil moisture maintained the strength of the soil against the force imposed on it (Taghavifar & Mardani, 2014).

Fig. (5) shows a combined interaction of both tire pressure and depth of tillage and their interactions in bulk density values. The results showed that there is a direct relationship between tire pressure and bulk density. Increasing the tire pressure from 50 to 150 kPa resulted in an increase in the bulk density values by 2.3%. It is due to the decrease in the area of contact of the tire with the field ground which increases the pressure on the unit area due to the increase in air pressure. The results also indicated that the lowest value of bulk density was recorded at a tire pressure of 50 kPa and tillage depth of 15 cm, and it was 1.31 $Mg.m^{-3}$. Whereas, the highest bulk density was recorded at a tire pressure of 150 kPa and a tillage depth of 50 cm, and it was 1.40 $Mg.m^{-3}$. The reason for this is attributed to the combined effect of these two factors, where the depth of 50 cm increased the dynamic weight of the tractor wheels, while the tire pressure 150 reduced the contact area and thus increased soil compaction and thus increased bulk density.

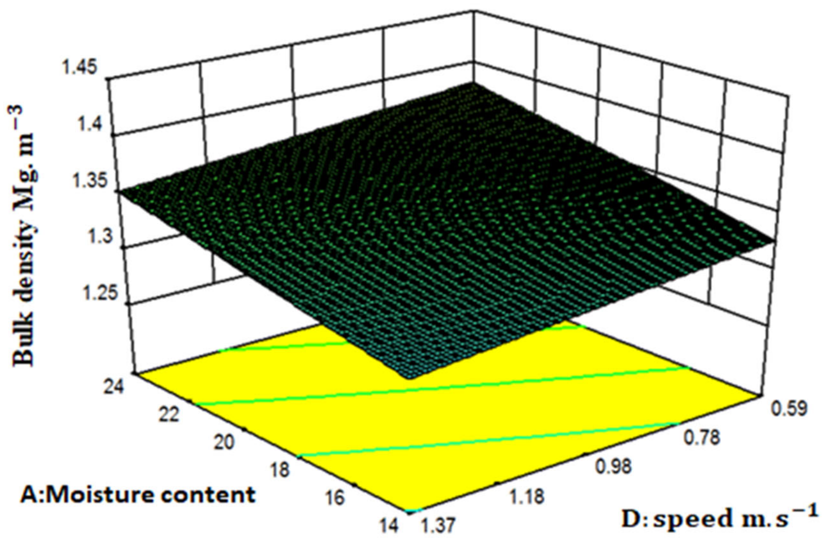


Fig. (4): The effect of soil moisture content and forward speed on bulk density

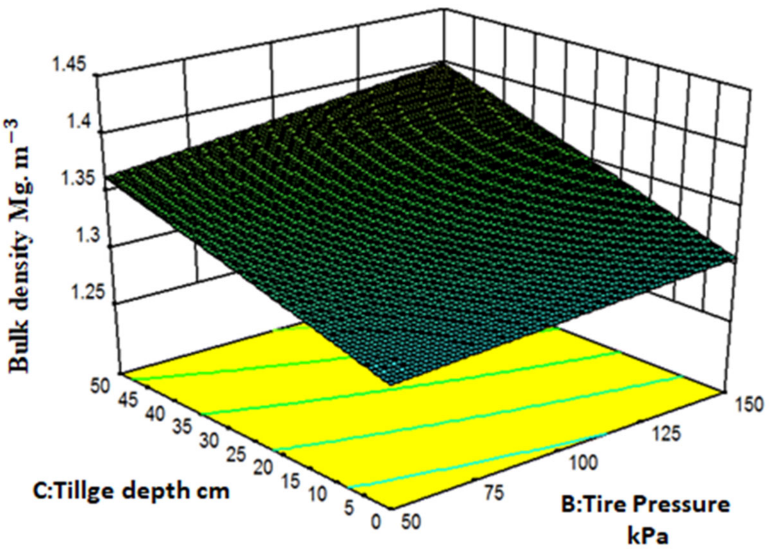


Fig. 5. The effect of tire pressure and tillage depth on bulk density

Fig. (6) illustrates the effect of tractor forward speed, tire pressure, and their interactions on bulk density values. The lowest bulk density value was recorded at the highest forward speed used in the experiment, 1.37 m.s^{-1}, and the lowest tire pressure was 50 kPa, and it was 1.325 Mg.m^{-3}. Whereas, the highest bulk density value at the highest tire pressure is used 150 kPa and the lowest forward speed of the tractor is 0.59 m.s $^{-1}$, which is 1.365 Mg .m^{-3}. The reason for this is that the high speed reduces the time of the tractor remaining on the field ground while reducing the tire pressure increases the contact area and thus reduces the bulk density values. These results are in agreement with Shahgholi & Abuali (2015).

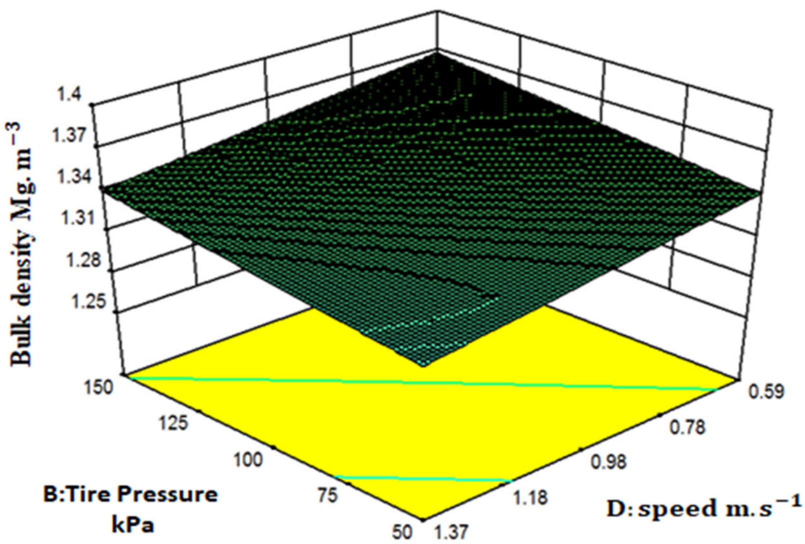


Fig. (6): The effect of tire pressure and forward speed on bulk density

Fig. (7) shows an amount of effect on bulk density when any of the four influencing factors (moisture content, tire pressure, depth of tillage, and forward speed of the tractor) changes independently. It was found that the most important factor in relation to the bulk density is the depth of plowing and its effect is 6%. The results showed that the next factor affecting the bulk density is the moisture content by 4%, then the forward speed of the tractor by 2.4%, while the tire pressure comes in the fourth-order with an impact rate of 2%. It is also noted that the relationship of soil moisture, tire pressure, and depth of tillage was positive with bulk density, while the relationship was inverse between forward speed and bulk density.

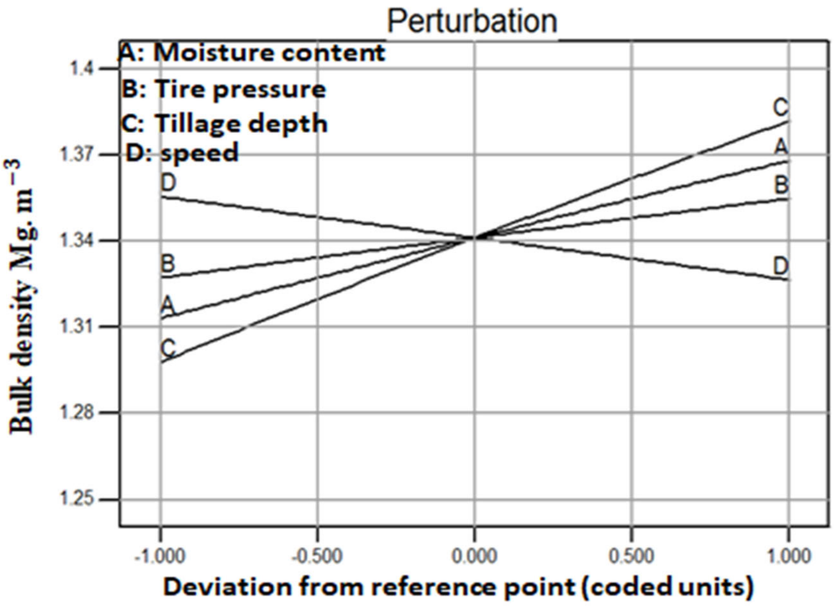


Fig. (7): The effect of studied factors on bulk density

The predicted values of bulk density were found by adopting and introducing all the factors under study, namely soil moisture content, tire pressure, depth of tillage, tractor speed, and their interactions (Fig. 8). Which gave the best results based on the value of the coefficient of determination, which is R^2 = 0.8675 under different field conditions.

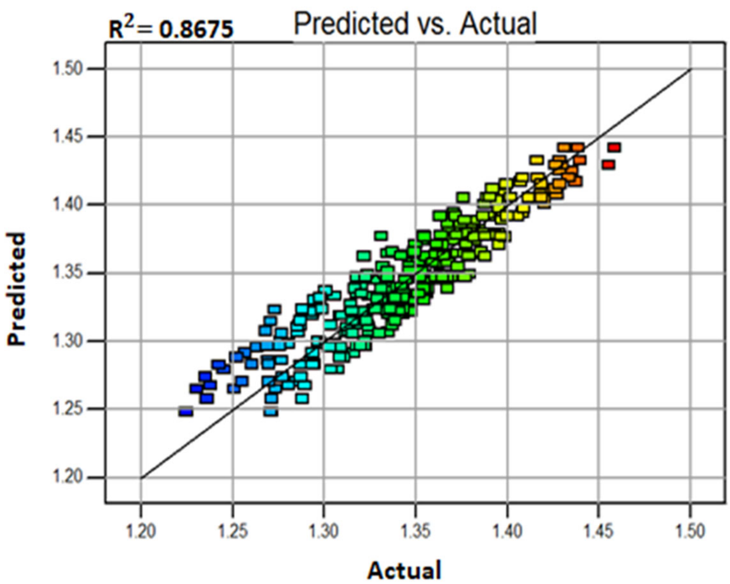


Fig. (8). Relationship between the predicted bulk density and the field-calculated bulk density

The fitted model for the bulk density is represented in Eq. 6:

$$\textit{Dry Bulk Density} = 1.77 + (0.02 * \text{moisture content}) + (7.45\text{E} - 004 * \text{tire pressure}) + (3.06\text{E} - 003 * \text{tillage depth}) - (0.15 * \text{speed}) + (4.02\text{E} - 006 * \text{moisture content} * \text{tire pressure}) + (1.830\text{E} - 004 * \text{moisture content} * \text{tillage depth}) - (3.19\text{E} - 003 * \text{moisture content} * \text{speed}) + (2.34\text{E} - 005 * \text{tire pressure} * \text{tillage depth}) + (7.81\text{E} - 005 * \text{tire pressure} * \text{speed}) + (1.46\text{E} - 004 * \text{tillage depth} * \text{speed}) \quad (6)$$

ANN Model

Table (4) shows the best topology and statistical parameters for ANN models using different bulk density training algorithms. As a whole, all training algorithms showed satisfactory results. Levenberg-Marquardt (Trainlm) produced an outstanding performance with an MSE of 0.00226 and R^2 of 0.986. Moreover, this performance was occurring at an epoch of 100. Hence, the best model for predicting the bulk density under different field conditions is the 4-8-1 architecture. The weakest among training algorithms was Graded origin with momentum (train-gdm) with topology 4-1-1, epoch of 99, R^2 of 0.953 and MSE of 0.01195.

Table (4): Different ANN structures for bulk density prediction

Training Algorithm	Optimum topology	Epochs	MSE	R^2
Levenberg-Marquardt (Train-lm)	4-8-1	31	0.002263	0.986
Bayesian regulation (train-br)	4-6-1	46	0.004757	0.973
Ratios graded with adaptive learning rate (train-gda)	4-7-1	99	0.007288	0.966
Resilient (train-rp)	4-9-1	96	0.009293	0.960
Graded origin with momentum (train-gdm)	4-1-1	99	0.011956	0.953

Fig. (9) shows the regression between actual and expected values of bulk density under different field conditions for training, validation, testing and all data sets. Where R values were equal to 0.9930, 0.9959, 0.9933 and 0.9935 for training, validation, testing, and all data, respectively. The inconsiderable difference between the expected and actual values confirmed the reliability of the network in predicting the bulk density.

Fig. (10) shows the result of the regression to train the neural network for MSE for all epochs and notes the speed of the network's performance in reaching the best results. The value of the epochs was equal to 31. After this value is noted the stability of the mean square error curve, and this is an indication of the network reaching to appropriate and sufficient training.

Table (5): Analysis of variance for cone index

Source	Sum of Square	df	F-Value	p-value Prob > F
Model	2.419E+005	10	341.12	< 0.0001
A-Moisture content	29359.19	1	414.01	< 0.0001
B-Tire pressure	10586.85	1	149.29	< 0.0001
C-Tillage depth	1.816E+005	1	2561.03	< 0.0001
D-Speed	5536.19	1	78.07	< 0.0001
AB	34.52	1	0.49	0.4860
AC	4903.23	1	69.14	0.0001
AD	119.90	1	1.69	0.1946
BC	2056.39	1	29.00	0.0001
BD	151.74	1	2.14	0.1447
CD	126.52	1	1.78	0.1828
Residual	18366.78	259	000	000
Lack of fit	10069.91	79	2.77	<0.0001
Pure error	8296.87	180		
Cor Total	**2.603E+005**	**269**		

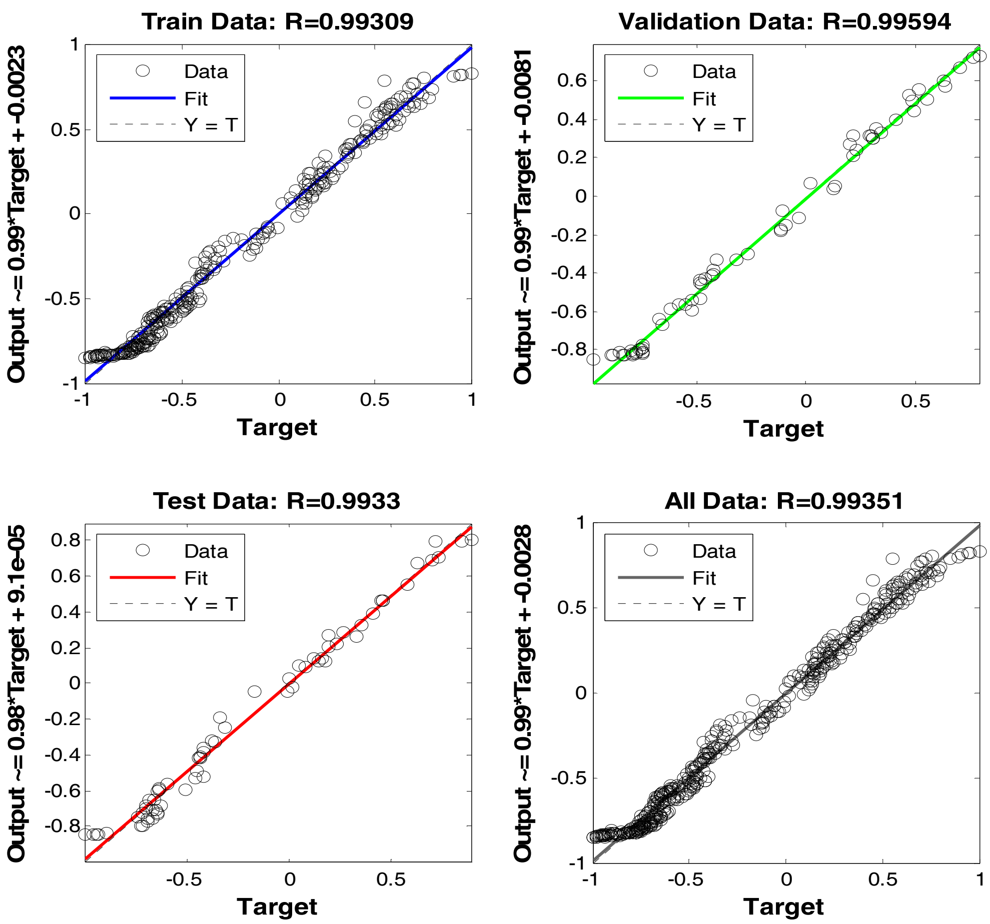


Fig. (9). Regression analysis for bulk density prediction based 4-8-1 topology and Levenberg-Marquardt training algorithm

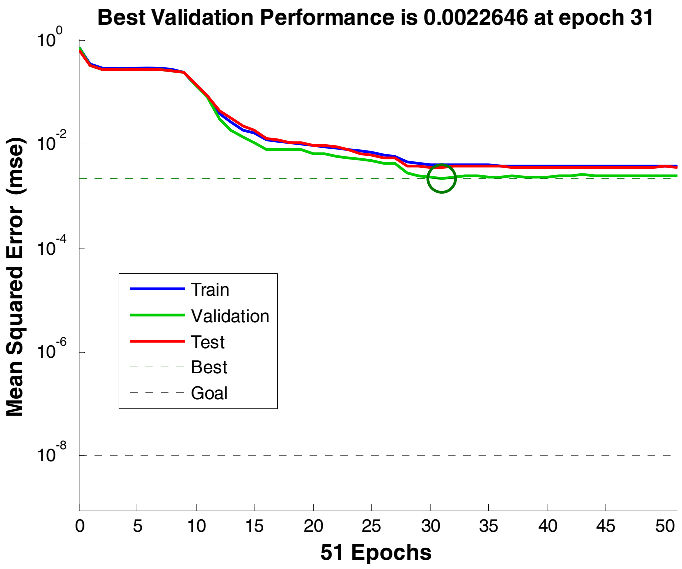


Fig. (10): Regression result of neural network training for MSE of all epochs for bulk density

Cone index

Mathematical models

As shown in table (5), moisture content, tillage depth, tire pressure and forward speed had a significant effect on cone index ($p<0.0001$). The interactions between soil moisture content- tillage depth and tire pressure - tillage depth were significant. As for the rest of the interactions, they did not have a significant effect on the cone index. But the lack of fit was significant ($p<0.05$), which means that the model cannot be applicable to the data. Fig. (11) shows the relationship between soil moisture content and tire pressure on the cone index. The results showed that there was a significant effect of tire pressure and soil moisture, while their interactions had no significant effect on the values of soil penetration resistance (cone index). Increasing the tire pressure from 50 kPa to 150 kPa led to an increased in the cone index value by 8%. The reason for this may be that the increase in tire pressure led to a decrease in the area of contact with the ground, which increased the soil pressure, thus increasing the values of soil penetration resistance. These results are consistent with the findings of Pagliai *et al.* (2003) and Zhukov (2015). The results also showed that soil moisture affected soil penetration resistance values, as increasing the moisture content from 14% to 24% led to a decrease in the soil penetration resistance value by 13.5%. The reason for this is that the increased moisture content has weakened the soil. In addition, the water membranes around the soil particles acted as a lubricant, which greatly contributed to reducing the friction between the cone head with soil. Thus facilitating the penetration of the cone into the soil. These results correspond with those obtained by Tang *et al.* (2016). The results also indicated the effect of the bilateral interaction between tire pressure and soil moisture content, which was not significant. The pressure of 50 kPa and the moisture content of 24% gave the lowest value of soil penetration resistance of 3.2 MPa. Whereas, the moisture content of 14%

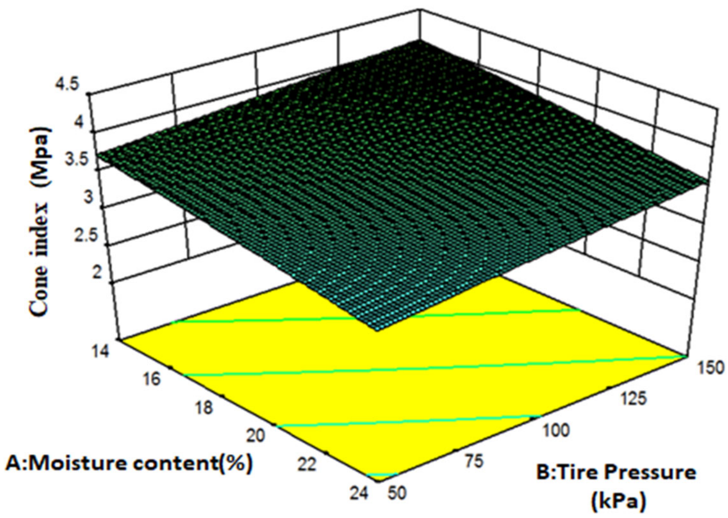


Fig. (11): The effect of moisture content and tire pressure on cone index

and the pressure of 150 kPa gave the highest value of soil penetration resistance, reaching 4.15 MPa. The results showed a highly significant effect of the depth of tillage and soil moisture and their interactions on the values of soil penetration resistance (Fig. 12). Increasing the tillage depth from 15 cm to 50 cm led to an increase in the penetration resistance of the soil by 27%. This is due to the fact that increasing the depth means increased tire slippage, which increases soil compactness. In addition, the increased required force for traction led to increasing the vertical force of the tires per area unit, so the compaction increases on the field soil and thus increases the values of soil resistance to penetration. The results also showed the dual effect between the depth of tillage and the soil moisture content on the values of soil penetration resistance. The highest value of soil penetration resistance was recorded at 14% moisture content and 50 cm tillage depth of 4.7 MPa. The lowest value of soil penetration resistance was recorded at 24% moisture content and 15 cm depth and was 3.2 MPa. The reason for this is attributed to the positive effect of increasing the depth and the negative effect of increasing the moisture content in increasing the cone index.

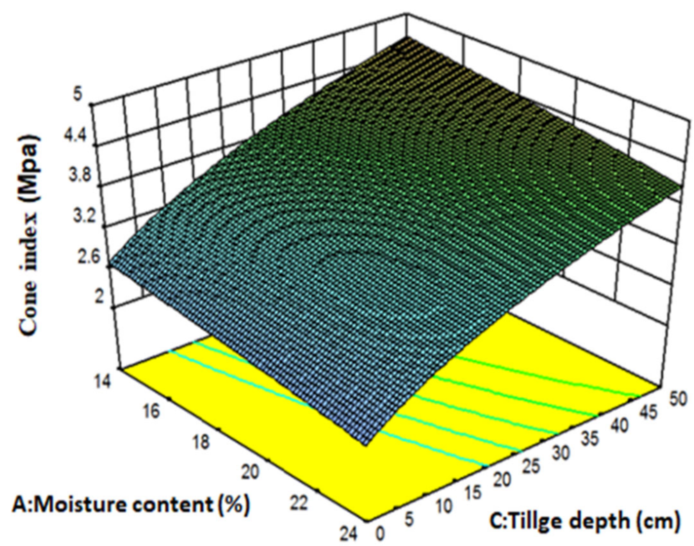


Fig. (12): The effect of moisture content and tillage depth on cone index

The results showed a highly significant effect of soil moisture and the forward speed of the tractor, while their interactions did not affect the value of soil penetration resistance (Fig. 13). Increasing the forward speed of the tractor from 0.59 to 1.37 m.s^{-1} reduced the value of soil penetration resistance by 11%. The reason for this is that increasing the speed means a reduction in the time of staying tires over the field ground, which reduced the chance of the tractor tires being compressed on the field soil and thus decreased the values of soil penetration resistance. These results are consistent with the results obtained by Taghavifar & Mardani (2014).

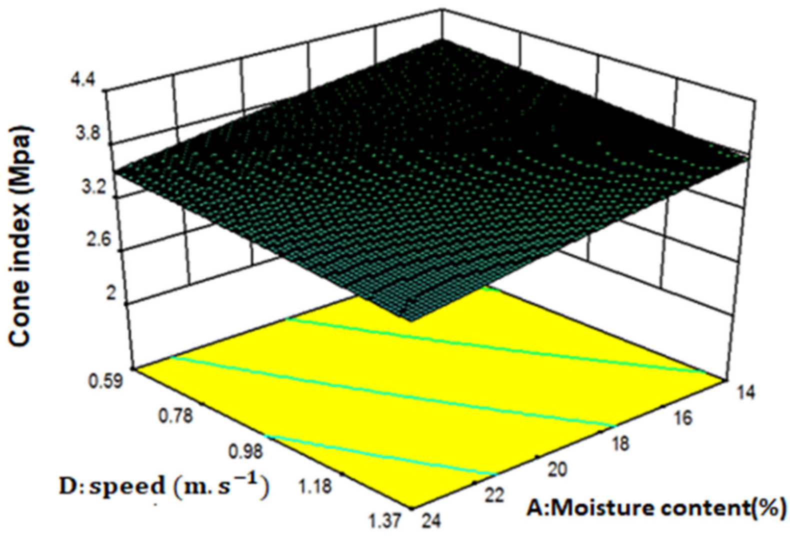


Fig. (13): The effect of moisture content and forward speed on cone index

Fig. (14) shows the relationship between tire pressure and depth of tillage and their overlaps on the cone index. The results showed that there was a significant effect of tire pressure, tillage depth, and their interactions on the cone index values. The highest value of soil penetration resistance was recorded at a tire pressure of 150 kPa and depth of 50 cm, with a value of 4.2 kPa. The lowest value of soil penetration resistance was recorded at a pressure of 50 kPa and a depth of 15 cm, and it was 2.4 kPa. The reason for this is that the depth of 50 cm recorded the highest traction force. The draft force increases the dynamic weight of the tires on the soil surface and thus increases the compaction of the soil under the tires. On the other hand, the increase in tire pressure led to a decrease in the contact area between the tire and the soil, consequently increased soil compacting. These results are in agreement with Błaszkiewicz (2019).

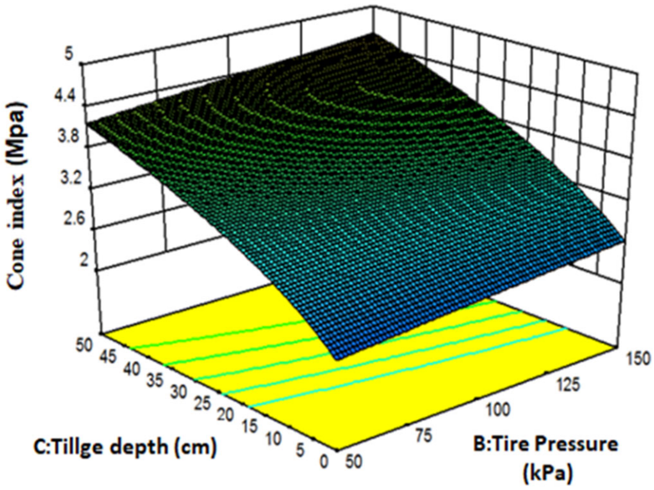


Fig. (14): The effect of tire pressure and tillage depth on cone index

Fig. (15) shows the magnitude of the effect on soil penetration resistance (cone index) when any of the influencing factors (moisture content, air pressure, depth of tillage, and forward speed of the tractor) change independently. It was found that the most important factor for soil resistance to penetration is the depth of tillage and its impact ratio is 6%, followed by moisture content, tire pressure, and forward speed by 4%, 2.4%, and 2%, respectively. These results are in agreement with the findings of Naranjo *et al.* (2014) who showed that increasing the depth affects the accumulation of soil in front of the wheels, which leads to an increase in penetration resistance. The results also showed that the effect of both tire pressure and tillage depth was directly affected by the cone index. On the other hand, the effect of both soil moisture and forward speed was inversely affected by the cone index.

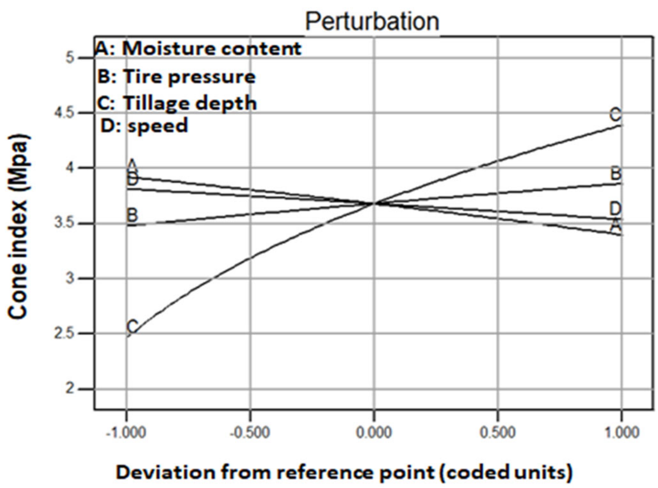


Fig. (15): The effect of studied factors on cone index

The relationship between the predicted values of soil penetration resistance was found by adopting and introducing all the factors under study, namely soil moisture content, tire pressure, depth of tillage, tractor speed and their interactions (Fig. 16). The close dispersion of the data around the unit slope line confirms the excellent performance of the developed model with a coefficient of determination (R^2) = 0.9294 under different field conditions.

The appropriate model for the cone index is represented in Eq.7, in which the coefficients are in the coded unit form.

$$\textbf{\textit{Cone index}} = 48.30 + (-1.20 * \text{moisture content}) + (0.04 * \text{tire pressure}) + (2.01 * \text{tillage depth}) - (25.22 * \text{speed}) - (1.75E-003 * \text{moisture content} * \text{tire pressure}) - (0.04 * \text{moisture content} * \text{tillage depth}) + (0.41 * \text{moisture content} * \text{speed}) + (3.63E-003 * \text{tire pressure} * \text{tillage depth}) + (0.05 * \text{tire pressure} * \text{speed}) - (0.11 * \text{tillage depth} * \text{speed}) \qquad (7)$$

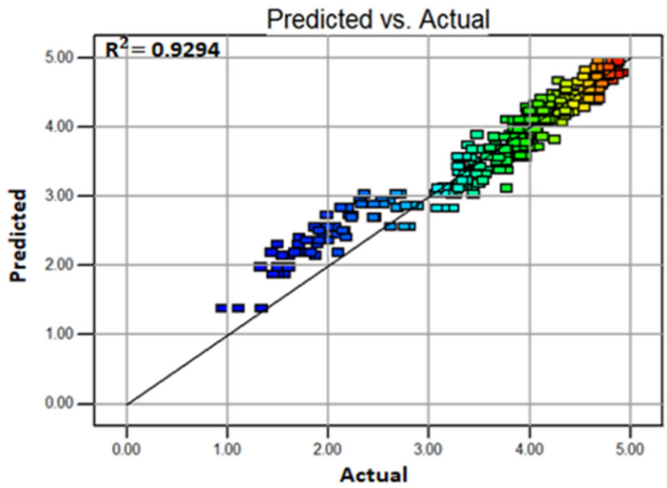


Fig. (16): Relationship between the predicted and the actual of cone index

ANN models

Table (6) shows the optimal structure and statistical criteria of ANN models using different training algorithms. The best performance was achieved by Levenberg-Marquardt (trainlm) in 85 epochs, giving minimum MSE equal to 0.005112 and greater (R^2) equal to 0.967 during the training process. Thus, the optimal structure for predicting the cone index was 4-7-1. The results also illustrated the rest of training algorithms used in prognostication of cone index was acceptable and reliable except Resilient (trainrp) which gave the highest MSE and lowest R^2 compared with other algorithms by 0.079532 and 0.82, respectively. On the other hand, Graded origin with momentum (train-gdm) did not answer predicting cone index.

Fig. (17) Illustrates the performance of the training network. It is evident from this figure that the MSE of training decreased with increasing the training period up to 92. After this value, the MSE of training was stabilized. Fig. 18 shows the correlation between actual and expected values of the cone index under different working conditions for training, validation, testing, and all data sets. The small difference between the predicted and measured values emphasized the reliability of the network in predicting the cone index. These results are consistent with the findings of Santos *et al.* (2012) who confirmed the ability of neural networks to predict soil penetration resistance.

Table (6): Different ANN structures for cone index prediction

Training Algorithm	Optimum topology	Epochs	MSE	R^2
Levenberg-Marquardt (Trainlm)	**4-7-1**	**92**	**0.005112**	**0.967**
Bayesian regulation (trainbr)	4-9-1	87	0.006591	0.943
Ratios graded with adaptive learning rate (train-gda)	4-8-1	99	0.043211	0.906
Resilient (train-rp)	4-5-1	96	0.079532	0.820
Graded origin with momentum (train-gdm)	Not answer	-	-	-

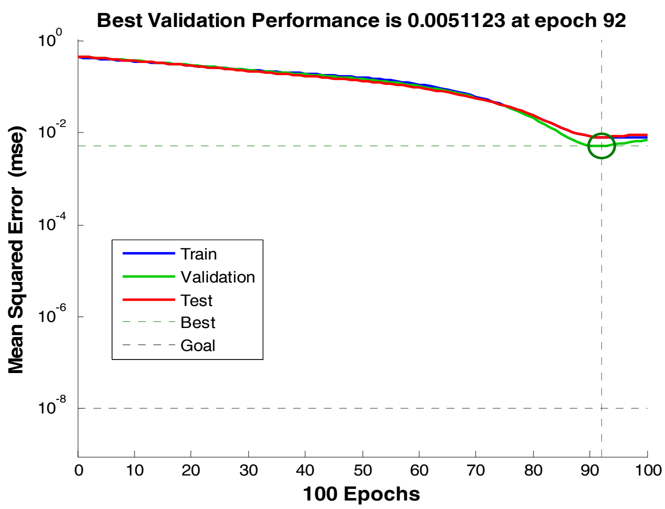


Fig. (17): The best validation performance of training LM to predict cone index

Table (7): Comparison of statistical performance between mathematical models and ANN for soil compaction criteria

Soil compaction criteria	Mathematical model		ANN model	
	MSE	R^2	MSE	R^2
Bulk density	0.002435	0.8675	0.002263	0.986
Cone index	0.907634	0.9294	0.005112	0.967

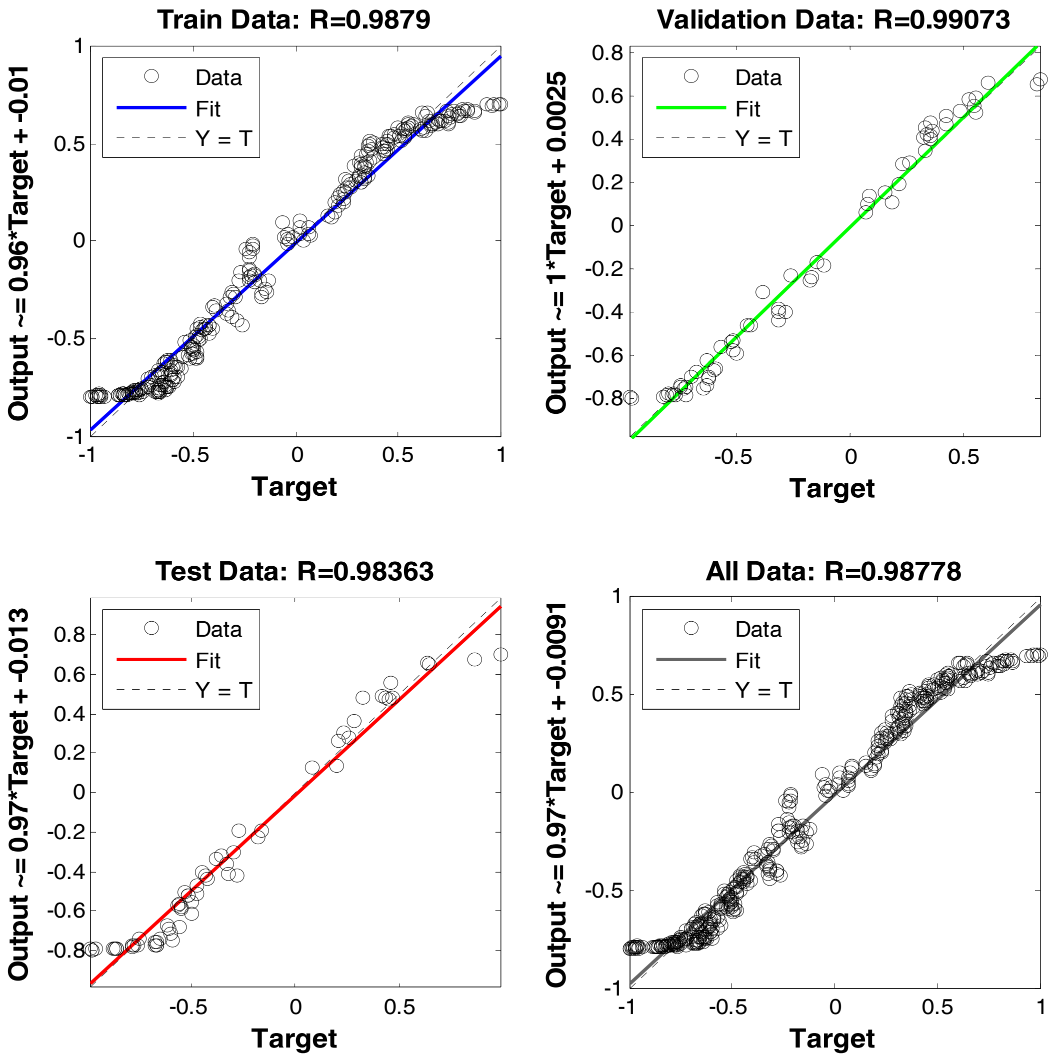


Fig. (18): Correlation between actual and predicted values of cone index in training, test, validation and all data sets

Table (7) illustrates the best results obtained from mathematical models and ANN models for studied parameters in this research with statistical criteria (MSE and R^2). The results show that all models had an acceptable performance for predicting soil compaction parameters (bulk density and cone index) under various field conditions. But the premium model yielded by ANN technique with MSE of 0.002263 and R^2 of 0.986 for bulk density. Artificial intelligent models (ANN) outperformed mathematical models for predicting cone index. ANN model produced the premium performance with MSE of 0.005112 and R^2 of 0.967. This is consistent with what was found by Almaliki *et al.* (2019) during their study to predict the tractive efficiency.

Conclusion

In this research, intelligent computational (artificial neural networks and Design Expert software) were used to predict soil compaction criteria (soil bulk density and cone index). Various training algorithms were tested by using Backpropagation neural networks. MSE and R^2 were approved as statistical criteria for evaluating soil compaction. It was found that the smart computing methods used achieved satisfactory results for predicting soil compaction parameters. Levenberg-Marquardt (trainlm) gave the best performance in training the neural network for predicting soil density and cone index compared to the rest of the used algorithms. Bulk density increased with increasing plowing depth, tire pressure, and soil moisture, while it decreased with increasing the forward speed of the tractor. On the other hand, increasing the front speed of the tractor and soil moisture reduced the cone index, while it tends to rise with increasing tillage depth and tire pressure. When comparing the performance of neural networks and mathematical models, it is noted that neural networks are superior to predicting soil compaction parameters. In general, it is possible to use ANN models to predict soil performance due to their excellent speed and accuracy of results.

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تقنيات الحوسبة الذكية للتنبؤ بمعايير ضغط التربة في ظل ظروف ميدانية واقعية

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المستخلص: الهدف الأساسي من هذا البحث هو تطوير بيئة محاكاة للشبكة العصبية الاصطناعية ANN ونماذج رياضية عالية الدقة للتنبؤ بمعايير ضغط التربة (الكثافة الظاهرية ومؤشر المخروط (مقاومة الاختراق)) في ظروف حقلية مختلفة. أجريت التجارب في أحد حقول كلية الزراعة – جامعة البصرة ، موقع كرمة علي ، في تربة طينية طينية. تم استخدام جرار CASE JX75T لدراسة تأثيره على انضغاط التربة في ظل ظروف حقلية مختلفة. اشتملت عوامل الدراسة على مستويات مختلفة من محتوى الرطوبة (14 و 24٪) ، وأعماق حراثة مختلفة (0 ، 15 ، 30 ، 45 ، 50 سم) وبسرعات مختلفة (0.57 ، 0.94 ، 1.34 م / ثا) وضغوط إطارات مختلفة (50 و 100 و 150 كيلو باسكال). تم تطوير بيئة ANN باستخدام خوارزمية الانتشار الخلفي باستخدام برنامج MATLAB بهياكل وخوارزميات تدريب مختلفة. استخدم برنامج Design Expert لتقييم العوامل المدروسة وإنتاج نماذج رياضية. أظهرت النتائج أن جميع المتغيرات المدروسة لها تأثير معنوي على معايير انضغاط التربة (الكثافة الظاهرية ودليل المخروط). كما أشارت النتائج إلى أن العامل الأكثر تأثيراً على الكثافة الظاهرية هو عمق الحراثة ، يليه محتوى الرطوبة ، والسرعة الأمامية ، وضغط الإطارات بنسبة 6٪ 4٪ ، 2.4٪ ، 2٪ على التوالي. وجد أن أهم العوامل المؤثرة في مؤشر المخروط هو عمق الحرث ونسبة تأثيره 6٪ يليه محتوى الرطوبة وضغط الإطارات والسرعة الأمامية 4٪ و 2.4٪ و 2٪ على التوالي. أفضل نموذج للتنبؤ بالكثافة الظاهرية في ظل الظروف الميدانية المختلفة هو التركيب 4-8-1. أنتجت Levenberg–Marquardt (Trainlm) أداءً متميزًا مع MSE قدره 0.00226 و R^2 يساوي 0.986. علاوة على ذلك ، كان هذا الأداء يحدث في الدورة 100 من تدريب الشبكة العصبية. للتنبؤ بمؤشر المخروط، تم تحقيق أفضل أداء بواسطة Levenberg–Marquardt (Trainlm) في 85 دورة من التدريب، مع إعطاء الحد الأدنى من MSE يساوي 0.005112 وأكبر (R^2) يساوي 0.967 أثناء عملية التدريب. وبالتالي ، كان التركيب الأمثل للتنبؤ بمؤشر المخروط هو 4-7-1.

الكلمات المفتاحية: الشبكات العصبية الاصطناعية، Design Expert، كثافة التربة، مقاومة الاختراق.