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Research Article

Modular Feed Forward Networks to Predict Soil Penetration Resistance from Tillage Technique and Working Depth

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Abstract

Conservation tillage systems merit further studies before their diffusion in organic agriculture as they can cause problems with crop nutrition and degradation of soil structure during the early years of their application. The objective of this study was to evaluate in short-term the impact of different tillage systems in organic farming (traditional tillage to superficial tillage without reversal) on soil resistance to penetration. Therefore, studies was based on an agricultural plan implemented on a sandy loam soil in the organic farming systems domain of the Higher Institute of Agronomy of Chott Meriem (Sousse, Tunisia) to compare the effects of three tillage techniques: conventional tillage (LT), "agronomic" tillage (LA) and superficial tillage (TS). Samples were performed at different depths corresponding to the limits of the studied equipments (10, 20 and 30 cm of depth). Experimental data was then used to develop the ANN model, where several configurations were evaluated. Soil resistance with time was found to be significantly influenced by tillage system and working depth. Under ST the resistance increases from 0 to 30 cm and then decreases beyond 30 cm of depth, suggesting that with ST the soil is more compact. However, pressures in their entirety are relatively low. The optimal ANN model was found to be a network with two hidden layers and four neurones in both the upper and lower levels of each hidden layers. This optimal model was able to predict soil resistance from different tillage techniques with a mean square error of 0.000 and a 0.489% error. The results showed very good agreement between the predicted and the desired values of soil resistance (R^2 = 0.98). The coefficient of determination was also very good (R^2>0.95), due to a small prediction error.

Keywords: *Tillage techniques, soil resistance, Modelling, ANN*

1. Introduction

Structure of the tilled layer of cultivated soil changes with times because of tillage itself, compaction under traffic and as a result of natural processes (root growth, faunal activity and weather). Tillage practices involving annual plowing without other soil management practices are increasingly being recognized to have deleterious effects on soil conditions (Briggs et al., 1998). Conservation tillage could benefit agricultural production by controlling topsoil loss from wind erosion and conserving soil moisture as a reserve against common summer droughts. Mechanized cultivation produces stresses within the soil, which cause fragmentation, compaction and displacement of soil. The combined effects of these processes alter the special arrangement, size and shape of clods and aggregates, and consequently, volume of pore spaces inside and between these units (Dexter, 1988). Ceasing to plough can reduce costs and environmental damage like erosion (Soane and Van Ouwerkerk, 1994) but plowing is still widely practiced in many countries. The main reason is that mouldboard plowing creates a desirable tilth, controls weeds, and buries fertilizers and residues of the preceding crops.The changes depend, for a given texture, on the soil conditions (structure and water content) when the mechanical stress is applied, and on the characteristics of the equipments (Koolen, 1994).

Penetration resistance is a physical attribute of soil that can be used to monitor and evaluate soil quality (Islam and Weil, 2000). Penetration resistance influences the growth of roots, and it can be used as a parameter for evaluating the effects of tillage systems on the roots' environment (Abrougui et al. 2012), the detection of compacted layers, the prediction of the traction force needed to perform mechanized processes and the prevention of the appearance of a physical barrier that can be reduce the development of the plants (Campanharo et al., 2009; Cunha et al., 2002). The determination of the soil penetration resistance is performed by a device called penetrometer, which allows the soil resistance to be measured quickly (Tavares and Ribon, 2008). According to Dexter et al. (2007), the resistance to penetration is

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governed by fundamental properties of the soil, such as shear strength, compressibility and the friction force from the soil-metal interaction during the trial using the penetrometer. Hence, soil penetration resistance can be estimated as a quantity called cone index. This quantity can be expressed as the ratio of force per unit area of the base of the cone at a determined depth (Campanharo et al., 2009; Cunha et al., 2002). Studies have been carried out to evaluate the influence of water content on the behavior of soil penetration resistance (Cunha et al., 2002). Mathematical models have also been developed to predict the penetration resistance from basic soil properties, such as soil composition, bulk density and water content (Cunha et al., 2002; Dexter et al., 2007; Singh and Kay, 1997). Estrade et al., (2000), described a new approach to modeling soil structure that takes into account the special variation in structure of the tilled layer at a field scale. It is based on the simulation of the changes over time in the percentage of compacted soil within the tilled layer in mechanized cropping, where the main factors responsible for change are tillage and traffic. Estrade et al., (2004), studied the morphological characterization of soil structure in tilled fields from a diagnosis method to the modeling of structural changes over time. The need to reduce the environmental impact of agricultural activities and to control soil structure degradation is one of the main aims of land management (Pagliai et al., 2004). They evaluated the effects of different types of management practices, namely tillage and manure application, on soil structural characteristics. In this context, the use of Artificial Neural Networks (ANN) can be considered an alternative approach for predicting soil penetration resistance from soil bulk density, water content, tillage technique and working depth. ANN have been employed to solve many problems in agriculture (Erzin et al., 2010; Kim and Gilley, 2008). Varella et al. (2002) used ANN for the determination of land cover from digital images. Khazaei and Daneshmandi (2007) used ANN to model the drying kinetics of sesame seeds. They concluded that the ANN technique presented better results than traditional mathematical modeling. Sarmadian et al. (2009) used ANN to model soil properties, and the results were better than the multivariate regression analysis, showing the effectiveness of the ANN technique. Recently, Trigui et al. (2011) used ANN model to predict sugar diffusivity as a function of date variety, temperature and diffusion period. The objective of the present research is to determine the effect of soil bulk density, water content and the tillage technique on soil penetration resistance measured from the cone index and use the data to develop an ANN model to predict soil penetration resistance as a function of bulk density, water content and tillage depth.

2. Material and Methods

Experiments were conducted at the Higher Institute of Agronomy on the east coast of Tunisia on a sandy loam soil, using a standard two-wheel-drive tractor equipped with single rear tires and having a total weight of 2.910 kg (1,715 kg on the rear axle) and a power of 59 Kw.To study the influence of tillage systems on soil physical properties, soil resistance to penetration, bulk density and water content were measured over time.

2.1 Experimental conditions

The experimental layout includes a studied factor: soil tillage under three different systems and three measured variables: soil resistance to penetration, dry bulk density and soil water content. A resumption of tillage for the three treatments is achieved by two passages of disc harrow (offset). The statistical design was a randomized complete block. The main experimental plot area, 40 by 30 m, was split into three blocks; each area was then split into three sub-plots for the three tested systems.

Treatment 1 (TS): reduced or minimum tillage using a disc harrow (Offset) at a maximum depth of 10 cm + 2 tillage resumptions spaced of 10 days, using a disc harrow; Treatment 2 (LA): medium tillage with disc plowing at a maximum depth of 20 cm + 2 tillage resumptions spaced of 10 days, using a disc harrow and Treatment 3 (LT): conventional deep tillage with mouldboard plowing at a maximum depth of 30 cm + 2 tillage resumptions spaced of 10 days, using a disc harrow.

Samples were collected from within each tilled plot not under the wheels passages at different dates spaced of 60 days, to measure suggested physical indicators of soil quality. Analysis of variance was performed at the 5% level of significance using the SPSS 17 software based on the variance-covariance structure. Multiple comparisons between significant parameters were carried out using the Tukey adjustment method.

2.2 Data generation

The evaluation of soil compaction is based on the determination of soil resistance to penetration (Vitlox and Loyer, 2002). It is a nondestructive method considering the importance of the experimental site. Furthermore, this method is more sensitive than the bulk density to characterize the differences in soil compaction (Allen and Musick, 1997). The used penetrometer is of electronic type, also called penetrologger. Coupled to a recorder, this device allows the storage and immediate processing of data. It consists of a force sensor, a recorder, a drill pipe, a cone, and an ultrasonic depth gauge. The apparatus is run by two ergonomic handles for easy access to various commands. The application of equal pressure on both handles pushes the cone vertically into the soil. A mechanism of integrated measuring allows recording the penetration resistance encountered during the phase of insertion of the cone (Abrougui et al., 2012). The measurements of soil resistance to penetration were done each 10 cm to a depth of 50 cm. Soil water content was measured jointly and was determined by drying the soil samples at 105°C (Keller et al., 2007). Soil density (g/cm^3) was measured by a soil cylindrical core (diameter = 5 cm, height = 5 cm) taken with a cylinder densimeter, the sample was collected every 10 cm, to a depth of 30 cm. We then obtained the dry mass of the sample after drying in an oven at 105° C for 24 hours (Yoro and Godo, 1990). The initial state of the parcel before tillage was characterized by homogeneous state with an average soil resistance to penetration of 3.63 MPa, an average bulk density of 2.3g/cm^3 and a water content of 7.67% on the horizon 0-30 cm.

2.3 Neural network selection

To predict soil resistance to penetration, simpler methods have therefore been investigated such as the artificial neural network (ANN) models which are now known as powerful data-modeling tools (Ochoa and Ayala, 2006). The major benefits of such a technique include: modelling without any assumptions about the nature of the phenomological mechanisms underlying the process; the ability to learn linear and nonlinear relationships between variables and directly from a set of examples; the capacity of modeling multiple outputs simultaneously and; a reasonable application of the model to unlearned data (Ochoa and Ayala, 2006). The development of an ANN model involves: the generation of data required for the training/testing of the model, the actual training/testing of the ANN model, the evaluation of the ANN configuration leading to the selection of the optimal configurations and the validation of the optimal ANN model with a data set other than that used for training. According to Trigui et al. 2011, Artificial Neural Networks (ANN) are massively parallel networks, are self-adaptive and are interconnected by basic structures called neurons. Neurons are processing units with limited learning capacity; however, their interactions allow the ANN to learn from a determined set of input data and their output patterns. Among the many neural network models proposed, the *NeuroSolutions* commercial software was used to develop the ANN model and more specifically, the Modular Feed Forward networks (MFF) was selected because of its special classes of Multilayer Perceptrons (MLP) where layers are segmented into modules (NeuroSolutions Software, 2012). These networks process their inputs using several parallel MLP and then recombine the results. This operation creates a structure within the topology which fosters specialization of functions in each sub-module. Modular Feed Forward (MFF) networks do not have full interconnectivity between the layers. Therefore, a smaller number of weights are required for the same size network or the same number of Processing Elements (PEs). This tends to speed the training and reduce the number of examples needed to train the network for the same degree of accuracy (NeuroSolutions, 2012).

Table 1 Main configuration parameters and their levels of neural networks used to predict Rp, the soil resistance to penetration

Factors	Levels
Learning rule	Momentum
Transfer	TanH Sigmoid
Number of hidden layer	1 and 2
Number of neurons in upper level	2 to 10
Number of neurons in lower level	2 to 10
Neural topology (Fig.2)	I
Iterations	1000 to 10.000

To select the number of hidden layers and the number of processing elements (neurons) in the hidden layers, a trial and error procedure is conducted to reach the required behaviour. In the present study, the ranges of settings for the main configuration parameters are shown in Table 1.

The optimal configuration was found using 1 and 2 hidden layers, with a range of 2 to 10 neurons in each hidden layers, and 1000-10000 learning runs. In this study, the performance of the ANN model was tested using one neural network topology described in Figure 1. In this work, a model was developed based on the ANN technique to predict the soil penetration resistance using the soil bulk density, water content, tillage system and date as the input data.

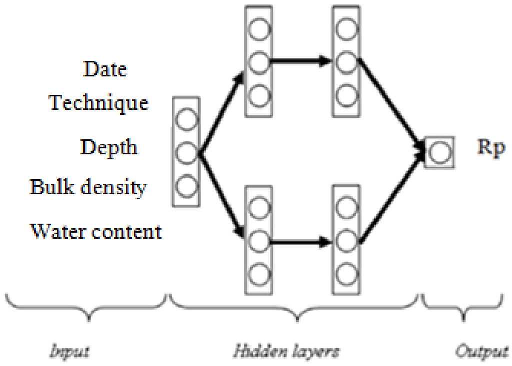

Figure 1 Neural network topology tested

2.4 Training and selection of optimal configuration

Once the ANN architecture was defined, the training was initiated and repeated several times to get the best performance (Ochoa and Ayala, 2006). The rule is to use at least 50% of the experiments at the training stage. The rest is distributed for validation and testing stage. The training, cross validating and testing of the model used 201, 120 and 80 experimental data points, respectively, representing 50, 30 and 20% of the complete data set. Validation is highly recommended to stop network training as it monitors the error using an independent data set and stops the training when this error starts to increase. This is considered as the best point of generalization. The model weights are frozen once the network is trained and the testing set is fed into the network to compare its output with the desired output (NeuroSolutions, 2012). The error minimization process is achieved by using the rule of momentum "momentum rule". In fact, the input vector was composed of soil bulk density, water content values and tillage system and the output consisted of the soil penetration resistance. To improve the ANN generalization capability, the output data were normalized, which allowed output values ranging from 0 to 5, according to Equation 1. In the first step of the training stage, the ANN architectures with the best performance were determined during the training process. Thus, only architectures that reached a root mean square error (RMSE) of 0.001 were selected. However, to avoid over training, ANN models with minimal dimensions were selected. In the second step of the training stage, a study was developed to determine ANN parameters such as learning rate and momentum. The networks were trained so that these parameters could be determined properly. In this step, the RMSE and the number of training epochs were considered for the selection of the ANN architectures. Once a given ANN was trained using the training data set, its performance must be evaluated using a validation set of data. The validation stage is essential to avoid ANN over-training. Thus, the performance of the ANNs selected were tested and compared using the determination coefficient (R^2) and the RMSE. The final ANN selection considered the lowest errors presented in the training and validation stages.

$$PRN(y) = 5 - \frac{PR(y)}{PRmax} \quad (1)$$

where:
$PR_N(y)$ = normalized penetration resistance;
$PR(y)$ = penetration resistance to be normalized;
PR_{max} = maximum value of the soil penetration resistance.
The performance of the various ANN configurations were compared using: the mean squared error (*MSE*) and the % Error; the Akaike information criterion (*AIC*) which measures the trade-off between training performance and network size, and; the *MDL* criterion (minimum description length) which is similar to the *AIC* in that it tries to combine the model's error with the number of degrees of freedom to determine the level of generalization. The goal is to minimize respectively the *ACI* and *MDL* terms to produce a network with the best generalization. The coefficient of determination, R^2, of the linear regression line between the values predicted by the neural network model and the desired output was also used as a measure of performance. The *MSE*, *AIC*, *MDL* and R^2 equations used to compare the performance of various ANN configurations are:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(R_D - R_P)^2 \quad (2)$$

$$AIC(k) = n\log(MSE) + 2k \quad (3)$$

$$MDL(k) = n\log(MSE) + 0.5k\log(n) \quad (4)$$

$$R^2 = \frac{RSS}{TSS} \quad (5)$$

where n is the number of exemplars of the training set, R_D and $R_P$are the desired and predicted values of soil resistance to penetration, respectively and k is the number of network weights. The coefficients *RSS* and *TSS* represent the regression sum of squares and the total sum of squares, and are defined respectively as:

$$RSS = \sum_{i=1}^{n}(f_i - \bar{f})^2 \quad (6)$$

$$TSS = \sum_{i=1}^{n}(Y_i - \bar{Y})^2 \quad (7)$$

where $\bar{f}$ and $\bar{Y}$ are the means of the observed data (Y_i) and predicted values (f_i) respectively.

3.Results and discussion

3.1 Soil resistance to penetration

Soil tillage significantly affects the resistance to penetration (Figure 2). On the surface, soil resistance is low because of the fine layer created by the disc harrow "offset" when preparing the soil before planting. Further in depth, there is a gradient of penetration resistance. Under conventional tillage (LT), resistance is lowest between 0 and 30 cm for different dates of measurement, corresponding to horizons homogenization and clods fragmentation. Beyond 30 cm of depth, we can observe an increase in the pressure with a maximum at 50 cm in march, may, july and september 2013, suggesting the existence of an old plow sole. Under superficial tillage system (ST), the resistance increases from 0 to 30 cm and then decreases beyond 30 cm, suggesting that with ST, the soil is more compact. Thus, the soil is more compact under no tillage techniques. However, pressures in their entirety are relatively low. Samples for soil water content measurements were conducted jointly with measurements of soil resistance to penetration. Soil resistance is inversely proportional to soil water content of. Measurements were performed at 10, 20 and 30 cm of depth for different tillage methods and different measurement dates. Indeed, the consistency of a fine or cohesive soil can be assessed by a mechanical resistance test. This consistency greatly varies with soil water content. When the water content decreases gradually, we noted that the soil passes successively through several states: a liquid state at high water content where soil behaves like a liquid and its resistance is almost zero; a plastic state where the soil is naturally stable, but after that an effort is applied, it is a seat to large deformations, largely non-reversible withoutsignificant change in volume and without cracks. Some soils, called thixotropic, have the ability to recover over time some of their resistance and solid state: soil has the same behavior of a solid, the application of a force causes only small deformations.

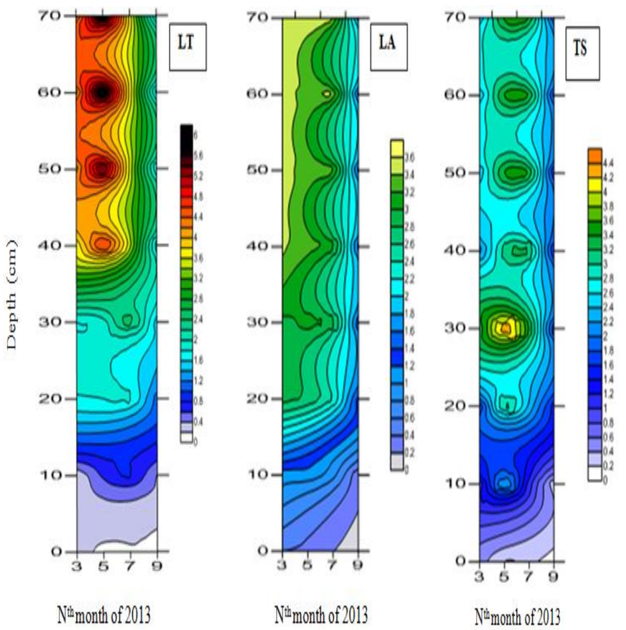

Figure 2 Distribution of soil resistance values (MPa) in terms of time for different modalities: conventional tillage (LT), agronomic tillage (LA) and superficial tillage (TS)

The statistical analysis presented in Table 2 indicates that tillage technique had the most significant effect on the soil resistance followed by dates (days after tillage) then depth.

Table 2 Statistical analysis of the effect of tillage technique, depth and measurement dates on soil resistance to penetration

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	577.215[a]	95	6.076	1964.164	.000
Intercept	1484.898	1	1484.898	480020.881	.000
Tillage Technique	2.180	2	1.090	14352.411	.000
Date	125.439	3	41.813	13516.778	.000
Depth	331.633	7	47.376	15315.204	.000
Technique * date	12.700	6	2.117	684.263	.000
Technique * depth	40.803	14	2.915	942.173	.000
Date * depth	30.734	21	1.464	473.117	.000
Technique * date * depth	33.726	42	.803	259.584	.000
Error	.594	192	.003		
Total	2062.707	288			
Corrected Total	577.809	287			

Note: R^2 = 0.999; adjusted R^2 = 0.998. The effect was tested using the method of General Linear Model Univariate Analysis

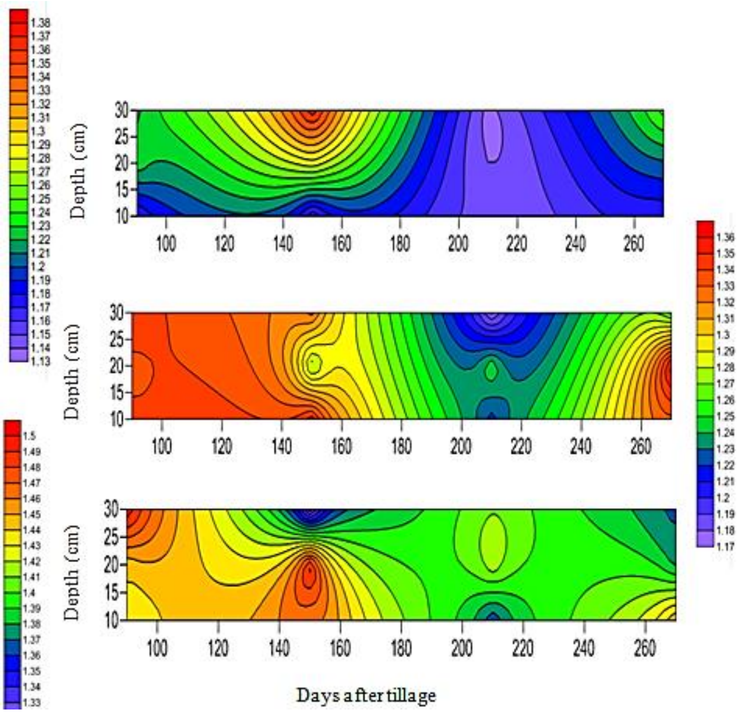

Figure 3 Distribution of bulk density (g/cm^3) in terms of time for different modalities: conventional tillage (LT), agronomic tillage (LA) and superficial tillage (TS)

3.2 Soil bulk density

After two years of practice, the harmful effects of tillage and mechanical action of the plow appear on soil structure especially in depth following the machinery passages and plow pans forming. The highest values obtained in the other modalities may be due to natural taking mass of sensitive soil (to wetting/desiccation and taking mass). This is confirmed by the results obtained during the second to third year of practice illustrated in figure 3. We note however that in depth, the beneficial effects of disc harrow "offset" occur. Unlike plowing, tractor traffic in surface helps to limit soil compaction in the worked horizon. Compaction can then be stopped by the mechanical action of tillage equipments. Under reduced tillage, stable aggregates rates are often similar to those observed under plowing because of aggregates destruction by the action of tillage equipments although this practice promotes the accumulation of organic matter in surface. Conservation practices that improve soil structure, such as the superficial tillage, no-till or ridges crop, provide some protection against soil compaction (Strudley et al., 2008). The deterioration of the soil structure caused by compaction also restricts oxygen supply for the roots, thebiological functioning of the soil (earthworm absence) and plant growth. The high soil density in compacted layer strongly restricts the expansion of the roots which leads to poor root development and nutrients absorption, leading to a decrease in biomass production (Tsague 2005). Since many soil properties are modified by the tillage technique,

Table 3 Performances of various ANN configurations once trained for the data set for the neural network MFF

	Processing elements (PE_S) in each Hl							
Hidden layer (Hl) number	Upper PE_S	Lower PE_S	Transfer	MSE	% Error	AIC	MDL	R
1	2	2	TANH	0.152	49.442	-16.366	-22.354	0.613
1	3	3	TANH	0.152	49.389	-2.496	-10.580	0.614
1	4	4	TANH	0.151	49.365	11.463	1.283	0.615
1	5	5	TANH	0.151	49.365	25.463	13.187	0.615
1	6	6	TANH	0.151	49.365	39.463	25.091	0.615
1	7	7	TANH	0.151	49.365	53.463	36.996	0.615
1	8	8	TANH	0.116	39.025	59.452	40.889	0.704
1	9	9	TANH	0.151	49.365	81.463	60.804	0.615
1	10	10	TANH	0.151	49.365	95.463	72.708	0.615
2	2	2	TANH	0.000	3.265	-184.134	-195.744	0.999
2	3	3	TANH	0.000	0.976	-220.251	-237.317	0.999
2	4	4	TANH	0.000	0.489	-184.367	-207.487	**0.989**
2	5	5	TANH	0.007	18.567	57.046	26.806	0.977
2	6	6	TANH	0.006	13.372	102.138	64.413	0.981
2	7	7	TANH	0.002	10.101	120.974	75.166	0.994
2	8	8	TANH	0.006	12.416	211.788	157.297	0.983
2	9	9	TANH	0.001	7.079	234.113	170.340	0.995
2	10	10	TANH	0.003	13.644	324.506	250.854	0.989
1	2	2	SIGM	0.011	33.042	-92.882	-98.870	0.858
1	3	3	SIGM	0.011	33.021	-78.796	-86.880	0.857
1	4	4	SIGM	0.012	33.276	-64.623	-74.802	0.856
1	5	5	SIGM	0.08	27.479	-59.492	-71.768	0.895
1	6	6	SIGM	0.04	92.834	4.213	-10.157	-0.275
1	7	7	SIGM	0.012	33.164	-22.006	-38.473	0.853
1	8	8	SIGM	0.012	32.925	-8.246	-26.809	0.854
1	9	9	SIGM	0.012	32.976	6.136	-14.522	0.852
1	10	10	SIGM	0.012	33.377	20.684	-2.069	0.849
2	2	2	SIGM	0.010	30.944	-59.914	-71.291	0.872
2	3	3	SIGM	0.012	37.827	-16.600	-33.666	0.846
2	4	4	SIGM	0.011	35.001	22.815	-0.538	0.860
2	5	5	SIGM	0.011	33.543	68.257	38.018	0.862
2	6	6	SIGM	0.012	37.659	121.671	83.947	0.844
2	7	7	SIGM	0.012	37.159	175.365	129.557	0.846
2	8	8	SIGM	0.011	33.128	230.231	175.740	0.862
2	9	9	SIGM	0.011	34.464	292.895	229.123	0.859
2	10	10	SIGM	0.008	29.097	350.564	276.912	0.895

a different soil profile is then developed depending on whether tillage is conventional or reduced. Improvement of soil properties and therefore of the profile by reduced tillage occurs gradually over many years (Abrougui et al., 2014). Generally, in the case of a transition from conventional tillage to reduced tillage or no-till usually takes 3 to 5 years before receiving significant effects on the soil profile.

3.3 Artificial Neural Network Performance

In this study, an ANN model was employed to predict soil resistance to penetration from soil bulk density, water content and tillage system as input data. The performance of ANN configuration was evaluated several times using the data set and the various configurations (Table 3). The ANN configuration that minimized the *MSE* value and the % Error, and that optimized R^2, were considered to be optimal. The verification of the ANN model performance is illustrated in Figure 4. The best ANN configuration from the network topology I used two hidden layers, with four neurones in both the upper and lower levels. The *MSE* and % Error for this optimal configuration were 0.000 and 0.489%, respectively. The results showed very good agreement between the predicted and the desired values of sugar diffusivity (R^2 = 0.98).

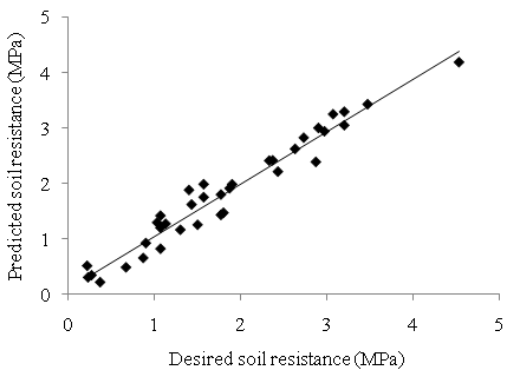

Figure 4 Correlation of desired versus neural network values of soil resistance after testing the data set for the ANN with 2 hidden layers and four neurons in both the upper and lower hidden layers.

The coefficient of determination was also very good (R^2>0.95), as a result of the small prediction error. The second best ANN model was obtained with two hidden layers and two neurones in both the upper and lower level for each layer. This ANN model also demonstrated very good agreement between the predicted and the desired values of soil resistance (R^2 = 0.99) but the % Error, *AIC* and *MDL* were also larger.

Conclusion

Soil structure is the result of the balance between compaction phenomenons (by passages of agricultural machinery including interventions in wet conditions), fragmentation by soil tillage), aggregation by moderate compaction and displacement by tillage. This result was demonstrated by the observation of average penetrometric profiles and soil density measurements. In general, plowed soils have lower structural stability than soils under superficial tillage where soil resistances and bulk densities are higher in surface but lower in depth below 30 cm with the absence of the soil compacted layer. This layer called "plow pan" is remarkable only under plowed soils. Indeed, soils classified as moderately stable to stable nevertheless saw their structural stability improved by the effect of carbon concentration in the surface layer under superficial tillage technique. A neural network based model was the optimal model, which consisted of two hidden layers with four neurones in both the upper and lower levels in each layer, was able to predict soil resistance values with a MSE of 0.000 and 0.489 % Error.

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