# ARTIFICIAL NEURAL NETWORK AND STEPWISE APPROACH FOR PREDICTING TRACTIVE EFFICIENCY OF THE TRACTOR (CASE JX75T)

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**ABSTRACT**

**The aim of this study is to develop and predict models of tractive efficiency using the artificial neural network and stepwise approach. The tractive efficiency of tractor (CASE JX75T) was measured experimentally. Experiments were conducted in the site of Basrah University. Which had silty clay soil texture. The field conditions included effect of two level of cone index (550 and 980 kPa), two level of moisture content (8 and 21%), three forward speeds (0.54, 0.83 and 1.53 m/s) and four level of tillage depths (10, 15, 20 and 25 cm). The results illustrated that both developed models (stepwise approach and ANN technique) had acceptable performance for predicting tractive efficiency of tractor under various field conditions. However, ANN model outperformed stepwise model, where 4-7-1 topology showed the best power for predicting tractive efficiency with R-squared of 0.97 and MSE of 0.0074 with Levenberg-Marquardt training algorithm. The analysis of variance demonstrated that the studied parameters had single significant effect on tractive efficiency. The most parameter influential on tractive efficiency was tillage depth followed forward speed, cone index and moisture content.**

**Keyword: soft computing techniques, modelling, field conditions, silty clay soil.**

مجلة العلوم الزراعية العراقية -2019 :50(4):1008-1017 المالكي وآخرون

**لشبكات العصبية والانحدار التدريجي للتنبؤ بكفاءة السحب للجرار (CASE JX75T)**

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**المستخلص**

**هدف هذه الدراسة هو تطوير نماذج للتنبؤ بكفاءة السحب باستخدام الشبكات العصبية وطريقة الانحدار التدريجي. اجريت التجارب في موقع جامعة البصرة ذات نسجة تربة طينية غرينية. الظروف الحقلية المؤثرة على كفاءة السحب تضمنت مستويان من مؤشر المخروط (550، 980 كيلو باسكال)، مستويان من رطوبة التربة (8 ، 21 %)، ثلاث سرعات أمامية (0.54 ، 0.83 ، و 1.53 م / ثانية) واربعة اعماق حراثة (10، 15، 20، 25 سم). اظهرت النتائج ان كلا النموذجين ( الشبكات العصبية و الانحدار التدريجي) اعطت نتائج ذات مصداقية عالية في التنبؤ بكفاءة السحب تحت ظروف حقلية مختلفة. كما تفوق نموذج الشبكات العصبية على الانحدار التدريجي حيث اظهرت الشبكة العصبية ذات التركيب (4–7–1) افضل قدرة في التنبؤ بكفاءة السحب (R–squared = 0.97 and MSE = 0.0074) باستعمال خوارزمية التدريب Levenberg–Marquardt. كما اظهر تحليل التباين ان كل العوامل المدروسة لها تاثير مفرد معنوي على كفاءة السحب وان اكثرها تاثيرا كان عمق الحراثة ويلية السرعة الامامية ومؤشر المخروط ورطوبة التربة على التوالي.**

**الكلمات المفتاحية: تقنيات الحوسبة الناعمة، النمذجة، ظروف حقلية، الترب الطينية الغرينية.**

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## INTRODUCTION

Tractive efficiency is one of the most important criteria to evaluate tractor performance during field operations. Tractive efficiency is transform input power into output power. The increasing tractive efficiency means more effective usage of the internal combustion engine's mechanical work. There are many various methods to measure tractive efficiency (14, 17, and 27). As far as previous studies were concerned, prominent interest was directed by researchers across study of the impact of operational parameters on tractive efficiency for any vehicle. Grisso et al. (12) explained that the efficient operation of farm tractor depended on: (a) mechanical efficiency of the drive train and maximizing fuel efficiency of the engine (b) maximizing attractive advantage of traction devices, and (c) adopt an optimum forward speed for a given tractor-implement system. The results from a research work conducted by Aday et al. (1) shows that the maximum traction efficiency of 2WD and 4WD tractors were 0.72 and 0.79 which occurred at traction wheels slip of 12% and 7%, respectively. The optimum traction efficiencies (the optimum tractor performance) were 0.78 and 0.85 that occurred at wheels slip of 17% and 8%, at the draft force of 22kN for 2WD and 4WD tractors, respectively. Peca et al. (19) studied the effects of engine speed and forward speed on the tractive efficiency in tractor operations. They reported that the overall power efficiency increased by 10-20% when the engine speed was reduced from 2200 to 1750 rpm. In recent years, artificial neural network (ANN) approach has illustrated to be essential as an exciting alternative way concerning the intricate system. ANN is one of the intelligent computational methods, which aims to offer a mapping between the input space (input layer) and the desirable space (output layer) by perception the essential relationships between the data using learning approach and the processors called the neurons. ANN consist of an input layer of nodes, an output layer and one or more layers of nodes in between. The middle layers called hidden layers. The hidden layer processes the received data from the input layer and provides the output layer with this processed data. Training is an operation that primarily drives to learning. Network learning is carried out when the connection weights between the layers change so that the difference between predicted and calculated values is suitable (15). Since agricultural systems and technologies are quite complex and uncertain, several researchers focused on ANN method for modeling of a different component of agricultural systems (3, 5, 8, 10, 13, 21, 22, 25 and 26). The complex nature of soil-tire interaction and the lack of any closed form mathematical description of the phenomena have driven researchers to employ stochastic soft computing techniques to perform nonlinear modeling successfully (4 and 23). Many researchers have shown the capacity of ANN versus regression approach such as research done by Rahimi and Abbaspour (20). They utilized ANN and stepwise multiple range regression methods for the forecast of tractor fuel consumption and their results explained that ANN provided better prediction compared to stepwise regression. Çarman and Taner (9) studied the interaction between slippage and tractive performance and to explain how ANNs could play a remarkable role in the simulation of these parameters. Bietresato et al. (7) investigated the predictive capability of several configurations of ANNs for estimating indirectly the performance (torque, brake specific fuel consumption (BSFC)) of diesel engines used in agricultural tractors. Ekinci et al. (11) assessed ANN and two types of Support Vector Regression (SVR) models to predict the tractive efficiency. The results illustrated that the ANN approach trained using Levenberge Marquardt algorithm provided more accurate results. Taghavifar et al. (24) studied the desired power estimation for the driving wheels of off-road vehicles. The experiments were conducted in a controlled soil bin facility using single-wheel tester. The MSE of 0.022 was obtained as the most optimal ANN-genetic algorithm configuration using Levenberg Marquardt training algorithm. The aim of this study is to develop models for predicting the tractive efficiency of the tractor (CASE JX75T) utilizing ANN and Design Expert software (stepwise approach). Then, to perform a comparison between ANN and stepwise to select the optimum model.

## MATERIALS AND METHODS

### Experiments site and soil test

Field Experiments were implemented in the experimental field of the University of Basrah located in (19´´ 30´ 33° N 54´´ 47´ 44° E, Basrah province, Iraq). The soil texture at the experimental site was silty clay (49% silt, 20% sand, and 31% clay) with flat topography. Before the experiments, several soil samples were collected using a cylindrical core sampler from different depth levels of 0.1, 0.15, 0.20 m and 0.25 m at different parts of the field. Collected samples were immediately put in plastic bags to conserve moisture during transfer to the laboratory. Samples were weighted before and after drying in oven at 105˚C for 24 hour. The tests were carried out three times and the mean value was used. Moisture content and bulk density were calculated from equations 1and 2 respectively.

$$MC = \frac{WB-WA}{WB} \times 100 \qquad (1)$$

$$BD = ms/Vc \qquad (2)$$

where:

*MC*: Moisture Content (%)
*WB*: Wet weight of soil sample (g)
*WA:* Dry weight of soil sample (g)
*BD*: Bulk density (kg/m$^3$)
*ms*: Dry weight of soil in the cylinder (kg)
*Vc*: Cylinder volume (m$^3$)

Cone Index explains the resistance to penetration into the soil per unit cone base area. The cone index and its gradient with respect to penetration depth have been used as a basis for predicting off-road vehicle performance. Cone index values were obtained by taking penetrometer readings at 5 cm increments to depths of 25 cm at several locations of the plots using a cone penetrometer according to ASABE Standards S313.2 with a cone base area of 130 mm$^2$ and 30º (2).

**Table 1. Corresponding calculated bulk density and moisture content at different cone index values**

| | | |
|---|---|---|
| **Moisture Content (%)** | **8** | **21** |
| **Bulk Density (kg/m$^3$)** | **1015** | **1340** |
| **Cone index (kPa)** | **550** | **980** |

Two tractors were used in this research. The first tractor was a 55 (kW) CASE JX75T tractor produce by India which was used to provide energy for pulling the utilized plow in the experiments. The second tractor was Massey Ferguson 285 (56 kW) which was utilized for mounting the plow with it. The specifications of these tractors were showed in Table 2. The experiments were implemented utilizing a conventional tillage system which includes a moldboard plow. Which consist of three furrows. Furrow width was set to 33 cm, and its maximum tillage depth was 30 cm. The total work width of moldboard plow was 99 cm.

**Table 2. Specifications of used tractors in experiments**

| Specifications | CASE JX75T Model | Massey Ferguson 285 Model |
|---|---|---|
| No. of cylinders | 4CYL | 4CYL |
| Power (kW / hp) @ 2500 rpm | 75 / 55 | 77 / 56 |
| Max. torque (Nm @ rpm) | 242Nm @ 1500 rpm | 248 Nm @ 1300 rpm |
| Fuel Tank Capacity (Liter) | 62 | 120 |
| Transmission clutch | Mechanical | Mechanical |
| Total number of speeds | 8 forward, 2 reverse | 8forward, 2 reverse |
| PTO speeds (rpm) | 540 | 540 |
| Wheelbase 2WD / 4WD (mm) | 2160 / 2200 | 2100 / 2290 |
| Ground clearance under rear axle (mm) | 555 | 450 |
| Type Size 2WD Front/Back | 16 – 7.50 / 30 -16.9 | 24 -12.4 / 30 -18.4 |

**Experimental parameters**

The experiments were carried out in the farm with various field conditions using three tractor forward speeds and four depths of moldboard plow. These parameters were used at two moisture contents levels and two cone indices of soil as shown in Table 3. All experiments had three replications resulting in a total of 144 tests.

**Table 3. Input parameters used in experiments**

| Moisture content (%) | Cone index (kPa) | Forward speed (m/sec) | Depth (cm) |
|---|---|---|---|
| 8 | 550 | 0.54 | 10 |
| 21 | 980 | 0.83 | 15 |
| | | 1.54 | 20 |
| | | | 25 |

**Calculation of tractive efficiency**

Tractive efficiency is calculated using the relation between output power and input power (27) as follows:

$$TE\ (\%) = \frac{OutputPower}{Inputpower} \times 100 \qquad (3)$$

$$TE = \frac{Drawbar\ power}{Axele\ Power} \times 100 \qquad (4)$$

$$TE = \frac{NT}{GT}\frac{Va}{Vt} \qquad (5)$$

Where:

*NT*: Net traction (kN)

*Va*: Actual velocity (m/sec)

*Vt*: Theoretical velocity (m/sec)

$G_T$: Gross traction (kN). Which is equivalent to net traction (*NT*) and rolling resistance (*Rr*).

**Mathematical model**

In this work, Design Expert software (Version: 8.0.6.1) was utilized for predicting a mathematical model of tractive efficiency for the tractor (CASE JX75T Model). A total of 144 tests were conducted under different field condition (two level of moisture content, two level of cone index, three forward speed and four tillage depth) for produce acceptable models of tractive efficiency

**Design of artificial neural network**

In this study, considering four factors of moisture content, cone index, tillage depth and forward speed, changes in the tractive efficiency of tractor under different conditions are acquired. The proposed neural network topology and the input and output parameters for the network are shown with the different number of layers. An artificial neural network with one layer has been used, containing neurons in each layer. The data of moisture content, cone index, tillage depth and forward speed are considered as input to the network as well as the tractive efficiency data acquired from experimental results are considered as an output. To train the network, data were first randomly divided into three parts, so that 70% of the data for training, 15% of the data for model validation and 15% of the data for testing the network were used. During the training, when the error between the training and validation data increases, the training process is interrupted. Prior to the utilization of dataset for model development, the inputs and target output were normalized or scaled linearly between -1 and 1 in order to increase the accuracy, performance and speed of ANN. The schematic architecture of the used ANN is shown in Figure 1. The Levenberg-Marquardt (LM) training algorithm is one of the most widely used algorithms because it conducts network training very fast and diminishes the level of error obtainable (2 and 15). As mentioned above, the Levenberg-Marquardt (LM) training algorithm was utilized to update the artificial neural network weights. The values of the correlation coefficient ($R^2$) and mean square error (MSE) were used to evaluate the obtained results (23 and 24).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \qquad (6)$$

$$R^2 = \frac{[\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})(x_i - \bar{x})]^2}{\sum_{i=1}^{N}(\hat{x}_i - \bar{\hat{x}})^2 \times \sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (7)$$

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

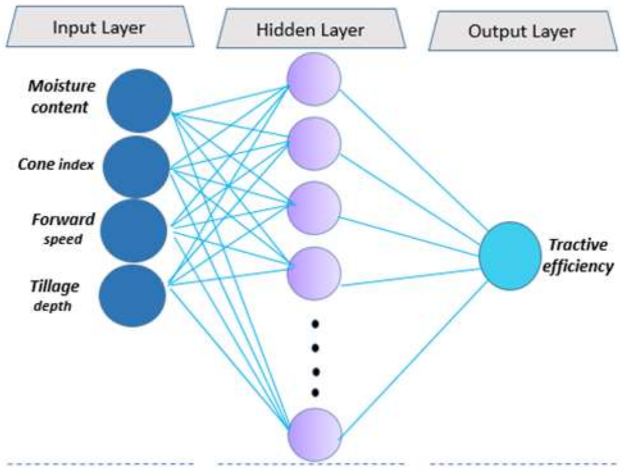


**Figure1. Schematic architecture of the developed ANN model**

## RESULTS AND DISCUSSION

Two different models (Stepwise method and ANN) were used for evaluating the tractive efficiency parameter in tractor (CASE JX75T Model). A stepwise approach was used to analyze acquired data from field during tillage operation under various field condition, and to develop a mathematical model for predicting tractive efficiency. The data were abbreviated by taking average of treatments. For selecting more powerful and more reliable models, a variety of several polynomial models were analyzed by using Design Expert software. In order to optimize and diminish the number of nominee regressors, a stepwise regression algorithm, as a most widely used variable selection technique (18) was applied, resulting in the reduced models (Table 4). The ANOVA Table was utilized to determine the effect of moisture content, cone index, plowing depth and forward speed and their binary interaction effect on the tractive efficiency (Table 5). The results showed that the single effect of the parameters on the tractive efficiency was significant at probability level (P<0.0001). Also, the interaction between parameters had significant effect between them (p<0.05), except the interaction between (moisture content - tillage depth) and (moisture content – speed).

**Table 4. Summary of statistics of reduced quadratic models**

| | | | |
|---|---|---|---|
| Std. Dev. | 0.012 | R-Squared | 0.936 |
| Mean | 0.64 | Adj R-Squared | 0.927 |
| C.V. % | 1.88 | Pred R-Squared | 0.928 |
| PRESS | 0.024 | Adeq Precision | 58.96 |

**Table 5. Analysis of variance for tractive efficiency**

| Source | Sum of Squares | df | F- Value | p-value Prob > F |
|---|---|---|---|---|
| Model | 0.29 | 10 | 262.30 | < 0.0001 |
| A-MC | 0.014 | 1 | 92.32 | < 0.0001 |
| B-CI | 0.027 | 1 | 173.13 | < 0.0001 |
| C-Depth | 0.039 | 1 | 249.99 | < 0.0001 |
| D-Speed | 0.058 | 1 | 369.05 | < 0.0001 |
| MC-CI | 0.013 | 1 | 65.27 | 0.0421 |
| MC-Speed | $2.79\times10^{-3}$ | 1 | 2.16 | 0.1424 |
| MC-Depth | $3.84\times10^{-3}$ | 1 | 2.69 | 0.0966 |
| CI-Speed | 0.024 | 1 | 24.25 | 0.0329 |
| CI-Depht | 0.0043 | 1 | 63.71 | 0.0448 |
| Speed-Depth | 0.016 | 1 | 104.6 | 0.0121 |

### Effect of parameters

The results showed that the tractive efficiency was increased by 2% with increasing of moisture content from 8 to 21% (Figure 2). With increasing of moisture content, topsoil of filed becomes softer with less friction which will lead to decreasing rolling resistance that reflected in increasing tractive efficiency. The results also revealed that with increasing cone index from 550 to 980 led to increase tractive efficiency by 6%. This is due to improve features of traction with increase cone index which represent soil strength such as traction force, rolling resistance and slippage. Meanwhile, the effect of interaction between moisture content and cone index led to increase tractive efficiency by 8%.

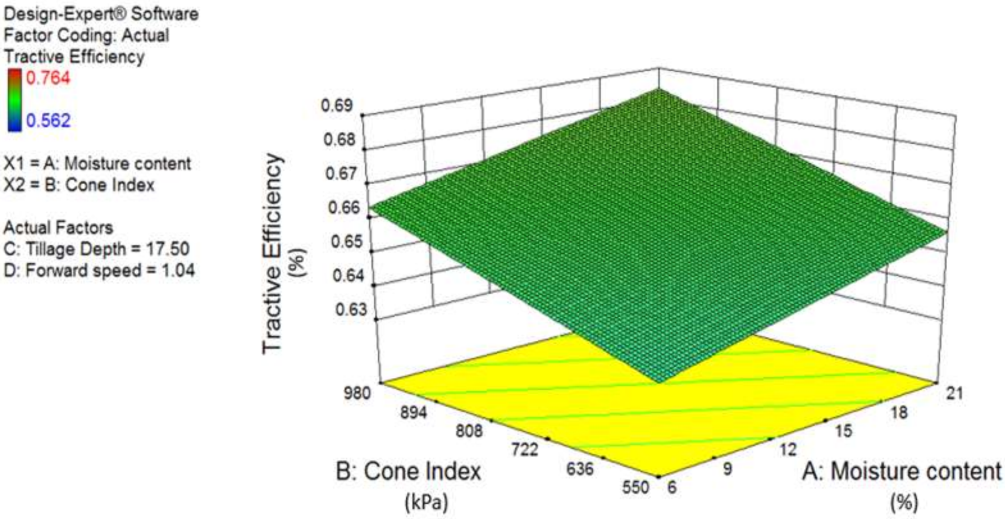


**Figure 2. Effect of moisture content and cone index on tractive efficiency**

The impact of forward speed on tractive efficiency was negative (Figure 3). Where increasing forward speed from 0.54 to 1.53 m/s led to decrease of tractive efficiency by 10%. This could be return to with increasing forward speed, the power loss due to slip and rolling resistance was greater than power achieved from increasing traction force. On the other hand, the interaction between the cone index and forward speed was affirmative when the cone index increase and forward speed decrease.

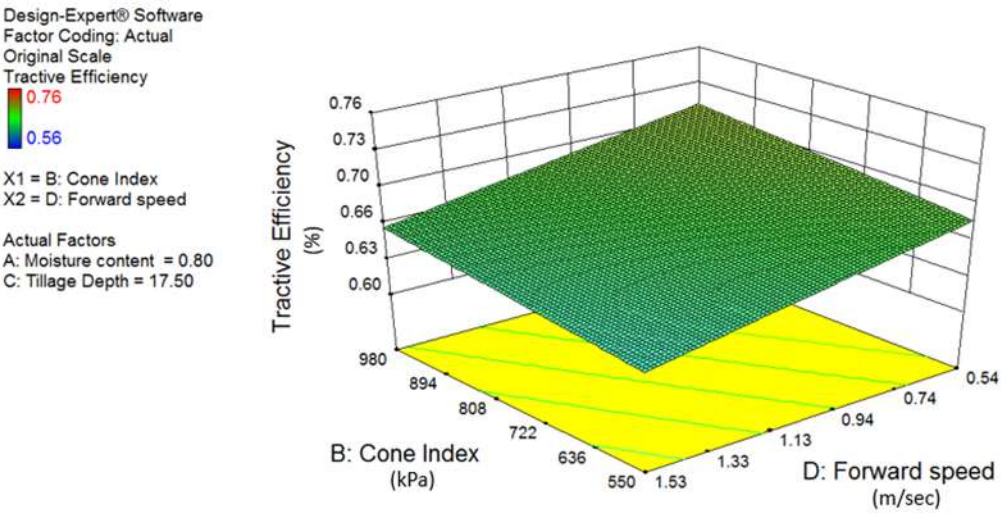


**Figure 3. Effect of cone index and forward speed on tractive efficiency**

Figure 4 illustrated the effect of tillage depth and cone index and their interaction on tractive efficiency. With increment tillage depth, tractive efficiency was increased gradually even reaches the maximum value (at point 19cm) then begins to decline. The reason for increasing tractive efficiency may be attributed to increase traction force with increase tillage depth. Consequently, the increase gained power from traction force was greater than power loss due to slippage and rolling resistance. Which lead to increase ability of tractor to transform the available power at driving wheel to traction power at drawbar. On the other hand, the decline in tractive efficiency after the maximum value returns to increase power loss (slippage and rolling resistance) greater than gained power from traction force.

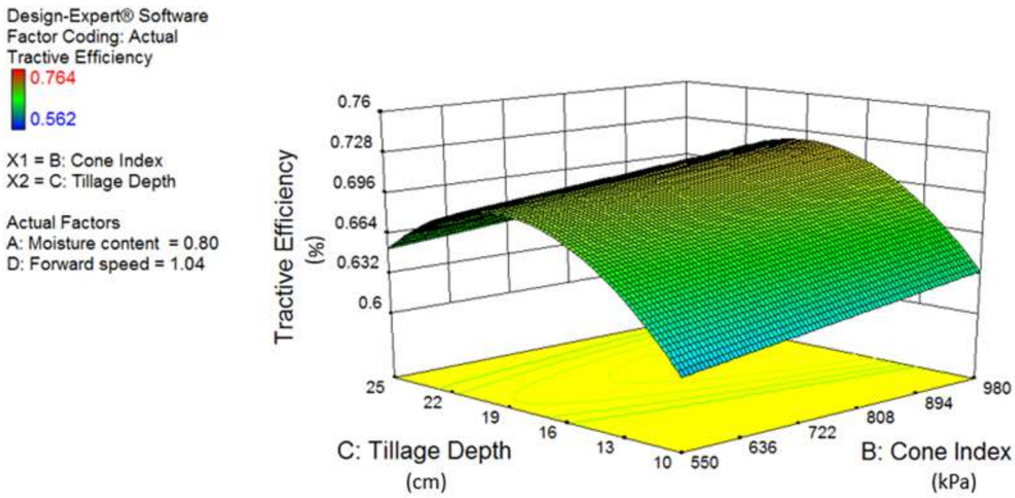


**Figure 4. Effect of cone index and tillage depth on tractive efficiency**

The maximum tractive efficiency was 0.73 which occurred at tillage depth 19cm and forward speed 0.54 m/sec (Figure 5). It can be seen that the most parameter influential on tractive efficiency was tillage depth followed by forward speed, cone index, and moisture content.

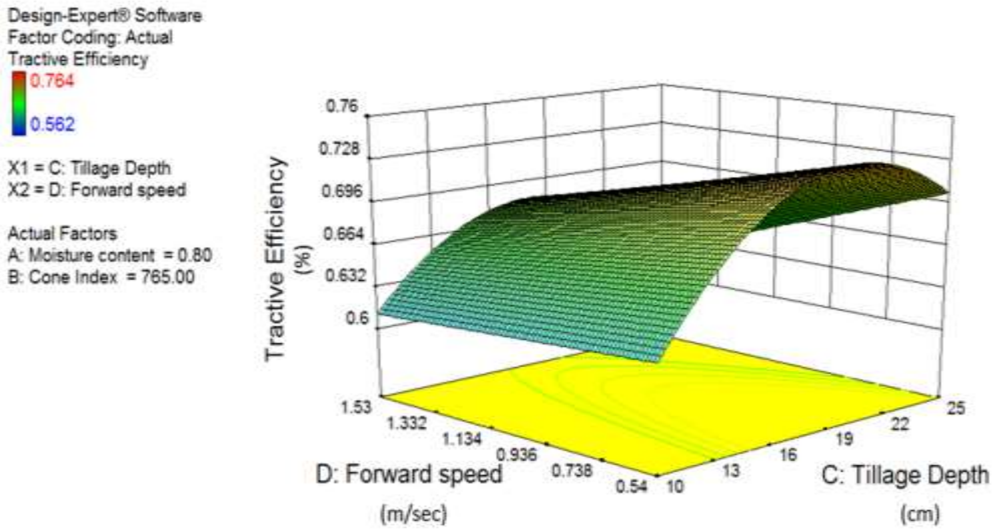


**Figure 5. Effect of forward speed and tillage depth on tractive efficiency**

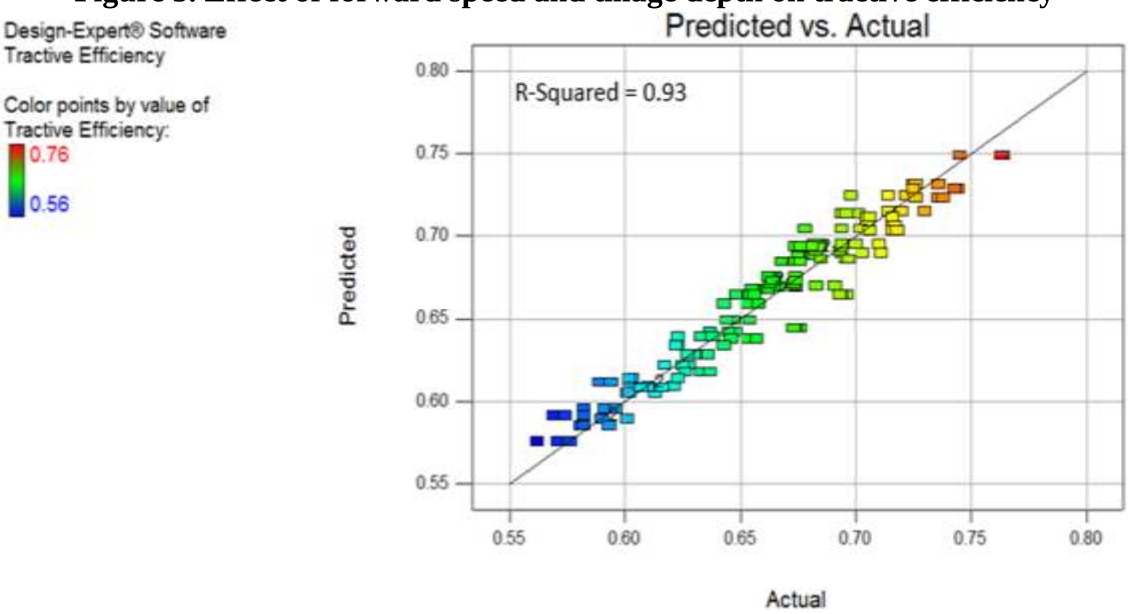


**Figure 6. Correlation between actual and predicted tractive efficiency**

Figure 6 demonstrates the predicted values versus experimental values. Close scattering around unity slope line confirms the satisfactory performance of the developed model. The convenient model for predicting the tractive efficiency utilizing a stepwise approach under various field condition is represented in Equation 8, in which the coefficients are in the coded unit form.

**Tractive efficiency**

$$+1.14+0.25*MC+0.014*CI+0.022*Speed-0.024*Depth-2.550E-003*CI*Speed-0.017*Speed*Depth-0.065*(Speed)^2 \quad (8)$$

The obtained results demonstrate that the ANN model with 4-7-1 structure in the single hidden layer through the implementation Levenberg-Marquardt training algorithm had the best performance with R-Squared of 0.973 and MSE of 0.0074 for tractive efficiency prediction. Taghavifar and Mardani (23) obtained similar results but in the soil bin facility. They developed classic ANNs to estimate tractive efficiency. To this aim, a soil bin facility equipped with a single wheel-tester was employed considering input parameters of wheel load, speed, slippage at three different levels. They obtained MSE equal to 1.5676 and $R^2$ equal to 0.97 for tractive efficiency. The performance of the network for training is demonstrated in Figure 7. It can be observed from this figure that MSE of training of the optimized network declined with increasing training epoch up to 15. After this value, the MSE of training was constant. The correlation between actual and predicted values of tractive efficiency under different working conditions for the training, validation, test and all datasets are shown in Figure 8. The inconsiderable variation between the predicted and measured values confirmed the accuracy of the network in predicting the tractive efficiency.

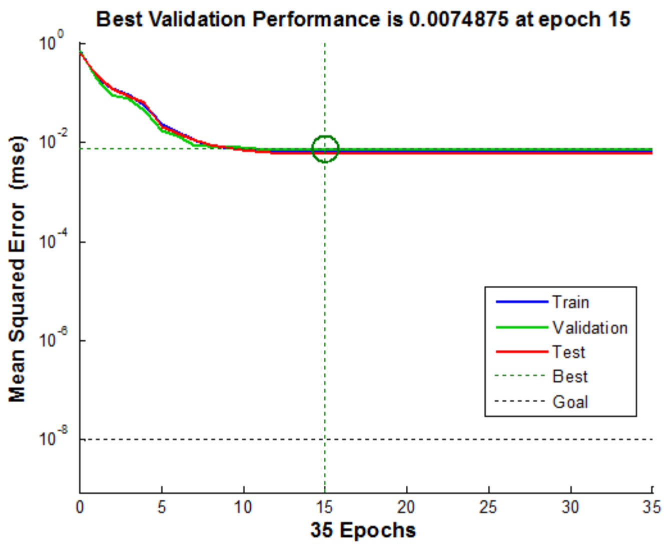


**Figure 7. Trend of MSE against epochs for trained networks of tractive efficiency**

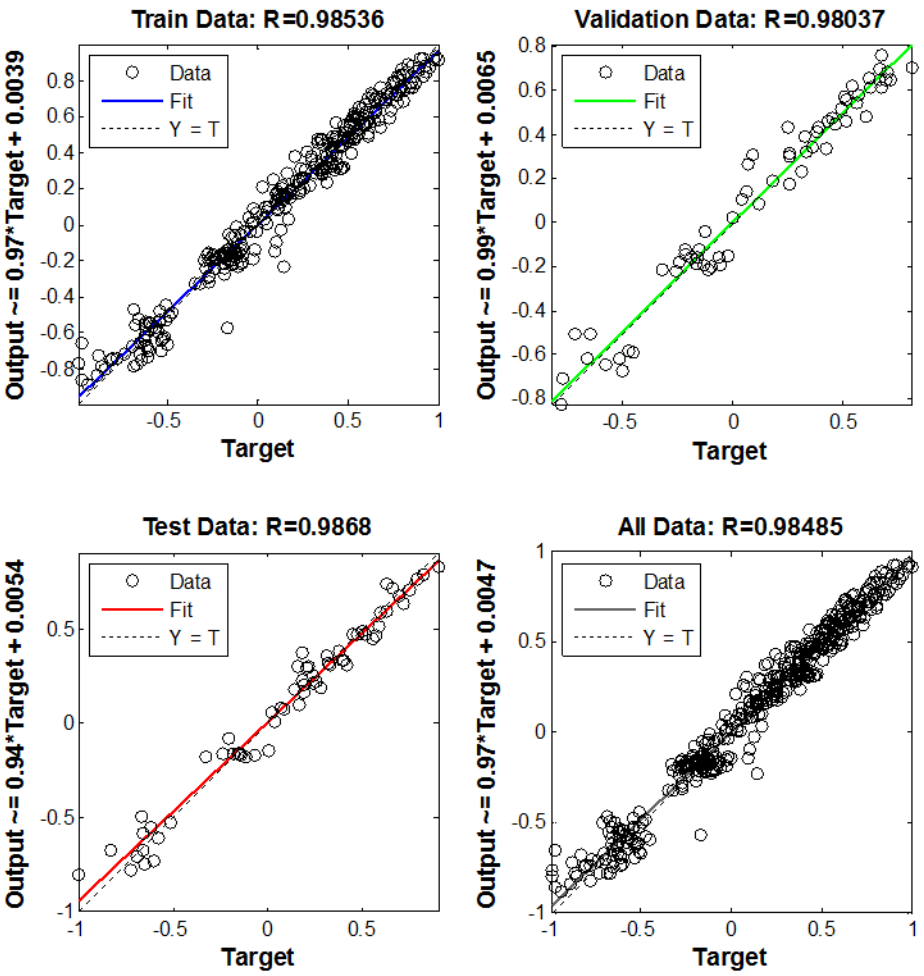


**Figure 8. Correlation between actual and predicted values of tractive efficiency in training, test, validation and all data sets**

Table 6 demonstrates the best results acquired from the stepwise approach and artificial neural network for studied parameters (moisture content, cone index, forward speed and tillage depth) in this research with statistical criteria (mean square error and R-squared). The results illustrate that both models had an acceptable performance for predicting tractive efficiency under various field conditions. However, the premium model yielded by ANN technique with MSE of 0.007 and $R^2$ of 0.97.

**Table 6. Comparison between Mathematical model and ANN model with criteria statistical**

| Mathematical model | | ANN model | |
|---|---|---|---|
| MSE | $R^2$ | MSE | $R^2$ |
| 0. 431 | 0.930 | 0.0074 | 0.973 |

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