

Using artificial neural networks and Mathematical models to simulate the impact of load distribution on tractor slip and rolling resistance under various field conditions.

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I. Abstract

Improving tractor performance is crucial for reducing the costs of agricultural operations. Tractor performance is influenced by several factors, including load distribution on the rear wheels and the front of the tractor. This study aimed to develop models to simulate tractor slip and rolling resistance using artificial neural networks (ANN) and Design Expert software. Experiments were conducted at the University of Basrah, College of Agriculture, on silty clay soil. The study included adding four weights to the rear tractor wheels (0, 150, 200, 250 kg), four front weights to the tractor (0, 90, 120, 150 kg), three plowing depths (10, 20, 30 cm), and three forward speeds (1.95, 3.43, 4.90) km/h. The results showed that artificial neural networks provided highly reliable predictions for tractor wheel slip and rolling resistance under various field conditions. The neural network using the Levenberg-Marquardt training algorithm showed the best prediction capability for slip ($R^2=0.9407$, $MSE=0.00947$) and rolling resistance ($R^2=0.9773$, $MSE=0.00436$). The Design Expert software also performed well in predicting slip and rolling resistance, with determination coefficients of $R^2=0.9989$ and $R^2=0.9837$, respectively. The results indicated that increasing the rear wheel weight from 0 (no additional rear weight) to 250 kg reduced slip by 22% and increased rolling resistance by 120 N. Increasing the front weight from 0 (no additional front weight) to 150 kg reduced slip by 11% and increased rolling resistance by 30 N. Increasing the depth from 10 to 30 cm resulted in a 140% increase in slip with no significant effect on rolling resistance. Increasing the forward speed from 1.95 to 4.9 km/h increased slip by 16% and rolling resistance by 165 N.

Keyword: ANN, Adding Weight, Modelling, Slippage, Rolling Resistance

II. Introduction

The performance of tractors and economic feasibility are important principles in tractor and machinery agricultural operations (1). Optimizing machinery use is essential to reduce agricultural production costs. Tractor performance parameters include wheel slip, fuel consumption, drawbar pull, forward speed, and working depth (2), (3). Rolling resistance and tractor wheel slip are important topics that arise from soil and wheel interactions (4). The power provided by the tractor engine is converted into drawbar pull through the interaction between the tractor wheels and the soil to increase the required drawbar pull for pulling implements and reducing fuel consumption. Between 20-50% of tractor power is lost during the interaction between the wheels and the soil surface due to slip and rolling resistance (5). Rolling resistance is defined as the



energy consumed per unit area due to tractor loading (6). Rolling resistance affects tractor performance, as an increase in rolling resistance leads to increased fuel consumption. (7). (8) found that increased additional weight resulted in reduced slip rates. (9) confirmed that increasing the additional weight of the tractor's drive wheels positively affects reducing wheel slip, as adding weight increases the contact area of the wheels with the soil due to flattening, thereby reducing fuel consumption. (10) explained that additional weight at the front of the tractor reduces tractor wheel slip and thus reduces fuel consumption. (11) concluded that tractors do not always operate under constant working conditions, so it is not possible to determine the ideal additional weight suitable for all working conditions.

Artificial neural networks (ANNs) are methods inspired by the central nervous system, as found in the human brain, using features such as the speed of communication and information processing (12). (13) studied modeling the effect of tractor forward speed on traction efficiency using simple linear regression modeling, noting that parameters, assumptions, and model constants change with varying experimental conditions. Slip resistance and wheel rolling resistance lead to tractor power loss, necessitating a more efficient system using mathematical modeling to predict tractor performance (14). (15) developed models for predicting traction efficiency using ANNs and stepwise regression under different field conditions of forward speeds, depths, and moisture levels, showing high reliability in predicting traction efficiency under varying field conditions. Computer simulation and modeling help predict the performance of agricultural tractors, allowing mathematical modeling to analyze issues related to tractor performance to improve tractor design and increase performance efficiency (16). (17) confirmed that ANNs play an important role in predicting tractor performance, enabling agricultural engineers to make accurate decisions, improve agricultural operations, and increase productivity by determining optimal operating conditions. (18) conducted a study predicting fuel consumption using ANNs, showing that mathematical models and ANNs performed well in predicting fuel consumption parameters under different field conditions based on statistical parameters such as the coefficient of determination (R^2) and mean square error (MSE). (19) created a model using the backpropagation algorithm to predict drawbar pull, achieving an R^2 coefficient of determination between 0.915 and 0.934 for validating the ANN model. (20) studied the ability to predict drawbar pull, fuel consumption, rolling resistance, and traction efficiency using ANNs, developing an ANN model with backpropagation algorithms using MATLAB software with a 6-7-1 topology, achieving an R^2 value of 0.995 and an MSE value of 0.00024. (21) developed models to predict traction efficiency using ANNs, showing that ANNs performed well in predicting traction efficiency under different field conditions, achieving an MSE value of 0.007 and an R^2 value of 0.97. ANNs have proven to be highly accurate and reliable in artificial intelligence technology, with agricultural scientists employing ANNs in agricultural applications to develop a model for determining slip, recording an R^2 value of 0.9977, demonstrating that the ANN model is trustworthy and capable of determining the relationship between inputs and tractor wheel slip (22). Tractor performance plays a major role in improving productivity and efficiency. Predicting tractor performance is complex as it involves many factors such as operating conditions, soil conditions, and tractor specifications. (23) developed a simulation environment using ANNs and highly accurate models to predict soil pressure under different field conditions. The ANN environment was



developed using the backpropagation algorithm, achieving an MSE value of 0.00226 and an R^2 value of 0.986.

The research aims to use ANNs to study the impact of load distribution on the front and rear wheels of the agricultural tractor on its performance (slip and rolling resistance).

1. Martials and Methods

1.1. The tractors and equipment used in the experiment

Two tractors were used in the experiment: the first was a CASE JX75T, and the second was a MASSEY FERGUSON 440 Xtra. The experiment utilized a mounted chisel plow designed to break the soil without turning it. The plow consisted of seven shanks arranged in two rows: the first row had four shanks, and the second row had three shanks, with a distance of 60 cm between each shank in the same row.

1.2. Study Factors

The experiments were conducted in one of the fields belonging to the College of Agriculture, University of Basra, at the Karmat Ali site, on clayey loamy soil. The experiment was carried out after delineating the field area and determining the main factors, which included four loads for the rear tractor wheels (0, 150, 200, 250 kg), and four loads for the front of the tractor (0, 90, 120, 150 kg). Three tillage depths (10, 20, 30 cm) were used with a chisel plow. The tractor operated at three forward speeds ((G1=1.95), (G2=3.43), (G3=4.9)) km/h.

1.3. Transducers , Sensors and Measurements

A Load Cell device (model H3-C3-3.0t-6B-D55) was used to measure the pulling force. It is an S-shaped device connected between the two tractors. The load cell was connected to the main data processing unit, and the readings for the pulling force were obtained in Newton.

The rolling resistance of the main tractor (CASE JX75T) was measured at three forward speeds and with four weights on the front of the tractor and four weights on the rear wheels. The tractor was put in neutral and pulled by another tractor, with the force required to pull it representing the rolling resistance.

To measure the tillage depth of the chisel plow, ultrasonic waves using an Ultrasonic sensor were employed. This sensor measures the round-trip time of the ultrasonic waves, calculating the distance between the sensor and the object it hits using Equation (1). The tillage depth was calculated using Equation (2) as per (24).

$$\text{The measured distance (md)} = (T * V) / 2 \quad (1)$$

where:

T: The time interval between the transmitted and received wave

V: speed of sound (340 m s⁻¹)

To calculate the depth of plowing, the following equation is used:

$$\text{Tillage depth} = DF - DT \quad (2)$$

where:



DF: Plow height on a flat tiled ground (cm)

DT: Plow height in the field during operation (cm)

The fifth wheel technique with an Encoder Sensor was used to measure the theoretical speed of the tractor on a paved surface without loading the tractor (without slip). The wheel was attached to the first tractor (CASE JX75T), and the Encoder sensor was connected to a data collection unit mounted near the driver and linked to a laptop. The fifth wheel technique consists of a free-moving wheel with a circumference of 1250 mm, two gears with 21 and 8 teeth, respectively, and an Encoder sensor that generates 360 pulses per revolution of the sensor shaft (Figure1). The gear ratio was found to be 2.625, meaning a total of 945 pulses per revolution ($2.625 * 360$). Dividing the wheel circumference (1250 mm) by the number of pulses per wheel revolution (945 pulses) gives a distance of 1.32 mm per pulse. This known distance, combined with the time data input into the processing unit, allows for calculating the theoretical speed in meters per second (25) , (26) , (27).

The actual speed was measured using the fifth wheel technique, which is also used to measure the theoretical speed. The actual speed is calculated when the tractor is loaded in the field, resulting in a different actual speed compared to the theoretical speed due to the slippage of the drive wheels. The data is stored in the data collection unit.

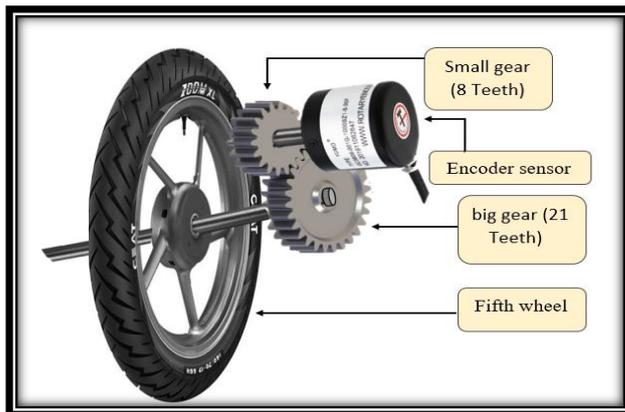


Figure 1: The device for measuring theoretical and actual speeds

The percentage of slip (%) was calculated using the theoretical forward speed (V_t) and the actual speed (V_a) of the tractor, using equation number (3) as utilized by (28).

$$(3) \quad Sp = \frac{V_t - V_a}{V_t} \times 100$$

Where:

Sp = Percentage of slip (%)

V_t = Theoretical speed (m/s).

V_a = Actual speed (m/s).

A data acquisition unit (Arduino) of type Arduino Mega 2560 was used to store and process the data. It was mounted on the main tractor (CASE JX75T) and connected to the computer via a USB cable. Figure 2 illustrates the equipment and tools used in the experiment.

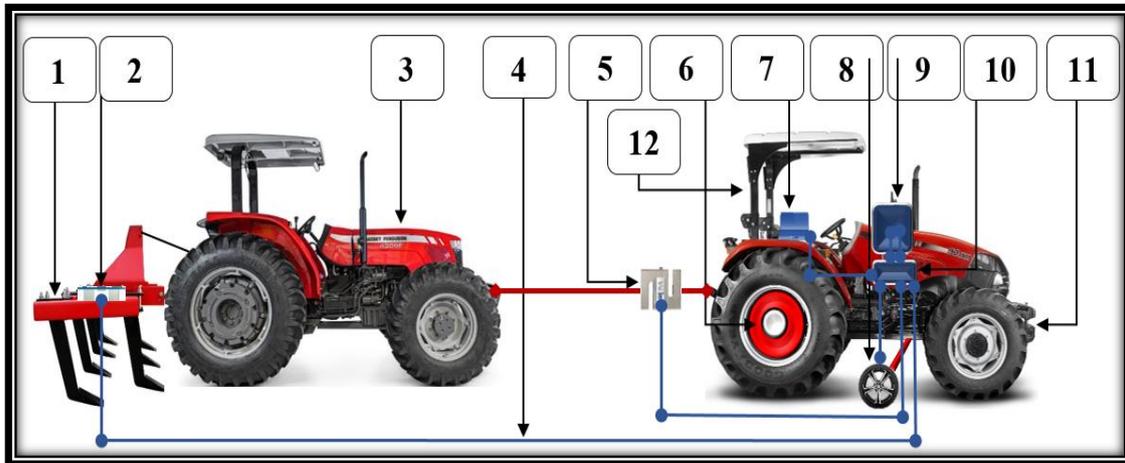


Figure (2) a schematic diagram illustrating the system and the equipment used in the experiment, consisting of the following components: 1- Agricultural implement (Plow) 2- Tillage depth measurement using Ultrasonic 3- Secondary tractor 4- Connecting wires 5- Load cell 6- Additional weight for rear tractor wheels 7- Laptop computer 8- Fifth wheel 9- Fuel consumption measuring device 10- Data collection and processing unit 11- Additional weight for tractor front 12- Main tractor.

1.4. Data analysis

Design Expert Software (Version: 8.0.6.1) was used for statistical data analysis, significance testing, and providing an ANOVA table, as well as drawing relationships between the inputs and outputs of the research (29).

Artificial neural network (ANN) models were also used with the backpropagation algorithm through input software. The artificial neural networks consist of three layers: an input layer, a hidden layer, followed by an output layer. The data is divided into subgroups (three groups), selected randomly. The first group is estimated at 70% and used for training purposes, the second group at 15% for model validation, and the third group also at 15% for testing purposes. Figure (3) shows the structure of the artificial neural network with the input layer, hidden layer, and output layer.

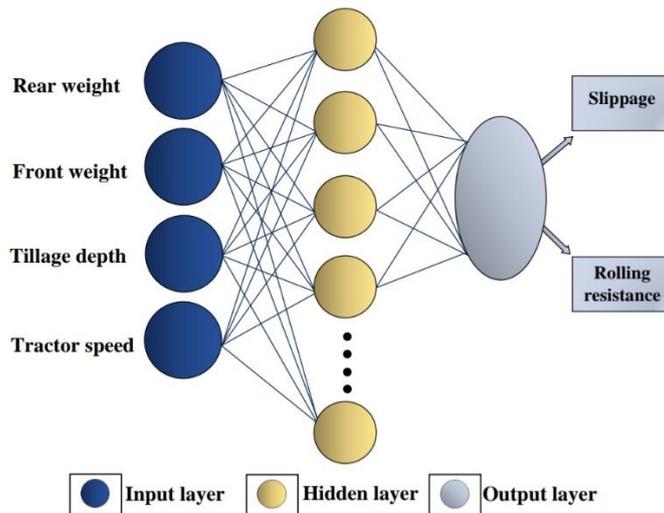


Figure (3) the structure of the artificial neural network with the input layer, hidden layer, and output layer.

III. Result and Discussion

1.5. Slippage

The figure (4) illustrates the effect of both the rear wheel weight and the front weight of the tractor, as well as their interaction, on the slip ratio. The results showed a decrease in slippage with the increase of both front and rear weights. Tractor slippage decreased by 22% when the weight increased from 0 kilograms (without adding weight) to 250 kilograms, due to increased cohesion of the rear wheels with the soil, deeper embedding of the wheel lugs in the soil, greater soil strength under the wheels, and increased contact area of the wheels with the ground due to their flattening. Additionally, increasing the front weight from 0 kilograms (without adding weight) to 150 kilograms for the front of the tractor reduced slippage by 11%, attributed to the increased cohesion of the front wheels with the soil, which is directly proportional to the load applied on the front axle. The highest slip ratio was 22% with rear and front weights of 0 and 0 kilograms respectively (without adding rear and front weights), and the lowest slip ratio was 16% with rear and front weights of 250 and 150 kilograms respectively. These results are consistent with (30) , (31).

Design-Expert® Software
Factor Coding: Actual
Slippage



X1 = A: Rear weight
X2 = B: Front weight

Actual Factors
C: Tillage depth = 20.00
D: Tractor speed = 3.43

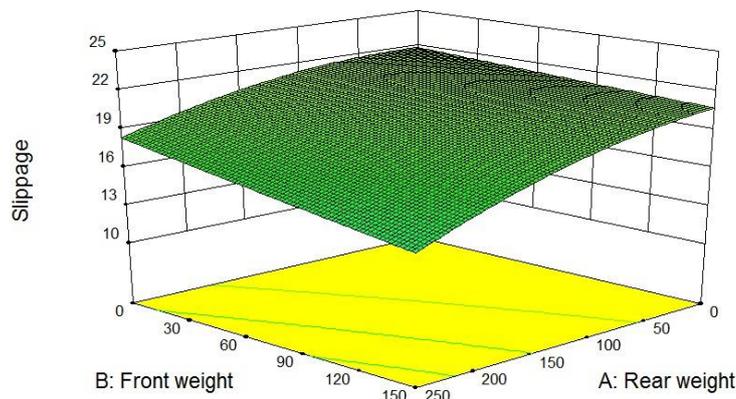


Figure (4). The effect of rear weight and front weight on the slip ratio

Figure (5) illustrates the effect of both rear weight and plowing depth, as well as their interaction, on the slip ratio. The results showed an increase in slippage with increased plowing depth, where increasing the plowing depth from 10 to 30 cm led to a 140% increase in slippage. This is due to the increased load resulting from greater soil resistance as depth increases. The highest slip ratio was 28% at a rear weight of 0 kilograms and a depth of 30 cm, while the lowest slip ratio was 10% at a rear weight of 250 kilograms and a depth of 10 cm. These results are consistent with (32) , (33).

Design-Expert® Software
Factor Coding: Actual
Slippage



X1 = A: Rear weight
X2 = C: Tillage depth

Actual Factors
B: Front weight = 75.00
D: Tractor speed = 3.43

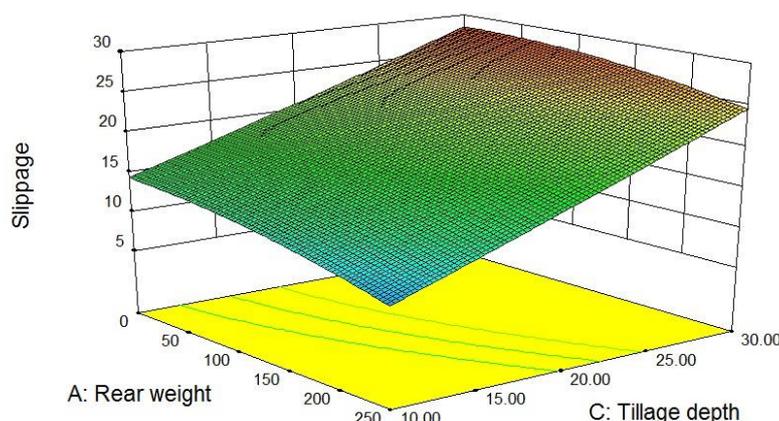


Figure (5) Effect of Rear Weight and Plowing Depth on Slip Ratio

Figure (6) illustrates the effect of rear weight and forward speed, as well as their interaction, on the slip ratio. The results showed an increase in slippage with increased forward speed. Increasing the forward speed from 1.95 to 4.9 m/s led to a 16% increase in slippage. This is due to the reduced time for the tractor wheels to grip the ground. Higher forward speed results in a faster process of soil layer separation and fragmentation, causing the soil to react more strongly when cut, thereby increasing the time needed to displace the soil and the energy consumed. The highest slip ratio was



22% at a rear weight of 0 kilograms and a speed of 4.9 m/s. The lowest slip ratio was 15% at a rear weight of 250 kilograms and a speed of 1.95 m/s. These results are consistent with (34).

Design-Expert® Software
 Factor Coding: Actual
 Slippage
 30.6122
 4.10256
 X1 = A: Rear weight
 X2 = D: Tractor speed
 Actual Factors
 B: Front weight = 75.00
 C: Tillage depth = 20.00

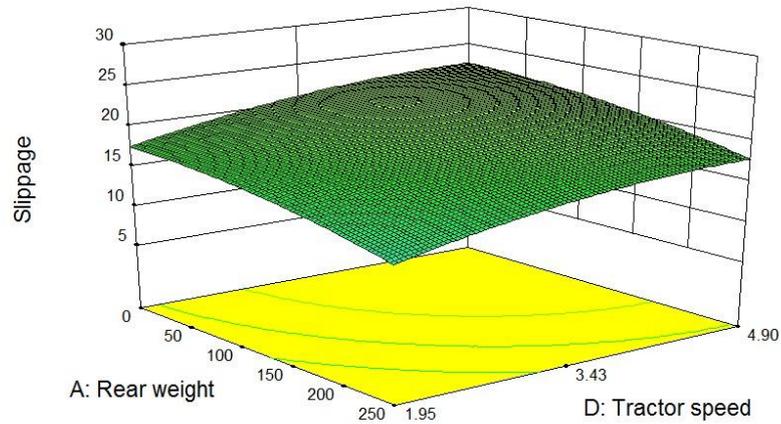


Figure (6) Effect of Rear Weight and Forward Speed on Slip Ratio

Figure (7) illustrates the effect of both front weight and plowing depth, as well as their interaction, on the slip ratio. The results showed that the highest slip ratio was 29% at a front weight of 0 kilograms and a depth of 30 cm, and the lowest slip ratio was 12% at a front weight of 150 kilograms and a depth of 10 cm. These results are consistent with (35).

Design-Expert® Software
 Factor Coding: Actual
 Slippage
 30.6122
 4.10256
 X1 = B: Front weight
 X2 = C: Tillage depth
 Actual Factors
 A: Rear weight = 125.00
 D: Tractor speed = 3.43

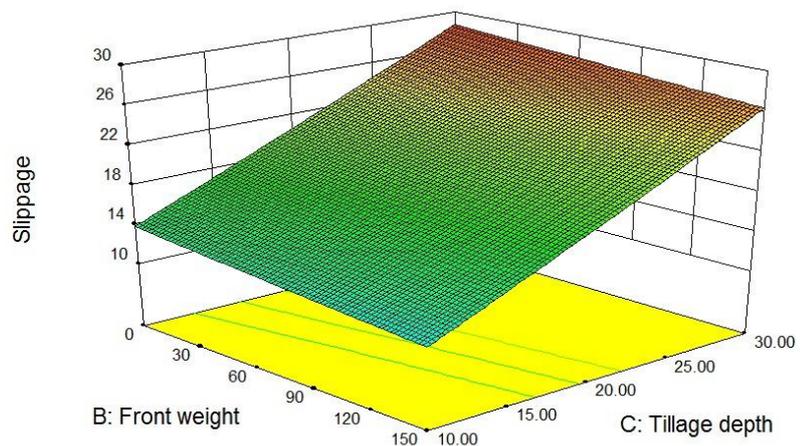


Figure (7) Effect of Front Weight and Plowing Depth on Slip Ratio

Figure (8) illustrates the effect of both front weight and forward speed, as well as their interaction, on the slip ratio. The highest slip ratio was 23% at a front weight of 0 kilograms and a forward speed of 4.9 m/s, and the lowest slip ratio was 16% at a front weight of 150 kilograms and a forward speed of 1.95 m/s.



Design-Expert® Software

Factor Coding: Actual

Slippage

30.6122

4.10256

X1 = B: Front weight

X2 = D: Tractor speed

Actual Factors

A: Rear weight = 125.00

C: Tillage depth = 20.00

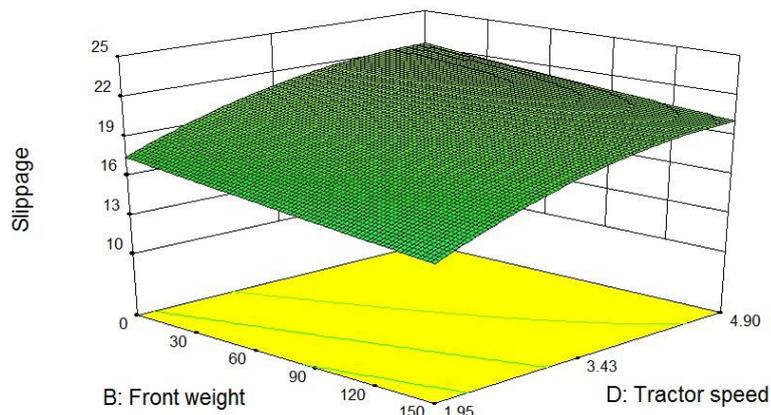


Figure (8) Effect of Front Weight and Forward Speed on Slip Ratio

Figure (9) illustrates the effect of both plowing depth and forward speed, as well as their interaction, on the slip ratio. The highest slip ratio was 28% at a depth of 30 cm and a speed of 4.9 m/s, and the lowest slip ratio was 10% at a depth of 10 cm and a speed of 1.95 m/s. These results are consistent with (36).

Design-Expert® Software

Factor Coding: Actual

Slippage

30.6122

4.10256

X1 = C: Tillage depth

X2 = D: Tractor speed

Actual Factors

A: Rear weight = 125.00

B: Front weight = 75.00

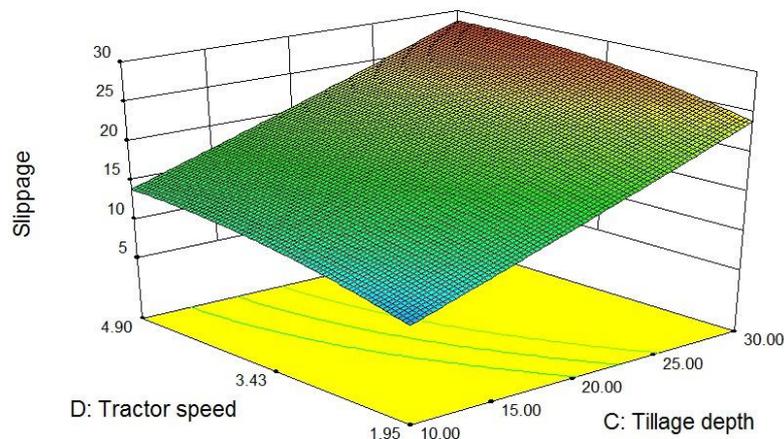


Figure (9) Effect of Plowing Depth and Forward Speed on Slip Ratio

Figure (10) illustrates the importance of each variable on agricultural tractor slippage. The results indicated that plowing depth is the most influential factor on slippage, followed by rear weight, then forward speed, and finally front weight. It can also be observed that rear weight and front weight have an inverse and positive impact on tractor slippage.

Design-Expert® Software
Factor Coding: Actual
Slippage

Actual Factors
A: Rear weight = 125.00
B: Front weight = 75.00
C: Tillage depth = 20.00
D: Tractor speed = 3.43

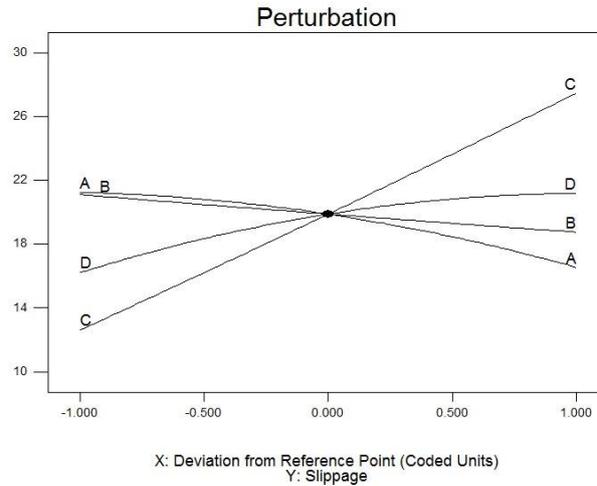


Figure (10) Impact of Changes in Any of the Four Factors (A, B, C, D) on Slip Ratio

Figure (11) shows the relationship between calculated slip values in the field and expected values, then deriving slip values by identifying key factors including rear weight, front weight, plowing depth, and forward speed of the tractor, along with their interaction. This relationship is represented by an equation for the studied factors, as mentioned in the equation (4), achieving the best prediction performance with a determination coefficient (R^2) of 0.9837.

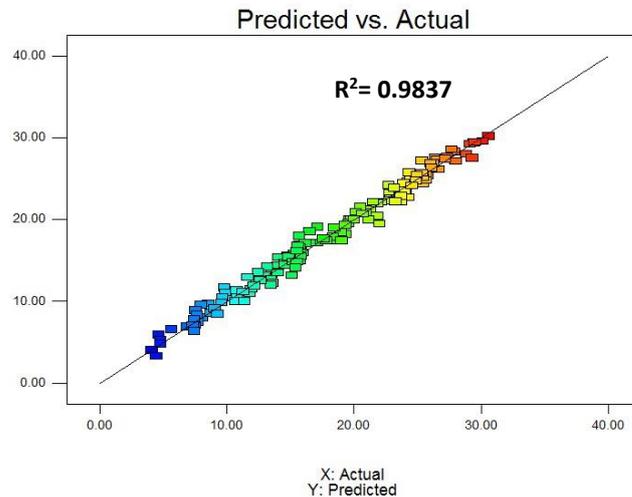


Figure (11) The Relationship Between Predicted Slip Ratio and Field-Measured Slip Ratio

The final equations in terms of actual factors for Slippage

$$= -3.91623 - 4.27741E-003 * \text{Rear weight} - 0.012617 * \text{Front weight} + 0.65342 * \text{Tillage depth} + 5.52848 * \text{Tractor speed} - 6.25187E-005 * \text{Rear weight} * \text{Front weight} + 3.55187E-004 * \text{Rear weight} * \text{Tillage depth} - 3.23094E-004 * \text{Rear weight} * \text{Tractor speed} + 6.68783E-005 * \text{Front weight} * \text{Tillage depth} + 6.40405E-004 * \text{Front}$$

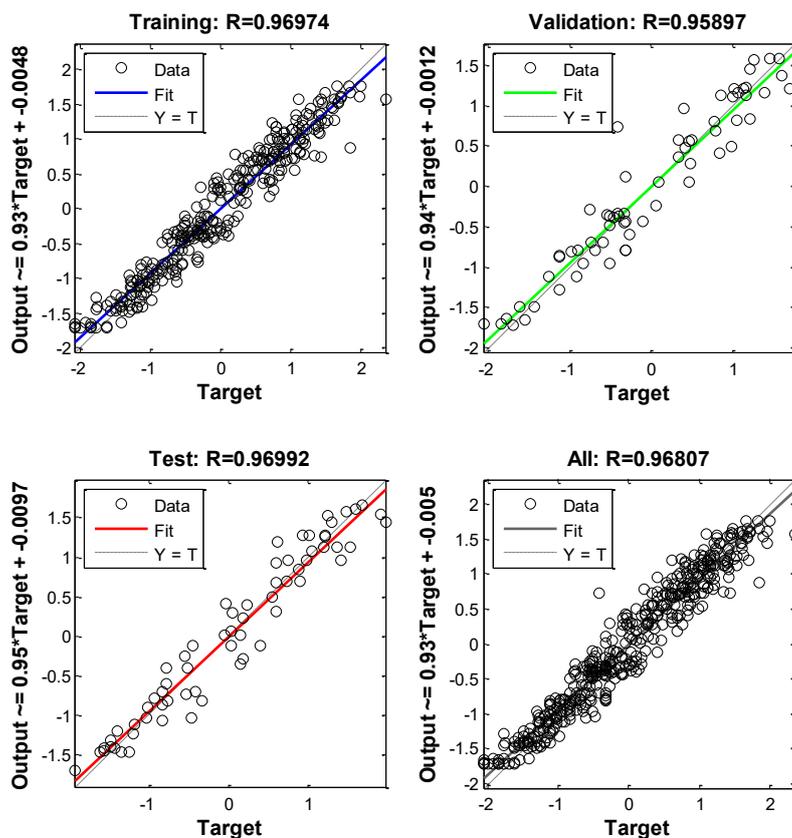


$$\begin{aligned} & \text{weight} * \text{Tractor speed} -6.48300\text{E-}003 * \text{Tillage depth} * \text{Tractor speed} -6.33588\text{E-}005 \\ & * \text{Rear weight}^2 + 8.21092\text{E-}006 * \text{Front weight}^2 + 1.54360\text{E-}003 * \text{Tillage depth}^2 - \\ & 0.54340 * \text{Tractor speed}^2 \end{aligned} \quad (4)$$

The results indicate that the performance of artificial neural networks (ANN) using the Levenberg-Marquardt algorithm provides high accuracy in predicting slip ratios. It achieved the best performance with determination coefficient (R^2) and Mean Squared Error (MSE) values of 0.9407 and 0.009475 respectively. The regression plots illustrate the relationship between actual and predicted values for the ANN in the training sets, using 70% of the data with a correlation coefficient of 0.9697 (Figure 12-a), 15% for validation with a correlation coefficient of 0.9589 (Figure 12-b), and 15% for testing with a correlation coefficient of 0.9699 (Figure 12-c). Figure 12-d demonstrates the overall data convergence on the unity slope line, indicating good model performance with a correlation coefficient of 0.9680 .

Additionally, Figure 13 shows differences in MSE for training, validation, and testing samples over the number of cycles, where after the 9th cycle, the neural network exhibited the best performance with the lowest MSE around 0.009475. Overall, these results demonstrate that the ANN model successfully learns from the training dataset to accurately predict slip ratios, as evidenced by the linear equations plotted on the vertical axis of Figures (12-a,b,c,d).





Figures (12-a, b, c, d) ANN Model for Predicting Slip Ratio Using Levenberg-Marquardt Training Algorithm

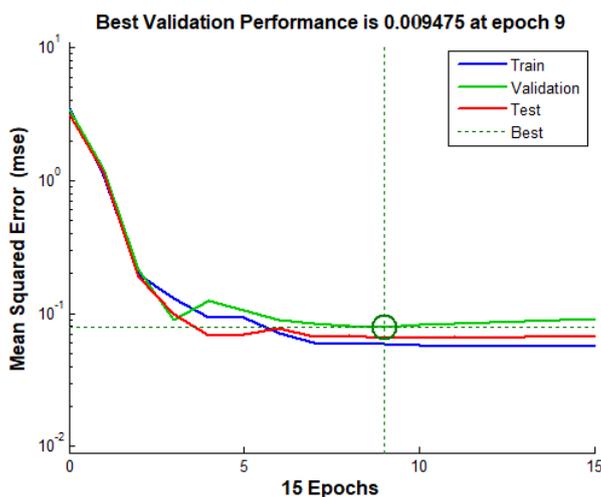


Figure (13) Regression Result for Neural Network Training on MSE for Slip Ratio

1.6. Rolling resistance



Figure (14) illustrates the impact of rear wheel weight and front tractor weight, and their interaction on rolling resistance. The results showed a significant increase in rolling resistance with increased rear wheel weight, increasing by 120 units when weight increased from 0 to 250 kilograms. Similarly, an increase in front tractor weight also resulted in increased rolling resistance, by 30 units when weight increased from 0 to 150 kilograms. The increase in rolling resistance with both rear and front weights is attributed to wheel sinking, soil compaction in front of the wheels, and increased wheel flattening due to additional tractor weight. The highest rolling resistance value was 1950 Newtons with a rear weight of 250 kilograms and a front weight of 150 kilograms, while the lowest rolling resistance value was 1720 Newton without any additional rear or front weight (0 kilograms each). These findings align with (37).

Design-Expert® Software
 Factor Coding: Actual
 Original Scale
 Rolling resistance
 2048
 1561.67
 X1 = A: Rear weight
 X2 = B: Front weight
 Actual Factors
 C: Tillage depth = 20.00
 D: Tractor speed = 3.43

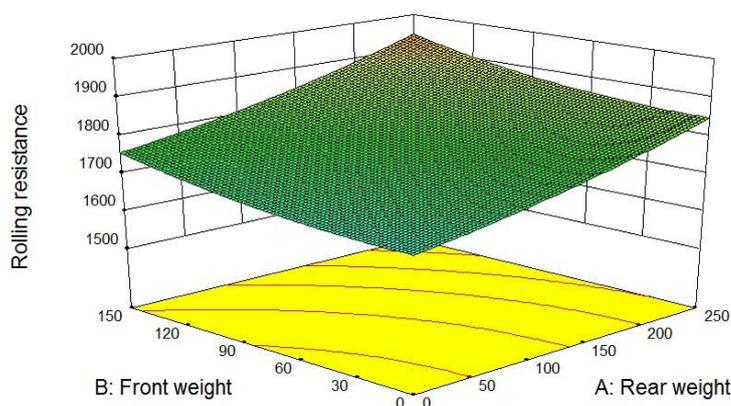


Figure (14) Impact of Rear Wheel Weight and Front Tractor Weight on Rolling Resistance

Figure 15 illustrates the impact of both rear wheel weight and plowing depth, and their interaction, on rolling resistance. The results indicated no effect of plowing depth on rolling resistance. The highest rolling resistance value was observed at a rear wheel weight of 250 kilograms and a plowing depth of 30 cm, measuring 1890 Newton. The lowest value, 1700 Newton, was recorded at a plowing depth of 10 cm and no additional rear wheel weight (0 kilograms).

Design-Expert® Software

Factor Coding: Actual

Original Scale

Rolling resistance

2048

1561.67

X1 = A: Rear weight

X2 = C: Tillage depth

Actual Factors

B: Front weight = 75.00

D: Tractor speed = 3.43

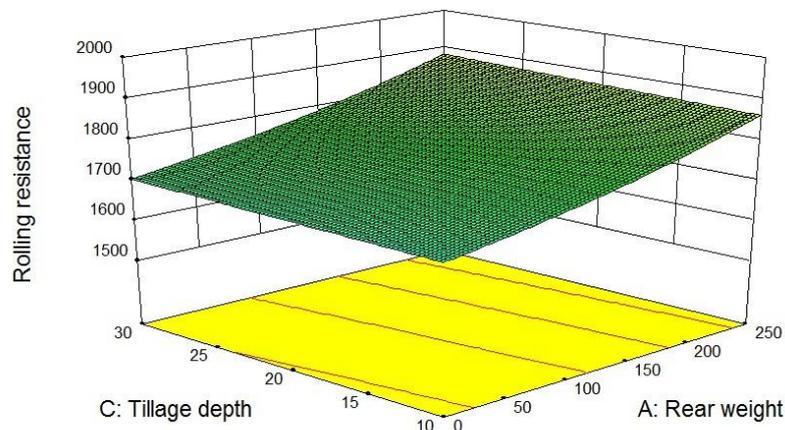


Figure (15) The Effect of Rear Wheel Weight and Plowing Depth on Rolling Resistance

The figure (16) illustrates the effect of rear wheel weight of the tractor, forward speed, and their interaction on rolling resistance. The results show a significant increase in rolling resistance with increased forward speed. Specifically, rolling resistance increased by 165 units when speed increased from 1.95 to 4.90 m/s, attributed to the increased force required to push the soil forward, thereby increasing the opposing force to the tractor movement. The highest rolling resistance recorded was 1980 newton at a rear weight of 250 kilograms and a forward speed of 4.90 m/s, while the lowest value was 1620 newton at zero rear weight and a forward speed of 1.95 m/s. These findings were documented in (38).

Design-Expert® Software

Factor Coding: Actual

Original Scale

Rolling resistance

2048

1561.67

X1 = A: Rear weight

X2 = D: Tractor speed

Actual Factors

B: Front weight = 75.00

C: Tillage depth = 20.00

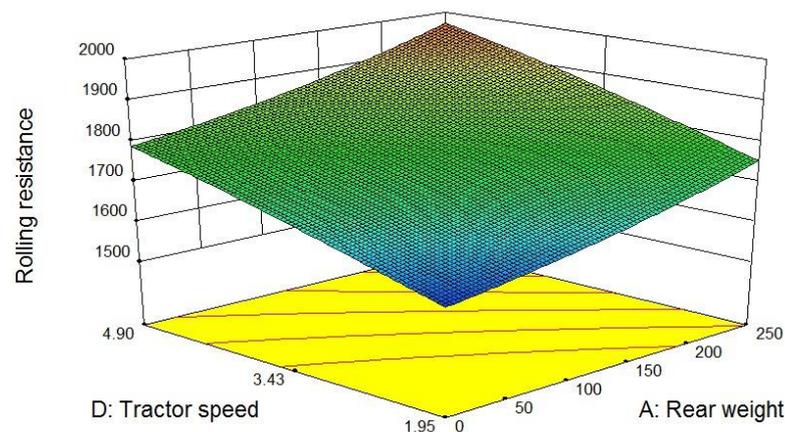


Figure (16) The effect of rear wheel weight and forward speed on rolling resistance.

The impact of additional weight on the front of the tractor, depth, and their interaction on rolling resistance is illustrated in Figure (17). The results showed that the highest



rolling resistance value was 1850 nektons with a front weight of 150 kilograms and a depth of 30 cm. The lowest value was 1790 newton with no additional weight (0 kilograms) and a depth of 10 cm. Figure (18) demonstrates the effect of additional weight on the front of the tractor, forward speed, and their interaction on rolling resistance. A weight of 150 kilograms and a speed of 4.90 meters per second resulted in the highest rolling resistance value of 1930 newton, whereas 0 kilograms weight and a speed of 1.95 meters per second yielded the lowest value of 1670 newton. Figure (19) shows the impact of plowing depth, forward speed, and their interaction on rolling resistance. The results indicated that the highest rolling resistance value was 1880 newton at a depth of 30 cm and a speed of 4.90 meters per second, while the lowest value was 1680 newton at a depth of 10 cm and a speed of 1.95 meters per second.

Design-Expert® Software
 Factor Coding: Actual
 Original Scale
 Rolling resistance
 2048
 1561.67
 X1 = B: Front weight
 X2 = C: Tillage depth
 Actual Factors
 A: Rear weight = 125.00
 D: Tractor speed = 3.43

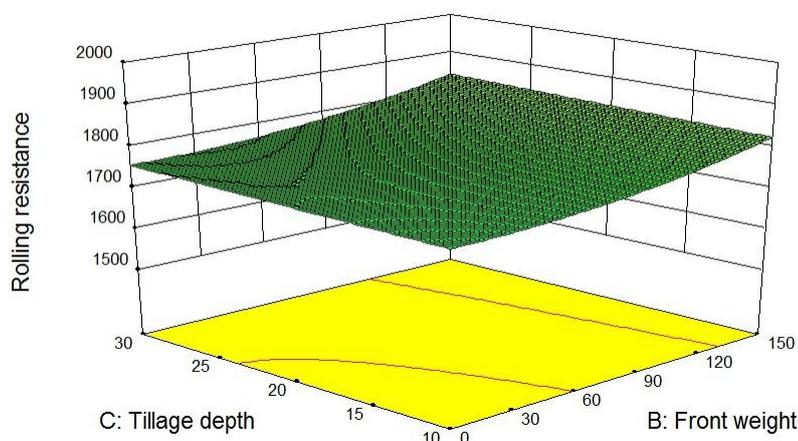


Figure (17) The impact of front weight and plowing depth on rolling resistance

Design-Expert® Software
 Factor Coding: Actual
 Original Scale
 Rolling resistance
 2048
 1561.67
 X1 = B: Front weight
 X2 = D: Tractor speed
 Actual Factors
 A: Rear weight = 125.00
 C: Tillage depth = 20.00

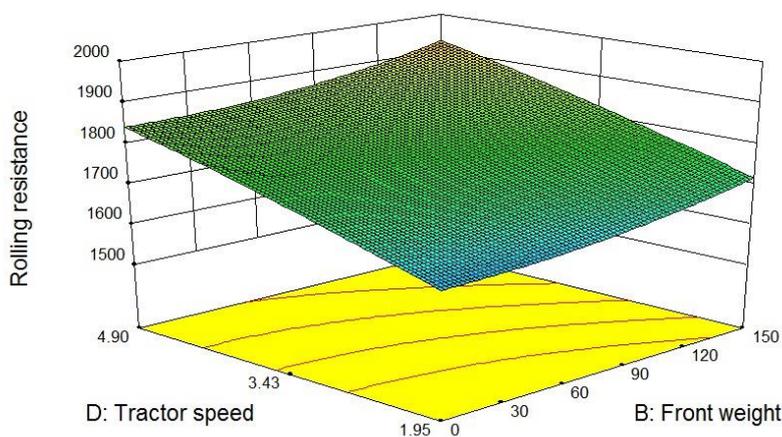


Figure (18) The impact of front weight and tractor speed on rolling resistance



Design-Expert® Software

Factor Coding: Actual

Original Scale

Rolling resistance

2048

1561.67

X1 = C: Tillage depth

X2 = D: Tractor speed

Actual Factors

A: Rear weight = 125.00

B: Front weight = 75.00

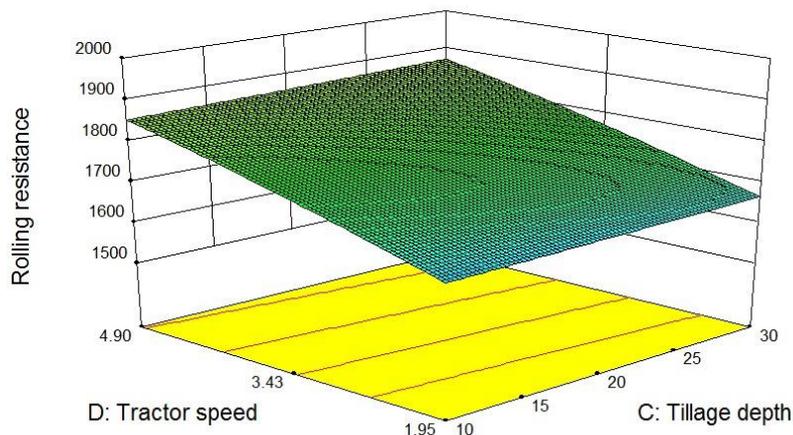


Figure (19) The impact of tillage depth and tractor speed on rolling resistance

Figure 20 illustrates the impact of each factor studied on rolling resistance. Forward speed is shown to have the greatest impact on rolling resistance, followed by the rear wheel weight of the tractor, and then the front weight of the tractor. Depth had no significant effect. All factors exhibited a direct proportional effect on rolling resistance.

Design-Expert® Software

Factor Coding: Actual

Original Scale

Rolling resistance

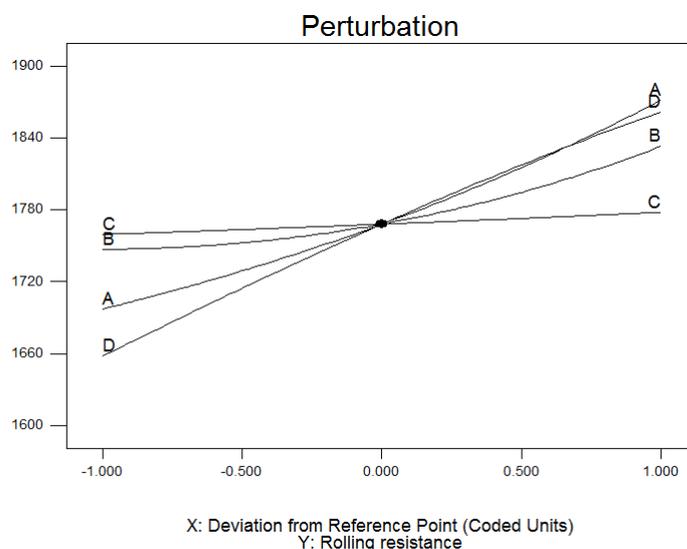
Actual Factors

A: Rear weight = 125.00

B: Front weight = 75.00

C: Tillage depth = 20.00

D: Tractor speed = 3.43



Here is the translation:

Figure (20) the extent of influence on rolling resistance when changing any of the four factors (A, B, C, D).

Figure (21) illustrated the relationship between the measured field rolling resistance values and the predicted values was established. After identifying the key factors (rear wheel weight, front weight, tillage depth, forward speed, and their interactions), the rolling resistance values were determined. The relationship between these studied



factors was represented by the equation (5) and showed the best performance in predicting with an R-squared value of 0.9989.

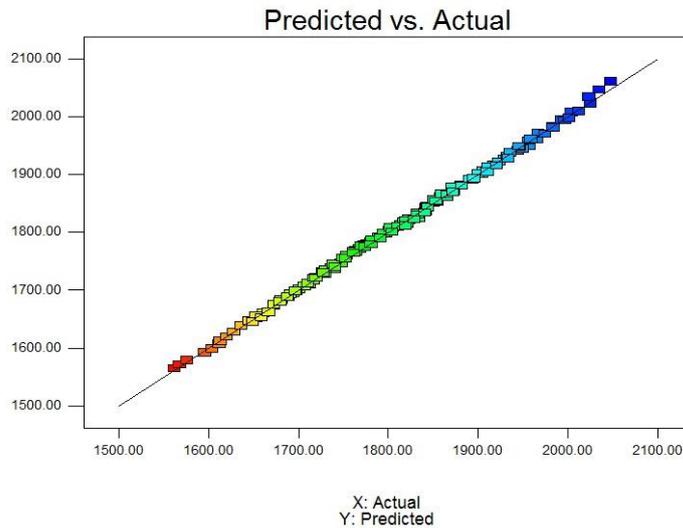


Figure (21) The relationship between the predicted rolling resistance and the field-measured rolling resistance.

The final equations in terms of actual factors for Rolling resistance

$$1/(\text{Rolling resistance}) = +7.09619\text{E-}004 - 1.87821\text{E-}007 * \text{Rear weight} - 3.64804\text{E-}008 * \text{Front weight} - 2.31275\text{E-}007 * \text{Tillage depth} - 3.90142\text{E-}005 * \text{Tractor speed} - 4.70158\text{E-}012 * \text{Rear weight} * \text{Front weight} - 1.54890\text{E-}010 * \text{Rear weight} * \text{Tillage depth} + 9.73029\text{E-}009 * \text{Rear weight} * \text{Tractor speed} - 7.36701\text{E-}011 * \text{Front weight} * \text{Tillage depth} + 1.06913\text{E-}008 * \text{Front weight} * \text{Tractor speed} + 1.05978\text{E-}008 * \text{Tillage depth} * \text{Tractor speed} - 2.46931\text{E-}010 * \text{Rear weight}^2 - 1.18048\text{E-}009 * \text{Front weight}^2 - 1.90064\text{E-}009 * \text{Tillage depth}^2 + 2.09568\text{E-}006 * \text{Tractor speed}^2$$

(5)

The results demonstrated excellent performance in prediction using the Levenberg-Marquardt algorithm, which enables accurate prediction of rolling resistance under field conditions. It achieved the best performance with coefficient of determination (R^2) and Mean Squared Error (MSE) values of 0.9773 and 0.004365 respectively. Regression plots illustrated the relationship between actual and predicted values using Artificial Neural Networks (ANNs) in the training set, achieving a correlation coefficient of 0.9920 (Figure 22-a). The validation set showed a correlation coefficient of 0.9887 (Figure 22-b), while the test set demonstrated the best prediction performance with a correlation coefficient of 0.9886 (Figure 22-c). Figure 22-d depicted significant convergence of scattered data points along the unity slope line, indicating robust model performance with a correlation coefficient of 0.9911. Figure 23 highlighted differences



in MSE across training and validation samples used in the network, showing that by cycle 12, the neural network achieved its best performance with an MSE value around 0.004365. Consequently, it can be concluded that the network successfully learned from the input training data, enabling accurate prediction of rolling resistance as depicted in Figures 22-a, b, c, and d.

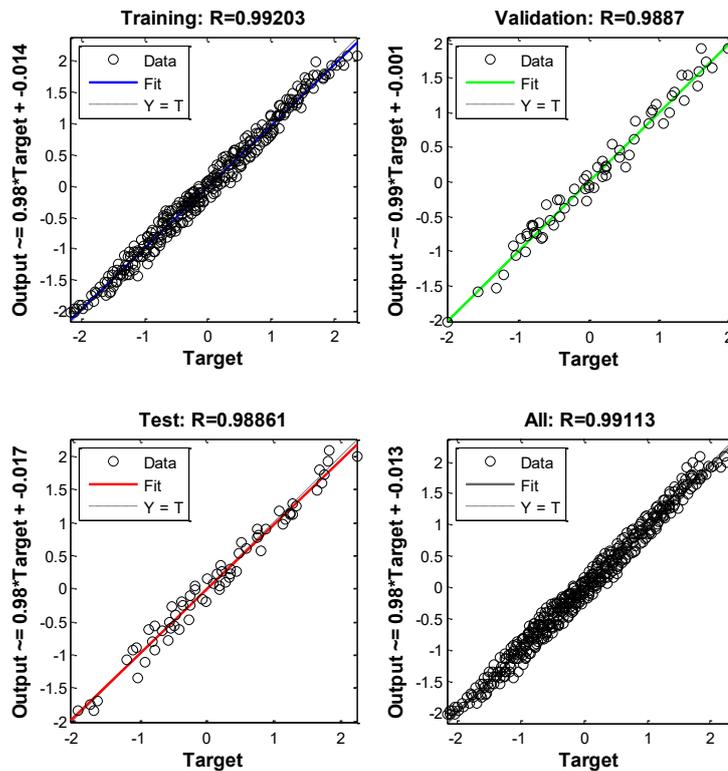


Figure (22-a, b, c, d) ANN Model for Predicting Rolling Resistance Using Levenberg-Marquardt Training Algorithm



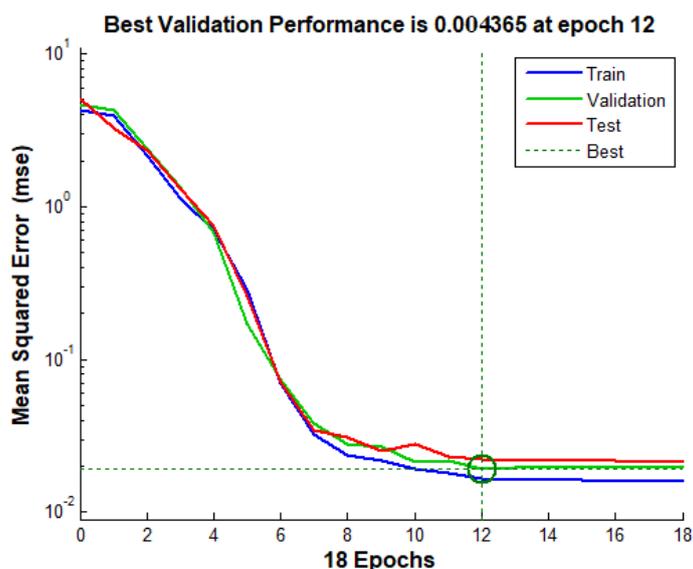


Figure (23) Regression Result for Neural Network Training on MSE for Rolling Resistance

2. Conclusion

This research presents a mathematical model to predict tractor slip and rolling resistance under the influence of adding different weights to the tractor's rear wheels and front axle in various field conditions. Using Artificial Neural Networks (ANN) and Design Expert software, reliable mathematical models were developed based on statistical data. The results showed that the most influential factor on slip was tillage depth, which had a direct effect with an impact percentage of 54%. This was followed by rear weight with an impact percentage of 30%, which had an inverse and positive effect on slip. The next factor was forward speed with a direct effect of 23.8%, followed by front weight with an inverse and positive effect of 11.4%. The results showed that increasing the rear wheel weight of the tractor reduced slip by 22%, while increasing the front axle weight reduced slip by 11%. Increasing the tillage depth resulted in a 140% increase in slip, and increasing the forward speed led to a 16% increase in slip. Regarding rolling resistance, the results indicated that forward speed was the most influential factor with an impact percentage of 10.7%. This was followed by the rear wheel weight and the front axle weight with impact percentages of 9.3% and 5%, respectively. All factors had a direct and negative impact on rolling resistance, except tillage depth, which had no significant effect (at a 0.05 significance level). The results showed that increasing the rear wheel weight of the tractor led to an increase in rolling resistance by 120 N, while increasing the front axle weight led to an increase of 30 N. Increasing the forward speed resulted in an increase of 165 N in rolling resistance. The interaction results

showed that a rear weight of 250 kg and a front weight of 150 kg provided the lowest slip ratio of 16% and the highest rolling resistance of 1950 N. The highest slip ratio of 22% and the lowest rolling resistance of 1720 N were obtained without adding any weight to the rear wheels (0 kg) and the front axle (0 kg) at a tillage depth of 20 cm and a forward speed of 3.43 m/s. The ANN and the mathematical models using Design Expert software provided highly accurate and reliable results for predicting tractor wheel slip and rolling resistance under the influence of adding different weights to the rear wheels and front axle in various field conditions. The ANN, using the Levenberg-Marquardt training algorithm, showed a high prediction accuracy for slip ratio ($R^2=0.9407$, $MSE=0.00947$) and rolling resistance ($R^2=0.9773$, $MSE=0.00436$). The mathematical models using Design Expert software provided the best performance for predicting slip ratio with an R^2 value of 0.9837 and rolling resistance with an R^2 value of 0.9989.

IV. References

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