Mathematical and Computational Applications, Vol. 17, No. 3, pp. 182-192, 2012

PREDICTION OF TIRE TRACTIVE PERFORMANCE BY USING ARTIFICIAL NEURAL NETWORKS

Kazım Çarman[1] Alper Taner[2]

[1]University of Selcuk, Faculty of Agriculture, Department of Agricultural Machinery, Selcuklu 42075, Konya, Turkey,
[2]University of Ondokuz Mayis, Faculty of Agriculture, Department of Agricultural Machinery, Samsun, Turkey
kcarman@selcuk.edu.tr

Abstract- The purpose of this study was to investigate the relationship between travel reduction and tractive performance and to illustrate how artificial neural networks (ANNs) could play an important role in the prediction of these parameters. The experimental values were taken in a soil bin. A 1-4-6-2 artificial neural network (ANN) model with a back propagation learning algorithm was developed to predict the tractive performance of a driven tire in a clay loam soil under varying operating and soil conditions. The input parameter of the network was travel reduction. The output parameters of the network were net traction ratio and tractive efficiency. The relationships were investigated using non-linear regression analysis and ANNs. The performance of the neural network-based model was compared with the performance of a non linear regression-based model using the same observed data. It was found that the ANN model consistently gave better predictions compared to the non linear regression-based model. Based on the results of this study, ANNs appear to be a promising technique for predicting tire tractive performance.

Key Words- Artificial neural networks, prediction, tire tractive performance

1. INTRODUCTION

Energy efficiency has become an increasingly important issue in the world. Much effort has been expended to develop cultural systems for crops that minimize fuel usage as well as to find alternative renewable fuels for crop production.

The relationship between soil and the tractive device is an important field of study. The soil-tire interface is responsible for approximately 20 to 55% of the losses of tractor power, a factor that drastically affects the amount of fuel used in drawbar - implement applications [1]. Gill and Vandenberg [2] estimated a national yearly fuel loss of 575 million liters due to poor soil-traction interfaces in agricultural applications alone. This factor multiplied by a conservative 2.00 dollars per gallon of diesel fuel equates to a 304 million dollar yearly loss solely in the agricultural production sector. This loss of energy by the pneumatic tire has prompted researchers to search for operational parameters that could improve tractive efficiency.

Developments of prediction equations for tire tractive performance have been the focus of much research. Two approaches can be used for the prediction of the traction driving force for a tire moving on a soil; mathematical modeling of the traction behavior at the tire–soil interaction [3,4] and dimensional analysis [5,6]. Schmulevich et al., [7] examined a simulation model to predict the effect of velocity on rigid wheel performance. The results corroborate that the effect of velocity on wheel performances cannot be neglected. Wheel performances such as maximum net tractive ratio and maximum tractive efficiency increase with increasing relative velocity.

A study was conducted to determine the accuracy of Wismer-Luth and Brixius equations in predicting net traction ratio of a high-lug agricultural tire by Elwaleed et al. [8]. The tire was tested on a sandy clay loam soil in an indoor University Putra Malaysia tire traction testing facility. Regression analysis was conducted to determine the prediction equation describing the tire torque ratio. The logarithmic model was found suitable in torque ration prediction. Tarhan and Çarman [9] developed two mathematical equations by dimensional analysis to predict the torque and power requirements at zero net traction for traction tires (6.5-12; 7.00-18) on a hard surface. Some structural and working parameters of the tire that affect the torque requirement, such as tire size, tire deflection, tire load, and rolling radius, were considered for the analysis. The ratio of tire width over tire diameter and the ratio of tire deflection over tire section height were found to be dimensionless terms radically controlling the torque and energy requirements of tires. The prediction equation closely followed the experimental results.

Soft computing technology is an interdisciplinary research field in computational science. At present, various techniques in soft computing such as statistics, machine learning, neural network and fuzzy data analysis are being used for exploratory data analysis. In recent years, the methods of artificial intelligence have widely been used in different areas including agricultural applications [10-12].

The performance values of a driven tire were calculated using a fuzzy expert system. The results were compared with the experimental data and it was seen that the results obtained from the fuzzy expert system were closer to the experimental data. The mean relative error and correlation coefficient between measured and predicted values of traction efficiency were found as 9.1 % and 0.987 respectively [13].

In this study, a statistical data-driven approach, i.e. artificial neural networks (ANNs), is introduced as an alternative to these mathematical models. ANNs are used in a wide range of engineering and non-engineering applications, such as, pattern recognition (spectroscopy, protein analysis, fingerprint identification), as well as behavior prediction and function approximation (stock market forecasting, energy demand forecasting, process control systems). These methods are inspired by the central nervous system, exploiting features such as high connectivity and parallel information processing, exactly like in the human brain. The characteristic feature of ANNs is that they are not programmed; they are trained to learn by experience [14,15].

An important stage of a neural network is the training step, in which an input is introduced to the network together with the desired output, and the weights are adjusted so that the network attempts to produce the desired output. The weights after training contain meaningful information, whereas before training they are random and have no meaning. When a satisfactory level of performance is reached, the training stops, and the network uses the weights to make decisions.

The aim of this study is to investigate the relationship between travel reduction to net traction ratio and tractive efficiency, and the construction of artificial neural networks for the prediction of the net traction ratio and tractive efficiency. Sampling data collected from a soil bin were used to validate the artificial neural networks. The prediction quality of the models proposed was evaluated and compared.

2. MATERIAL AND METHODS

This study was conducted under controlled conditions in a soil bin at the Department of Agricultural Machinery, Selçuk University, Turkey by using a single-wheel agricultural tire test machine as described by Çarman and Aydin [16]. The soil bin used in these tests was 20 m long, 2.25 m wide and 1m deep. This machine has provisions for operating the test tire and for controlling the dynamic load and drawbar pull and predetermined levels using a control system. Pertinent tire performance parameters were measured throughout each test.

Soil bins containing clay loam were used in the study. The average cone index of the soil was approximately 1500 kPa for a depth of 20 cm.

The tire used in this study was a 7.00-R18 and the lug height, total lug area of the tire and the drawbar height were 24.2 mm, 21% and 380 mm respectively. In the experiments, the tire was operated at dynamic loads of 4, 5 and 6 kN, at a constant forward velocity of 0.51 m/s and an inflation pressure of 150 kPa.

In test machine, an adjustable overload clutch was used to provide different drawbar pulls that varied between 1.25 and 3.40 kN. Forward velocity was measured using a speed sensor attached to the test machine. The dynamic rolling radius of the tire was determined with zero drawbar pulls on a concrete road surface. The distance travelled by three complete revolutions of the tire in a straight line was measured with a tape measure and divided by 6π to obtain the dynamic rolling radius [17].

The input torque was sensed by a torque transducer and was recorded using data logger.

The traction parameters used to describe the tractive performance are as follows: Tractive efficiency (TE):

$$TE = \frac{N_d}{N_a} \tag{1}$$

Net traction ratio (NTR):

$$NTR = \frac{P}{W} \tag{2}$$

Travel reduction (TE):

$$TR = \left(1 - \frac{V_a}{V_t}\right)100 \tag{3}$$

Where N_d is drawbar power, N_a is the axle power, W is the dynamic weight/normal load on wheel axle, P is the drawbar pull, V_a is the actual velocity and V_t is the theoretical velocity [16,18].

ANNs learn by using examples, namely patterns. In other words, to train and test a neural network, input data and corresponding target values are necessary. The examples in this study are numerical values determined by using experimental results, and 15 patterns were obtained from the experiments. Here, ANNs were used for modeling net traction ratio and tractive efficiency. The input for the network was travel reduction. The outputs were net traction ratio and tractive efficiency.

The experimental results were used to train and test the network. To train the network, 11 experimental results, from the total of 15, were used as data sets, while 4 results were used as test data. The architecture of the ANN was 1-4-6-2, 1 corresponding to the input value, 4-6 for the number of hidden layer neurons and 2 for the outputs.

The back propagation learning algorithm was used in the feed forward, two hidden layers ANN. Training of the network was performed by using the Levenberg–Marquardt [19,20], back propagation algorithms. These algorithms are iteratively adjust the weights to reduce the error between the experimental and predicted outputs of the network. Back propagation networks use the logarithmic sigmoid (logsig), the hyperbolic tangent sigmoid (tansig) or the linear (purelin) transfer functions. Logsig, tansig, and purelin are transfer functions. The selected ANN structure of the multi-layer is shown in Fig. 1. This ANN model consists of two hidden layers of tansig and tansig neurons followed by an output layer of one linear neuron. Linear neurons are those that have a linear transfer function.

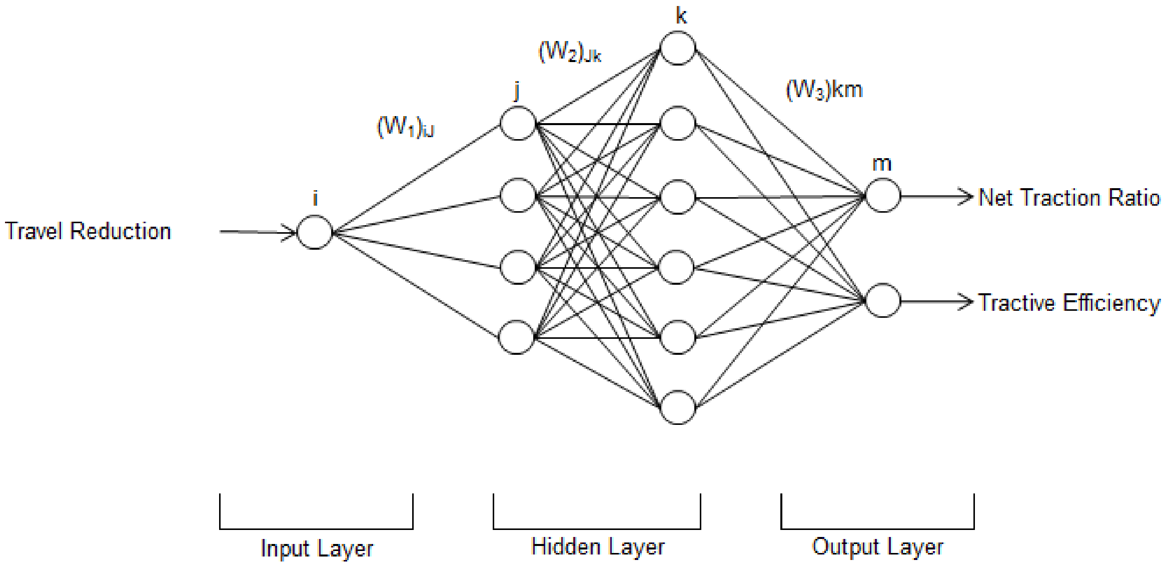

Figure 1. ANN architecture used for 4-6 neurons in two hidden layers

The best approach with minimum error is made with back propagation algorithm. A mathematical formula was developed by using the approach (Eq. 4). To calculate net traction ratio and tractive efficiency (y_m) used in this study.

$$y_m = \sum_k (W_3)_{k,m} . F_k + b_k \qquad (4)$$

The TANSIG transfer function (for second hidden layer) given in eq.(5).

$$F_k = \frac{2}{(1+e^{(-2*NET_k)})} - 1 \qquad (5)$$

$$NET_k = \sum_j (W_2)_{j,k} . F_j + b_j \qquad (6)$$

The TANSIG transfer function (for first hidden layer) given in eq.(7).

$$F_j = \frac{2}{(1+e^{(-2*NET_J)})} - 1 \qquad (7)$$

$$NET_j = \sum_i (W_1)_{i,j} . x_1 + b_i \qquad (8)$$

where i is the number of inputs, j is the number of neurons in the first hidden layer, k is the number of neurons in the second hidden layer, m is the number of outputs, W_1, W_2, W_3 are the weights of the connection, x is the input parameter, y is the output parameter and b is bias. The weights (W_1, W_2, W_3) are given in Table 1-3.

Table 1. Connection weight values for Eq. (4)

The number of outputs (m)	$(W_3)_{k1}$	$(W_3)_{k2}$	$(W_3)_{k3}$	$(W_3)_{k4}$	$(W_3)_{k5}$	$(W_3)_{k6}$
1	-0.2144	-0.373	-1.3462	-0.5746	-0.6634	-1.0085
2	-1.0739	-0.0514	-0.021	-0.0924	-0.1001	0.0322

Table 2. Connection weight values for Eq. (6)

The number of neurons in the second hidden layer (k)	$(W_2)_{j1}$	$(W_2)_{j2}$	$(W_2)_{j3}$	$(W_2)_{j4}$
1	1.1102	0.7258	1.4855	0.9173
2	0.8633	0.5674	1.8963	-1.2928
3	-0.0137	0.4685	-1.0618	-0.8691
4	-0.9962	0.4488	1.7544	-0.4327
5	1.297	-1.4068	-1.0625	-1.0952
6	-0.831	-0.6786	-2.0079	0.832

Table 3. Connection weight values for Eq. (8)

The number of neurons in the first hidden layer (J)	$(W_1)_i$
1	32.9994
2	-32.8009
3	32.7321
4	-32.8560

A computer program was performed under Matlab 7.0.4. In the training, an increased number of neurons were used in two hidden layers. When the network training was successfully finished, the network was tested with the test data.

In addition, the prediction of the model was obtained according to traditional methods (TM) of NTR and TE by using the Statistica software (Version 8.0). Travel reduction (TR) was used as a variable to obtain predicted equations.

The predictive ability of the developed systems (ANN and TM) were investigated according to mathematical and statistical methods. In order to determine the relative error (ε) of the system, the following equation was used [21].

$$\varepsilon = \frac{100\%}{\text{n}} \sum_{i=1}^{n} \left| \frac{y - \hat{y}}{y} \right| \tag{9}$$

Where n is the number of observations, y is the measured value and $\hat{y}$ is the predicted value.

The relative error gives the deviation between the predicted and experimental values and it is required to reach zero. In addition, goodness of fit (η) of the predicted system was calculated by the following equation [21,22].

$$\eta = \sqrt{1 - \frac{\sum_{i=1}^{n} (y - \hat{y})^2}{\sum_{i=1}^{n} (y - \bar{y})^2}} \tag{10}$$

Where $\bar{y}$ is the mean of measured values. The goodness of fit also gives the ability of the developed system and its highest value is 1.

3. RESULTS

The travel reduction of the tested agricultural tire on the soil in the soil bin increased with increasing drawbar pull, but decreased with increasing dynamic load (Fig. 2). The travel reduction varied from 6.1% to 40.5%. An increase of approximately 172% in drawbar pull resulted in a travel reduction increase of 469%, while an increase of 50% in dynamic load caused a 9.5 % decrease in travel reduction. For dynamic loads of 4, 5 and 6 kN, drawbar pulls varied between 1.25-2.95 kN, 1.61-3.15 kN and 1.85-3.40 kN, respectively. The effect of drawbar pull and dynamic load on travel reduction was statistically significant ($P < 0.01$). Drawbar pull was the major contributory factor on travel reduction as compared to dynamic load. The highest value of travel reduction was obtained at a dynamic load of 4 kN and drawbar pull of 2.95 kN.

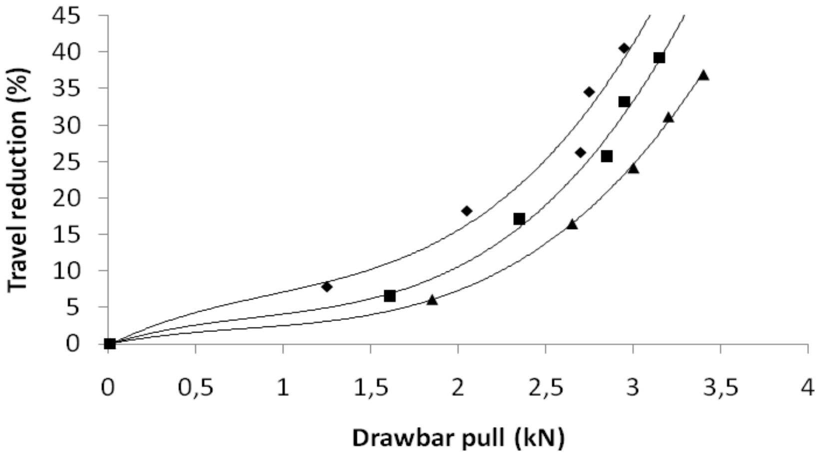

Figure 2. Effect of drawbar pull and dynamic load on travel reduction
(♦:4 kN, ■:5 kN, ▲:6kN)

Defining net traction ratio as a ratio of the drawbar pull to the dynamic load, the calculated average values of this quantity for different working conditions are shown in

Fig. 3. Net traction ratio varied between 0.308 and 0.737. While net traction ratio increased rapidly until a travel reduction of 20%, then it slowly increased with increasing travel reduction. An increase of approximately 564% in travel reduction resulted in a net traction ratio increase of 139%. The effect of travel reduction on net traction ratio was statistically significant (P < 0.01). The highest value of net traction

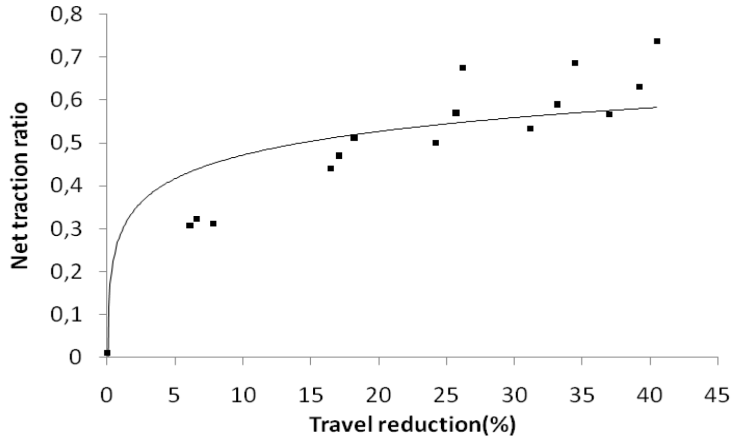

Figure 3. Effect of travel reduction on net traction ratio

ratio was obtained at a travel reduction of 40.5%. The results are similar to those reported by Bashford et al. [23], Bashford et al. [24], Elashry [25] and Esch et al. [26].

Tractive efficiency decreased with increasing travel reduction (Fig. 4). Tractive efficiency varied between 0.239 and 0.720. While tractive efficiency decreased sharply until a travel reduction of 20%, then it slowly decreased with increasing travel reduction. An increase of approximately 564% in travel reduction resulted in a tractive efficiency decrease of 201%. The effect of travel reduction on tractive efficiency was statistically significant (P < 0.01). The highest value of tractive efficiency was obtained at a travel reduction of 6.1%. The results are similar to those reported by Bashford et al. [23], Bashford et al. [24], Elashry [25] and Esch et al. [26].

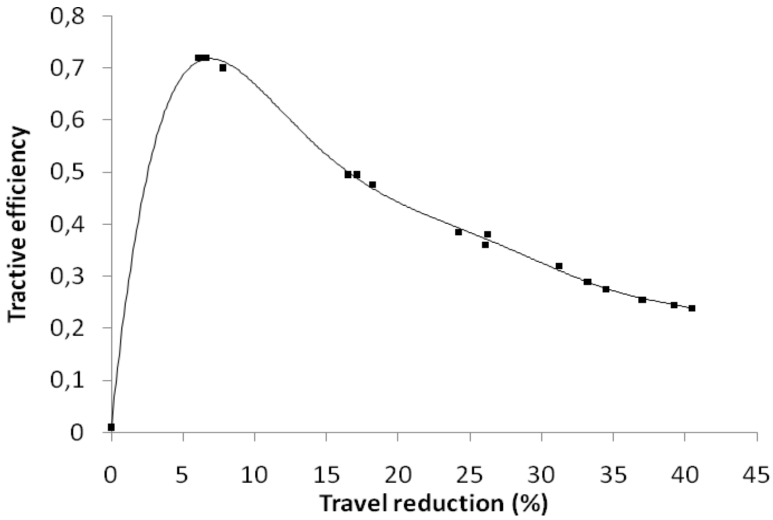

Figure 4. Effect of travel reduction on tractive efficiency

The results of the developed ANN were compared with the experimental results. For the testing data, the means of measured and predicted values of net traction ratio were 0.488 and 0.497 respectively. For tractive efficiency, the means of measured and predicted values were 0.466 and 0.462 respectively.
The correlations between measured and predicted values of net traction ratio and tractive efficiency in different working conditions are given in Figs. 5 and 6 respectively. The relationships were significant for all parameters. The correlation coefficients of the relationships were found to be 0.996 for net traction ratio and 0.999 for tractive efficiency.

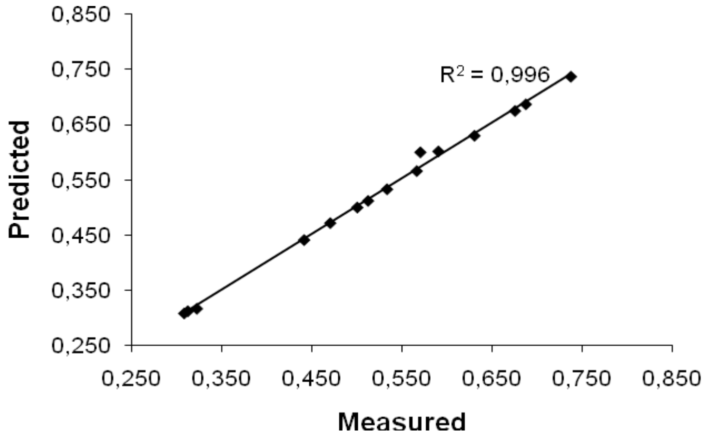

Figure 5. Correlation between measured values and predicted values of net traction ratio

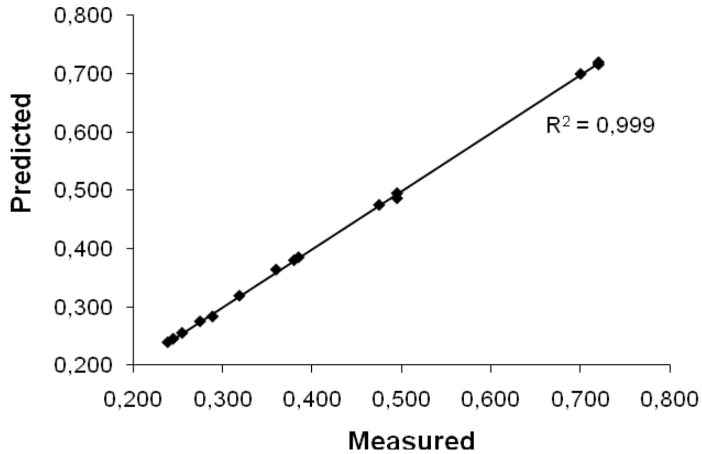

Figure 6. Correlation between measured values and predicted values of tractive efficiency.

For the testing data, the mean relative error of measured and predicted values (from ANN model) were 2.32% for net traction ratio and 1.33% for tractive efficiency. For all parameters, the relative error of the predicted value was found to be lower than the acceptable limits (10%) [22].
The non linear regression models obtained according to traditional methods are given below:

$$NTR = 0.130TR^{0.472}e^{-0.003TR} \quad (11)$$
$$TE = 0.960TR^{-0.048}e^{-0.030TR} \quad (12)$$

The goodness of fit (η) of the regression models developed were 0.923 for NTR and 0.994 for TE. The mean relative errors of net traction ratio and tractive efficiency values which were predicted by using regression models were 7.128% and 3.637%, respectively. The mean relative errors of the regression models were found to be greater than that of the ANN model.

The goodness of fit of the predicted (from the ANN model) values was found as 0.997 for net traction ratio and 0.999 for tractive efficiency. All values were found to be close to 1.0.

4. CONCLUSIONS

A neural network for the prediction of the net traction ratio and tractive efficiency of a driven tire was studied in this study. The overall results show that the networks can be used as an alternative way to find tire tractive performance in these systems. The LM, GD and GDM algorithms were studied, and the best results were obtained from the LM algorithm with 10 neurons in the hidden layer. The average values of the errors were well below 3%, and the maximum errors were below 6%. So, these ANN-predicted results can be considered within acceptable limits. The results show good agreement between the predicted and experimental values. Besides its numerical accuracy, the ANN model is much faster and easier to use, which makes it suitable for the generation of tire tractive performance.

The developed model can be used as a reference for further tractive performance studies. This system can be developed further by the addition of fuzzy logic to the system.

NOMENCLATURE

ANNs: Artificial neural networks
TE: Tractive efficiency
TR: Travel reduction
NTR: Net traction ratio
P: Drawbar pull
W: Dynamic weight/normal load
N_a: Axle power
N_d: Drawbar power
V_a: Actual velocity
V_t: Theoretical velocity
LM: Levenberg–Marquardt
GD: Gradient descent
GDM: Gradient descent with momentum
i: Number of inputs
j: Number of neurons in the first hidden layer
k: Number of neurons in the second hidden layer

m: Number of outputs
x: input parameter
b: Bias
F: Transfer function
NET: The sum of the multiplication products of the input parameters and their weights
W_1,W_2,W_3: Weights of the connection
TM: Traditional method
ε: Relative error
η: Goodness of fit
y: Measured value
$\hat{y}$: Predicted value
$\bar{y}$: Mean of measured values
n: Number of observations

5. REFERENCES

1. F.M. Zoz and R.D. Grisso, Traction and Tractor Performance. In ASAE Distinguished Lecture 27, Agricultural Equipment Technology Conference. ASAE Publication Number 913C0403. Louisville, KY, 2003.
2. R. Gill and G.E. Vanden Burg, Soil Dynamics in Tillage and Traction. In Agricultural handbook No. 316, ARS, USDA 511, 1968.
3. M.G. Bekker, Theory of land locomotion. Ann Arbor, MI: The University of Michigan Press, 1956.
4. Z. Janosi and B. Hanamoto, The analytical determination of drawbar pull as a function of slip for tracked vehicles in deformable soils. Paper No. 41, 1st International Conference on Mechanics of Soil-vehicle Systems, Torino, Italy, 1961.
5. R.D. Wismer and H.J. Luth, Off-road traction prediction for wheeled vehicles. *Transaction ASAE* **17(1)**: 8–10, 1974
6. W.W. Brixius, Traction prediction equation for bias ply tyres. ASAE Paper, No. 87–1622, ASAE, St. Joseph, MI, 1987.
7. I. Shmulevich, U. Mussel and D. Wolf, The effect of velocity on rigid wheel performance. *J Terramechanics* **35**: 189-207, 1998.
8. A.K. Elwaleed, A. Yahya, A. Zohadie, D. Ahmad and A.F. Kheiralla, Net traction ratio prediction for high-lug agricultural tyre. *J Terramechanics* **45**: 103-108, 2008.
9. S. Tarhan and K. Çarman, Modeling the torque and power requirements of traction tires of horticultural tractors using dimensional analysis. *Math and Comp Appl* **9(3)**: 427-434, 2004.
10. Safa M, Samarasinghe S, Mohsen M (2009) Modeling Fuel Consumption in Wheat Production Using Neural Networks. 18th World IMACS / MODSIM Congress, Australia, 775-781
11. Douik A, Abdellaoui M (2008) Cereal varieties classification using wavelet techniques combined to multi-layer neural Networks. 16th Mediterranean Conference on Control and Automation, France, 1822-1827

12. Kashaninejad M, Dehghani AA, Kashiri M (2009) Modeling of wheat soaking using two artificial neural networks (MLP and RBF) J Food Engineering 91:602–607
13. K. Çarman and A.Y. Seflek, Fuzzy expert system design for tyre traction performance. *J Agric Machinery Sci* **1(1)**: 63–68, 2004, [in Turkish].
14. D. Massie, Neural network fundamentals for scientists and engineers, in: Proceedings of ECOS'01, Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, First International Conference on Applied Thermodynamics, Istanbul, 2001.
15. J. Arriagada, P. Olausson and A. Selimovic, Artificial neural network simulator for SOFC performance prediction. *J Power Sources* **112**: 54–60, 2002.
16. K. Çarman and C. Aydin, Load and velocity effects on tire. International Conference on Agricultural Engineering, Szent Istvan University, Budapest, 2002.
17. D.R. Lee and K.U. Kim, Effect of inflation pressure on tractive performance of bias-ply tires. *J Terramechanics* **34(3)**: 187-208, 1997.
18. V.K. Tiwari, K.P. Pandey and A.K. Sharma, Development of a tyre traction testing facility. J Terramechanics **46(6)**: 293-298, 2009.
19. K. Levenberg, A method for the solution of certain nonlinear problems in least squares. *Quart Appl Math* **2**: 164-168, 1944.
20. D.W. Marquardt, An algorithm for least-squares estimation of nonlinear parameters. *J. Soc. Ind Appl Math* **11**: 431-441, 1963.
21. K. Çarman, Prediction of soil compaction under pneumatic tires a using fuzzy logic approach. *J Terramechanics* **45**: 103-108, 2008.
22. A. Taner, Design of radial centrifugal pumps using artificial neural network. D.Sc. Thesis. Graduate School of Natural and Applied Sciences of Selcuk University, Konya, 2007, [in Turkish].
23. L.L. Bashford, S. Al-Hamed and C. Jenane, Effects of tire size and inflation pressure on tractive performance. Applied Engineering in Agriculture **9(4)**: 343-348, 1993.
24. L.L. Bashford, M.F. Kocher and T.S. Tibbetts, Wide tires, narrow tires. SAE Technical Paper Series 1999-01-2784, 1-7, 1999.
25. E.R. Elashry, The tractive characteristics of a wide low-pressure tire and conventional tire under different soil conditions. 4th International Agricultural Mechanisation and Energy Congress, 824-837, 1990.
26. J.H. Esch, L.L. Bashford, K. Von Bargen and R.E. Ekstrom, Tractive performance comparisons between a rubber belt track and a four-wheel-drive tractor. Transaction ASAE **33(4)**: 1109-1115, 1990.