Journal of the Saudi Society of Agricultural Sciences (2014) **13**, 35–43

King Saud University

Journal of the Saudi Society of Agricultural Sciences

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FULL LENGTH ARTICLE

Application of artificial neural networks for the prediction of traction performance parameters

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Received 26 November 2012; accepted 2 January 2013
Available online 17 January 2013

KEYWORDS

Neural networks;
Inflation pressure;
Wheel load;
Contact area;
Rolling resistance

Abstract This study handles artificial neural networks (ANN) modeling to predict tire contact area and rolling resistance due to the complex and nonlinear interactions between soil and wheel that mathematical, numerical and conventional models fail to investigate multivariate input and output relationships with nonlinear and complex characteristics. Experimental data acquisitioning was carried out using a soil bin facility with single-wheel tester at seven inflation pressures of tire (i.e. 100–700 kPa) and seven different wheel loads (1–7 KN) with two soil textures and two tire types. The experimental datasets were used to develop a feed-forward with back propagation ANN model. Four criteria (i.e. *R*-value, *T* value, mean squared error, and model simplicity) were used to evaluate model's performance. A well-trained optimum 4-6-2 ANN provided the best accuracy in modeling contact area and rolling resistance with regression coefficients of 0.998 and 0.999 and *T* value and MSE of 0.996 and 2.55×10^{-12}, respectively. It was found that ANNs due to faster, more precise, and considerably reliable computation of multivariable, nonlinear, and complex computations are highly appropriate for soil–wheel interaction modeling.

1. Introduction

Soil–tool interactions have been discussed and investigated by many researchers due to highly complex behavior of soil that inhibits to obtain generalized yet highly valid models. Wheel as an imperative part of off-road vehicles portends sophisticated relations with soil. The significance of contact area in the domain of soil–wheel interactions is considerable (Taghavifar and Mardani, 2012). Contact area of tire, in addition to major parameters affecting contact area (i.e. tire inflation pressure and wheel load), is reliant on mutual and multiple actions between variables. These actions complicate to distinguish that contact area is chiefly impressed by which of variables. Furthermore, rolling resistance (RR) of wheel is a major production of soil–wheel interactions. RR in essence is the required energy to compact the soil beneath the wheel while traversing a definite distance. Consequently it is a resistive force against movement multiplied by the distance obtained as following.

$$R = b_w \int_0^{Z_{\max}} \left(\frac{K_C}{b} K_\varphi \right) Z^n dZ \tag{1}$$

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Peer review under responsibility of King Saud University.

Production and hosting by Elsevier

1658-077X
http://dx.doi.org/10.1016/j.jssas.2013.01.002

where n is sinkage exponent, b_w is tire width, b is the smaller dimension of the rectangular contact area, Z is the sinkage, and K_C and $K\varphi$ are the soil condition parameters, respectively. It should be noted that validity of equation above in order to predict rolling resistance based on soil deformation was offered by Wong (1984) that for wheel diameters more than 50 cm and sinkage levels less than 15% of wheel diameter. Additionally, RR relies on contact area since contact area defines the area of soil to be compacted. Contact area and RR interactions are influential on their determinations.

Artificial neural networks (ANN) are widely used to facilitate answering complicated problems in variety of science and engineering domains chiefly wherever conventional and mathematical modeling fail to succeed. Artificial neural networks have been carried out in an effectively manner in the fields of pattern recognition, modeling, and control (Haykin, 1999). A well-trained ANN, which is fundamentally inspired by human being neural system, is applicable to be utilized as a predictive model for a specific application in science. ANN models and their performance are relying on training experimental data followed by validating and testing the model by independent datasets. Accommodating multiple input variables, while it has the ability to improve its performance with new sets of data, multiple output variables can be efficiently predicted. Conventional models as well as mathematical ones are usually incapable of predicting complex nonlinear phenomena exempt from simplifying the models by neglecting interactions between parameters. This brings about rising inaccuracy. Furthermore, ANN advantages of much faster and more accurate calculations compared with mathematical or conventional methods as no prolonged repetitive calculations are needed. However, appropriate ANN topology is significant to attain simple models with lower mean squared error (MSE) and higher accuracy. Each input to the artificial neural network is multiplied by the synaptic weight, added together and dealt with an activation function. ANNs are trained by frequently exploring the best relationship between the input and output values creating a model after a sufficient number of learning repetitions, or training known as epochs (Jaiswal et al., 2005). After training, the model can be generalized with new input values to predict, simulate and re-establish the condition identified as testing procedure.

Modeling draught, as an index of RR, has long been discussed in the literature. Roul et al. (2009) successfully applied ANN model predicting the draught requirement of tillage implements under varying operating and soil conditions. Zhang and Kushwaha (1999) utilized RBF function in ANN to estimate draught of narrow blades in soil under multiple input variables. They stated that an appropriate neural network model could effectively predict the required draught for the blade. Literature survey further indicated that no outstanding attempt has been made to utilize ANN to predict RR and contact area simultaneously. Appropriate application of ANN in this case is highlighted when taking into account that conven-

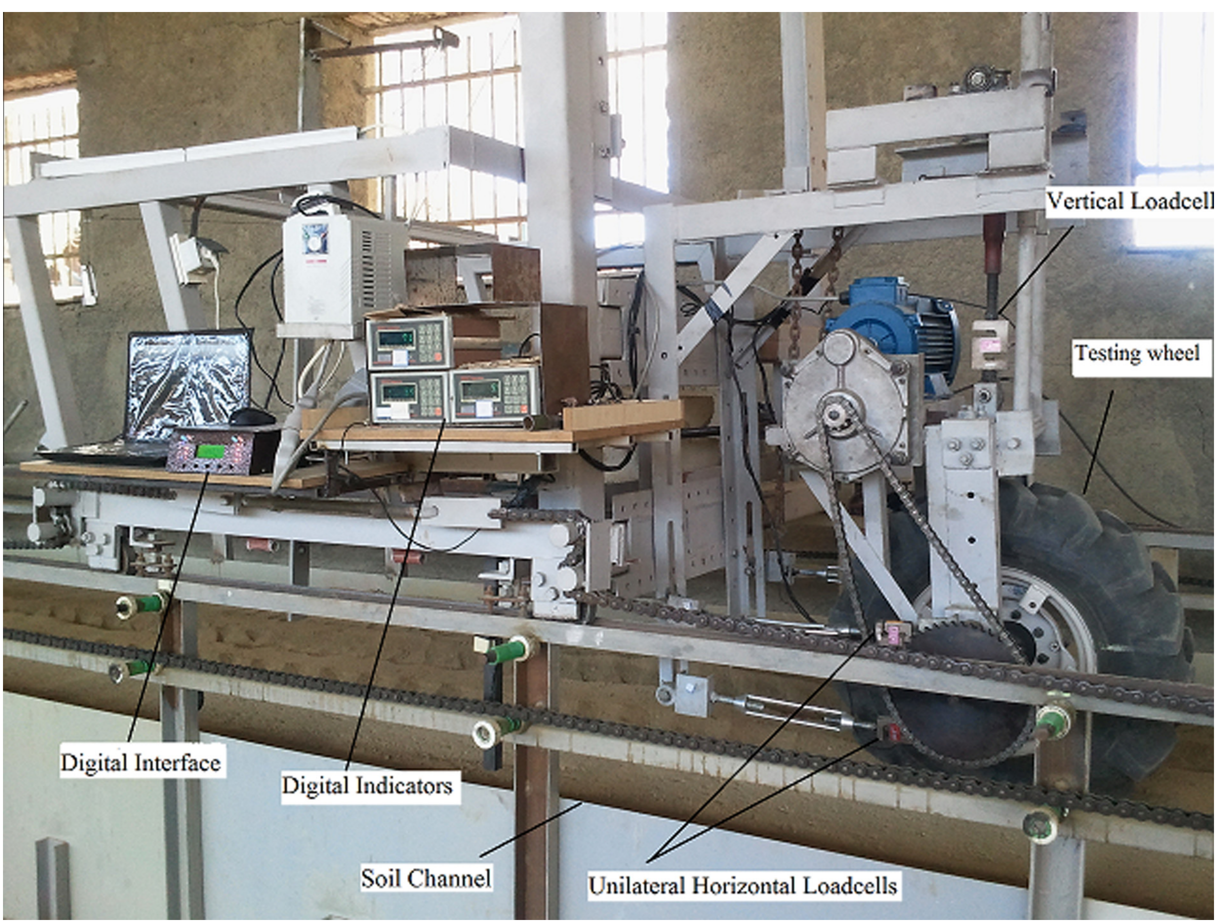

Figure 1 The picture of test soil bin facility.

Table 1 Summary of experiment conducted.

Soil texture	Tire type	Independent parameters		Dependent parameters
		Wheel load (kN)	Inflation pressure (kPa)	
Clay loam	220/65R21	1	100	
Sandy clay loam	9.5L-14	2	200	Contact area
		3	300	
		4	400	
		5	500	Rolling resistance
		6	600	
		7	700	

Table 2 Soil constituents and its measured properties.

Item	Value	
Sand (%)	34.3[a]	56.8[b]
Silt (%)	22.2[a]	23.1[b]
Clay (%)	43.5[a]	20.1[b]
Frictional angle (°)	32[a]	40[b]
Cone Index (kPa)	437[a]	382[b]

[a] Clay loam soil.
[b] Sandy clay loam soil.

tional models to predict objective parameters have no solution except considering one variable to be changed while others are stable, however, ANN settles this difficulty. Moreover, conventional and mathematical models fail to yield multiple output variables when ANN tackles to solve this deficiency. Given such complex relations, regression models are required for outputs.

The objectives of this research were to (1) develop an ANN model and evaluate the predictability performance on the basis of statistical criteria, (2) evaluate the effects of the ANN parameters on model performance, and (3) to propose a supervised ANN-based model generalized by two prominent soil and tire types used for output predictions.

2. Experimental investigation

A long soil bin was constructed in the Faculty of Agriculture, Urmia University, Iran. This soil bin features 23 m length, 2 m width and 1 m depth (Mardani et al., 2010). This long channel had the ability to hold a wheel carriage, a single-wheel tester, and different tillage tools to be moved altogether in the length of the soil bin. A three-phase electromotor of 30 hp was used to move a carriage through the length of soil bin by means of chain system along with the wheel-tester when the carriage had the ability to traverse at the speed of about 20 km/hr. Four S-shape load cells with the capacity of 200 kg were calibrated and then were located at proper places in parallel-horizontal pattern between the carriage and single-wheel tester. Load cells were interfaced to data acquisition system included a data logger, enabled monitoring the data on a screen and simultaneously, the data were transmitted to a computer. A single-wheel tester was assembled to the carriage system with four S-shape load cells to measure the rolling resistance alterations caused by motion of wheel in various treatments being tested (wheel loads were chosen as for test of principals). The utilized tires were 220/65R21 and 9.5L-14, 6 radial ply agricultural tractor tire. The system set up is shown in Fig. 1. Transmitted files recorded were subsequently imported to MATLAB software (version 7.6, 2008, Mathworks Company) for processing and post-processing. Summary of treatments being tested is shown in Table 1. In order to determine contact area experimentally, at each treatment, white powder was spread on the periphery of soil–tire interface to define contact area. A digital camera was used to take images of contact areas. Image processing method was then used to define contact area with superior performance taking into account the borders of contact.

The soil bin was filled with two soil textures of clay–loam and sandy clay–loam soil that exist in most regions of Urmia, Iran. Particular equipments were employed to organize soil bed including leveler and harrow since it is exceedingly crucial to have well-prepared soil inside soil bin for acquiring reliable and precise results from this experiment. Additionally, they were used since soil condition should be reverted to previous state. Soil constituents and properties are defined in Table 2.

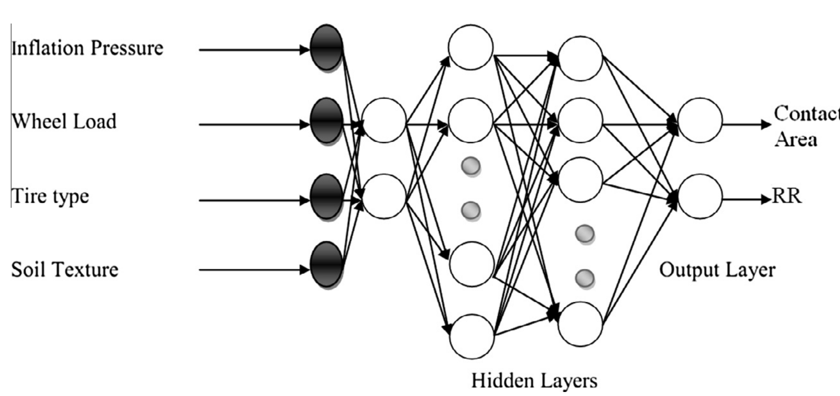

Figure 2 ANN general configuration for prediction of contact area and RR.

Table 3 Summary of various developed networks evaluated to yield the criteria of network performance.

Activation function	Training function	Network topography	MSE	*R*-value of contact area	*R*-value of RR	*T*
logsig	trainlm	(4,6,2)	2.55×10^{-12}	0.998	0.999	0.996
purelin	trainbfg	(4,6,5,2)	4.23×10^{-6}	0.995	0.994	0.987
purelin	traingdx	(4,6,5,2)	3.28×10^{-1}	0.959	0.942	0.989
purelin	trainrp	(4,6,2)	1.77×10^{-1}	0.994	0.993	0.961
purelin	trainscg	(4,6,2)	2.63×10^{-2}	0.990	0.982	0.967
Tansig	trainlm	(4,6,2)	1.27×10^{-4}	0.913	0.942	0.973
Tansig	traingdx	(4,6,5,2)	2.62×10^{-5}	0.998	0.987	0.977
Tansig	trainscg	(4,6,2)	1.35	0.996	0.994	0.884
purelin	trainlm	(4,6,5,2)	2.27×10^{-6}	0.997	0.989	0.982
Logsig	trainscg	(4,6,5,2)	1.75×10^{-5}	0.965	0.974	0.980
Logsig	traingdx	(4,6,5,2)	3.01	0.942	0.924	0.827

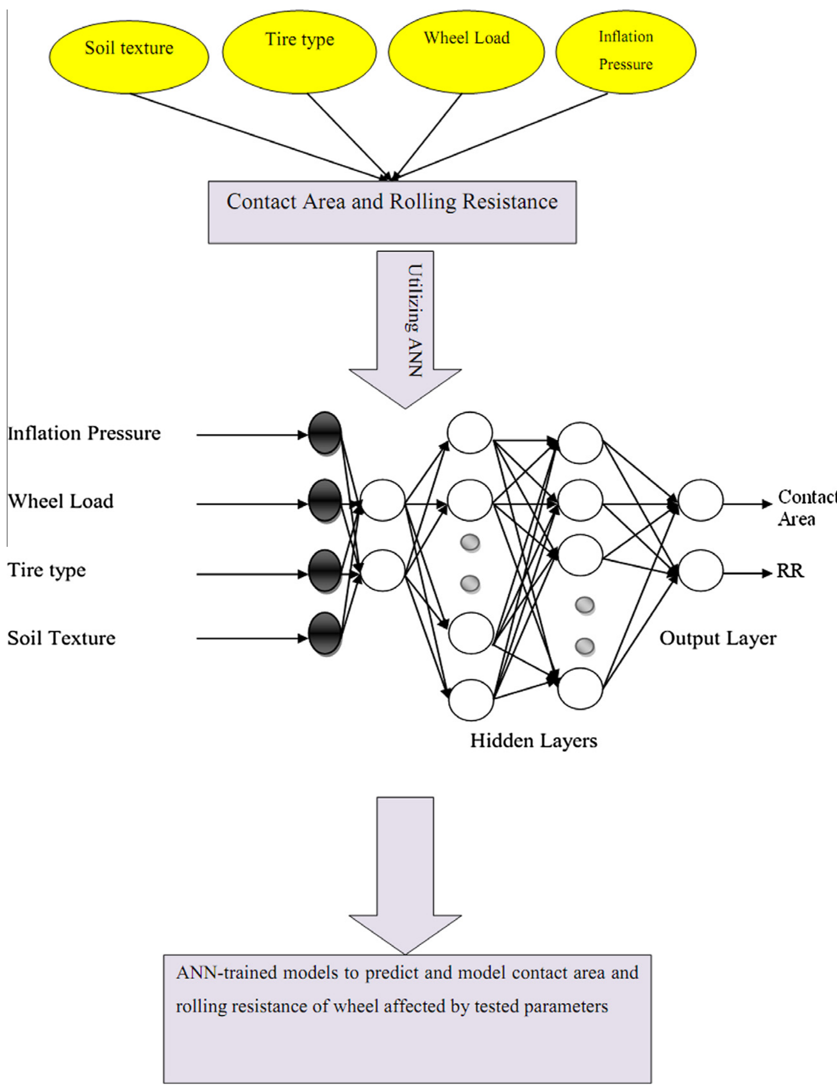

Figure 3 The general process of ANN application to predict output variables.

3. Neural network design

To achieve the best model, numerous structures of neural network were trained and then evaluated. ANN model was developed utilizing the experimental data as the input set in order to identify the effects of tire inflation pressure and wheel load by two commonly used tires and at two soil textures on contact area and RR. A multi-layered feed forward with back propagation algorithm varied from one to two hidden layers. The general configuration of multilayer artificial neural network of current research is depicted in Fig. 2. Back propagation algorithm is the technique

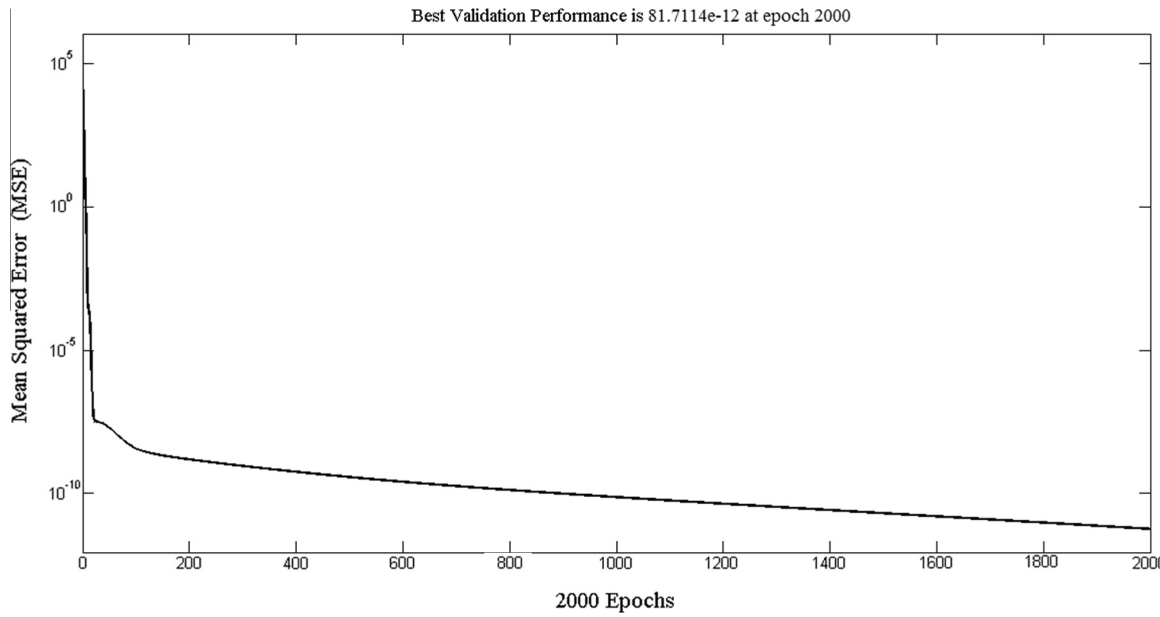

Figure 4 Validation error (MSE) curve.

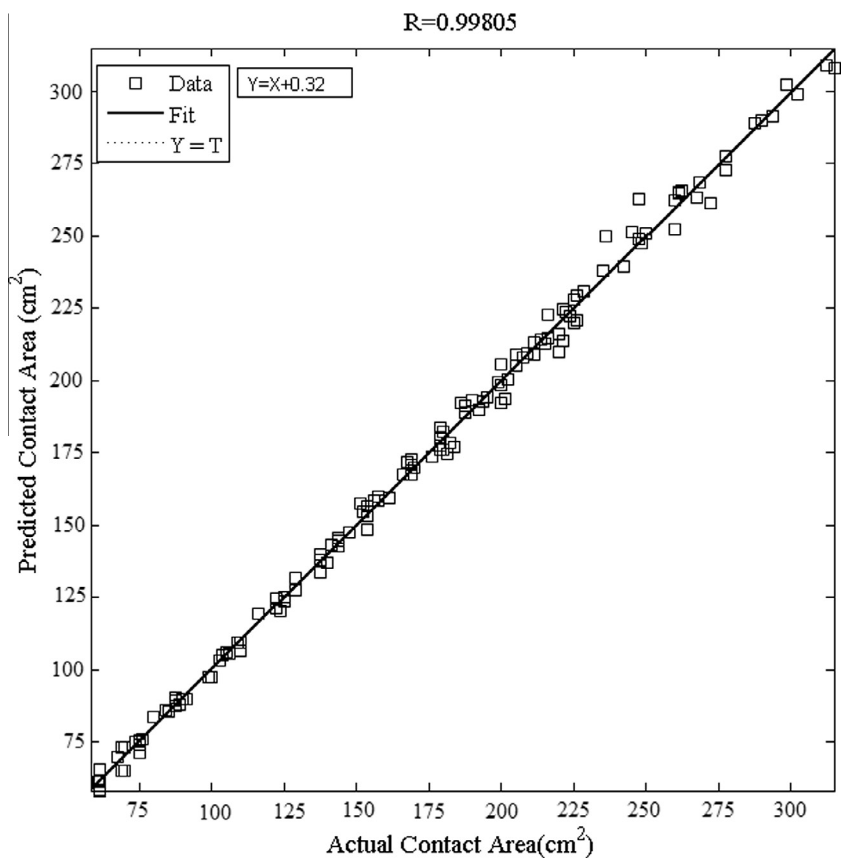

Figure 5 Correlation between the experimental data and predicted values of the ANN model for prediction of contact area.

calculating the gradient and the Jacobian, which involves performing computations backward through the network. The back propagation computation is derived using the chain rule of calculus until it can approximate a function. This algorithm minimizes error function expressed as following:

$$\text{Error} = \frac{1}{m}\sum_{m}\sum_{l}(d_{mk} - o_{lk}) \tag{2}$$

where m is the index of training pairs, l is the index of output elements, d_{mk} is the kth element of the mth desired model, and o_{lk} is the kth element of output data. The performance of the

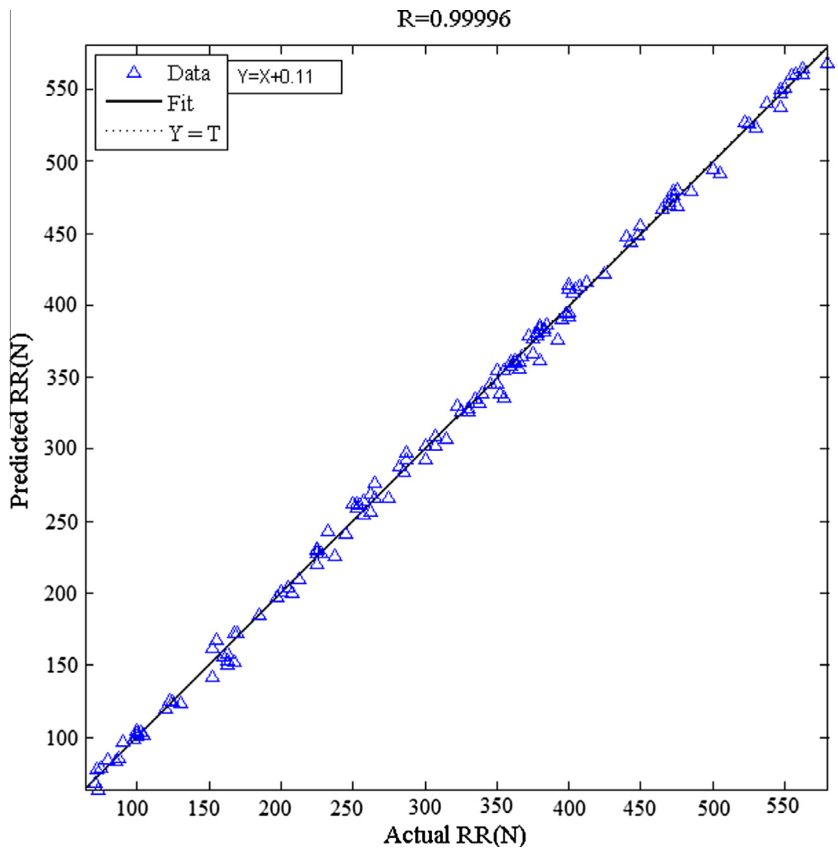

Figure 6 Correlation between the experimental data and predicted values of the ANN model for prediction of RR.

Table 4 Statistical specifications for the optimal model of the study for training and testing partitions of the study outputs.

	Contact area (m^2)		RR (N)	
	Train	Test	Train	Test
Min	0.013	0.012	4.241	5.524
Max	0.035	0.028	542.8	569.3
Mean	0.024	0.026	272.3	275.4
Standard deviation	0.008	0.011	2.091	5.263

trained model by the network is calculated by comparison between the ANN predicted outputs and the actual outputs of experimentations. Another criterion was T value that computes the scattering around the line (1:1), a T value close to 1 is prevailed. The T value is described as follows:

$$T = 1 - \frac{\sum_{i=1}^{N}(Y_{i,a} - Y_{i,p})^2}{\sum_{i=1}^{N}(Y_{i,a} - \overline{Y})^2} \tag{3}$$

where $Y_{i,a}$ and $Y_{i,p}$ are ith output variables obtained by experiment and neural network, respectively, $\overline{Y}$ is the average over N samples, and N is the number of samples used in each step. Since the range of input variables was different, in order to achieve fast convergence to minimal MSE, each of input variables was normalized in the range of -1 to 1 by following equation.

$$X_n = 2\frac{X_r - X_{r,\min}}{X_{r,\max} - X_{r,\min}} - 1 \tag{4}$$

where X_n denotes normalized input variable, X_r is the raw input variable, and $X_{r,\min}$ and $X_{r,\max}$ denote minimum and maximum of input variable, respectively. At the end of training and testing processes, error was computed by using the differences between experimental data and output data modeled with ANN.

A total of 392 data were available, so 392 arrays were generated. In the current study the back-propagation neural networks (BPNN) were trained utilizing datasets with 50% of data, 25% for validating the developed model and 25% for testing the de veloped model.

Four neurons in the first layer and two neurons in the last layer, as well as varying neurons in the interim layer were representatives of input data, output data and ANN developed neurons, respectively. The output of a neuron is defined as:

$$\text{Output} = f(\text{n}) \tag{5}$$

where

$$n = \sum_{i=1}^{s} w_i x_i + b \tag{6}$$

where x_i and w_i are the input data and the weights of neurons, respectively, b is the bias and $f(n)$ is the activation function. Activation function establishes the relation between inputs and outputs of a neuron. The utilized activation functions in configuration of ANNs in the case of this study were:

Linear transfer function (purelin):

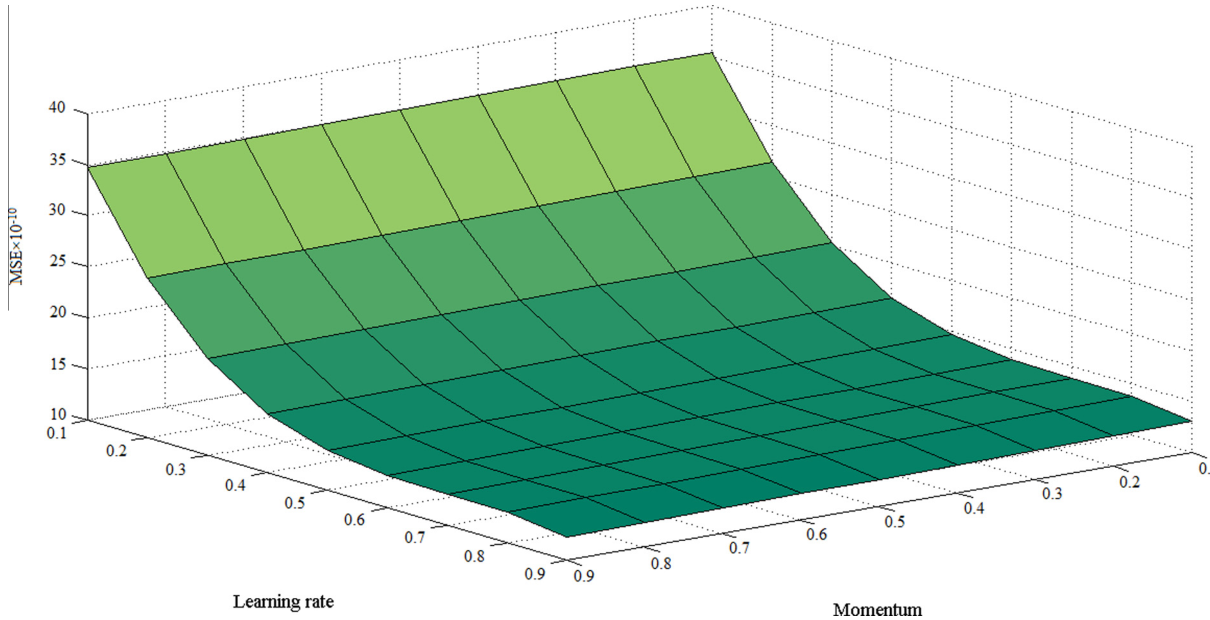

Figure 7 The effect of learning rate and momentum values on the learning ability of the ANN model.

$$f(n) = n \tag{7}$$

Log–sigmoik transfer function (logsig):

$$f(n) = \frac{1}{1 + e^{-n}} \tag{8}$$

Hyperbolic tangent sigmoid transfer function (tansig):

$$f(n) = \frac{2}{1 + e^{-2n}} - 1 \tag{9}$$

purlin function generates outputs in the range of $-\infty$ to $+\infty$, *logsig* function produces outputs in the range of 0 to 1, and *tansig* function produces outputs in the range of -1 to $+1$(M. Bouabaz, M. Hamami, 2008). In this study, however, many networks with several functions and topologies were examined which is briefly shown in Table 3. Of the used training functions, *trainlm, traingdx, trainrp, trainscg, and trainbfg* are known as the fastest and most profitable BPNN algorithm (Graupe, 2007).

trainlm is a network training function that updates weight and bias values according to Levenberg–Marquardt optimization and is often the fastest back propagation algorithm which is highly recommended as a first-choice supervised algorithm, albeit it needs more memory compared with the other algorithms. *traingdx* is a network training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate. It combines adaptive learn-

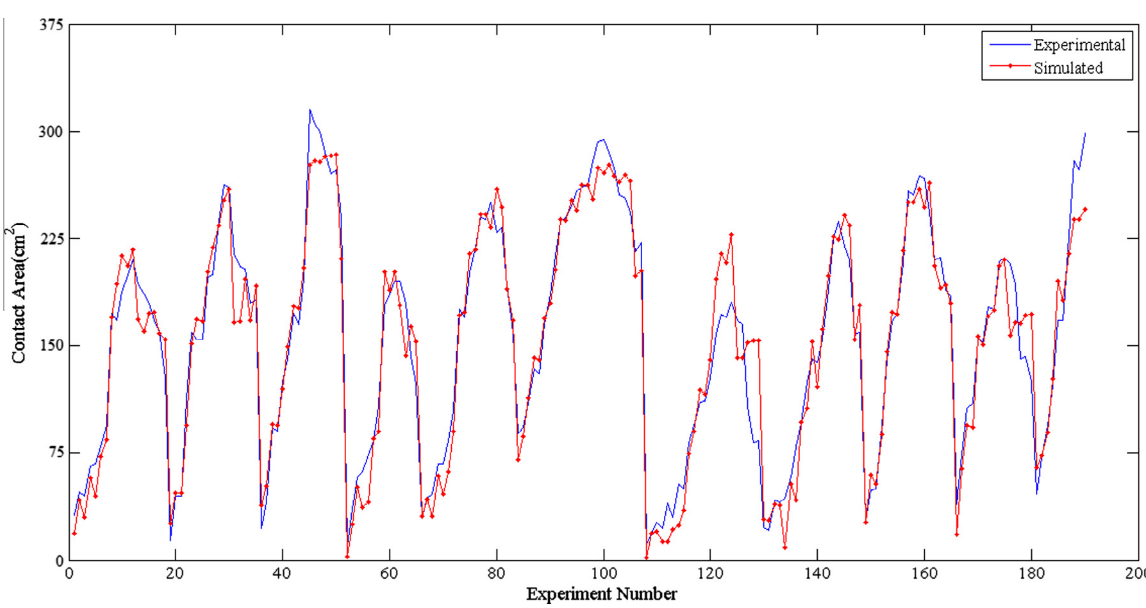

Figure 8 A comparison between predicted and measured values of contact area for experiment numbers of training partition.

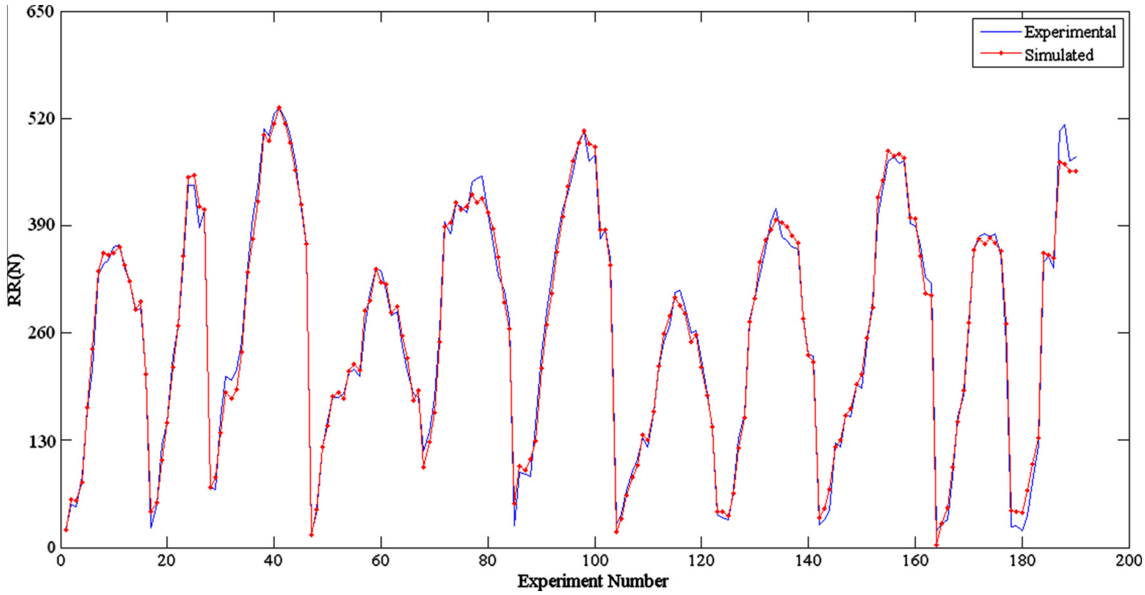

Figure 9 A comparison between predicted and measured values of RR for experiment numbers of training partition.

ing rate with momentum training rate. *trainrp* is a network training function that updates weight and bias values according to the resilient back propagation algorithm. *trainscg* is a network training function that updates weight and bias values according to the scaled conjugate gradient method. *trainbfg* is a network training function that updates weight and bias values according to the BFGS quasi-Newton method. The training and testing performance (MSE) was selected to be the error criterion along with regression coefficient, T value and structure simplicity. Where various training functions were initially developed, *trainlm*, *trainbfg*, and *trainscg* were selected. MATLAB software (version 7.6, 2008, Mathworks Company) was used to develop ANN predictive models. For more understanding, the general ANN workflow is depicted in Fig. 3.

4. Results and discussion

The topology, number of neurons within each layer is determined based on the complexity of the problem. The criterion R-value was chosen to decide which network can yield the optimum model. As well, Mean Squared Error (MSE) was selected as second criteria to evaluate the performance of each trained algorithms. Another criterion was T value that computes the scattering around the line (1:1), a T value close to 1 is prevailed. Furthermore, size and complexity of the network were a significant parameter, and consequently, smaller ANNs were chosen. Various training functions, transferring functions, and network topographies were utilized. Levenberg–Marquadt (*trainlm*) was successfully chosen as the optimum training function. The R- values in Table 3 demonstrate the correlation coefficient between the outputs and targets, T values are representatives of scattering around the selected line and MSE. The performance of the network for training is depicted in Fig. 4.

Of trained and developed networks, a few of them could suitably provide low error, where simplest ones were selected. The correlation between the experimental data and the predicted values of the ANN model for prediction of contact area and RR yielded are shown in Figs. 5 and 6, respectively. The scatter plots in these figures revealed that for both the output parameters, the predictability was satisfactory and data points were well concentrated around the selected ideal unity-slope line. For both the outputs, the linear adjustment between measured and estimated values gives a slope practically equal to 1. ANN advantages are fast, precise, and reliable computation of multivariable, nonlinear, and complex computations compared to mathematical, conventional, and numerical methods. Table 4 shows the statistical specifications for the optimal model of the study for training and testing partitions of the study outputs.

The learning rate equilibrates the error downing level subsequent to ongoing iterations. The learning rate presents the respective more or less portion of adjustment to the elder weight. The neural network may learn more quickly if the factor is set to a large amount. Nevertheless, if there is a large instability in the input set then the network may not learn very well or at all. In real terms, setting the learning rate to a large value is inappropriate and inhibitor to learning. In the case that learning rate is slow, adjustment of the factor to a small value and subsequent increase are prevailed. Momentum is mainly used to speed up the learning rate, particularly when learning rate is adjusted at a low level. The objective in ANN is to change iteratively the weights between the neurons for minimization of error which is related to learning rate and momentum by the steepest descent method. This can improve the learning rate in some situations, by helping to smooth out unusual conditions in the training set.

Fig. 7 shows the effect of learning rate and momentum values on the training MSE. Generally with increased learning rate, the training MSE tended to decrease in the range of tested values. This implies that in this range, the necessary weight adjustments were suitable. Also Fig. 7 shows that performance of the ANN model was negligibly affected by momentum. The optimal values of learning rate and momentum of ANN used to predict the process in the obtained supervised ANN model were 0.9 and 0.8, respectively. Moreover, comparisons between simulated and experimental data for outputs are depicted in Figs. 8 and 9. It demonstrates the compliance between the experimental output and the simulated output by optimal ANN model during experiment number.

Radial basis function (RBF) networks were also tested in this paper. Nevertheless, it was incapable to furnish superior model for output prediction with T value of 0.84, MSE of 0.828 and R-values of 0.934 and 0.957 for contact area and RR, respectively.

It should be noted that experimental tests revealed that the increase of tire inflation pressure as well as the decrease of wheel load resulted in a decrease of contact area. Furthermore, a decrease of tire inflation pressure and an increase of wheel load both resulted in an increase of RR.

Two more common soil textures and two tires widely used in Urmia region were used in this model for generalization in spite of which more works are required to demonstrate the generalized value of presented ANN model including more tire types and soil textures.

5. Conclusion

It is indicated that artificial neural networks (ANN) as a potent modeling method can effectively predict contact area of wheel with soil and RR particularly because they have complex and nonlinear behavior where mathematical, numerical and conventional models fail to model and predict multivariate relations. The results of utilizing various training algorithms revealed that a feed-forward back propagation ANN with topography of 4–6-2 neurons could achieve the optimum model. High values of coefficient of regression were obtained after training and testing the model and separately evaluating the objective parameters. R-value, MSE, and simplicity of model were the deciding criteria to select the optimum training algorithm.

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