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Wavelet neural network applied for prognostication of contact pressure between soil and driving wheel

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A R T I C L E I N F O

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A B S T R A C T

This paper describes the measurement of contact pressure in the context of wheel–terrain interaction as affected by wheel load and tire inflation pressure when fusion of the wavelet transform with the back-propagation (BP) neural network is applied to construct the wavelet neural network contact pressure prediction model. To this aim, a controlled soil bin testing facility equipped with single-wheel tester was utilized while three levels of velocity, three levels of slippage and three levels of wheel load were applied. Using image processing technique, contact area values were determined which were subsequently used for quantification of contact pressure. Performances of the different predictor models incorporated of various mother wavelets were evaluated using standard statistical evaluation criteria. Root mean square error and coefficient of determination values of 0.1382 and 0.9864 achieved by the optimal wavelet neural network are better than that of BP neural network. The proposed tool typifies a high learning speed, enhanced predicting accuracy, and strong robustness.

1. Introduction

The increasing global demand for food owing to the growing population rate makes the adoption of mechanized agriculture an unavoidable step in farming procedures. Multiple traversing of agricultural wheeled vehicles in order to perform various processes along with the augmented size of the pertinent vehicles has put added stresses on the soil beneath the traversing tire. The interaction between the wheel and soil drastically influences the soil physical characteristics thorough contact pressure which forms the unwanted soil compaction. The disadvantages of the soil compaction have already been covered in the literature frequently [1,2]. Contact area plays a strong role in the determination of the contact pressure and thus in the formation of soil compaction [2]. In Ref. [3], the effect of soil structure and physical properties was reported to be effective on determination of contact pressure, however, on non-compacted soil, peak pressures are equal to that of the inflation pressure. In [4], dynamic load and inflation pressure effects on contact pressures of a tire were evaluated on a firm clay soil. As an index of induced pressure at soil–tire interface, vertical stress propagation in a soil profile was performed as affected by tire size, inflation pressure and wheel load [5]. For instance, soil stress at topsoil

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part, as a direct function of contact pressure, was assessed under the effect of wheel load and tire inflation pressure with the wheel loads of 11, 15 and 33 kN at inflation pressures of 70, 100 and 150 kPa [6]. Although the attempts on determination of contact pressure have both been performed experimentally and analytically, the resultant data should be processed for developing a model that has the considerable capability to be applied with satisfactory accuracy. Due to the stochastic nature of machine dynamics and nonlinear behavior of soil, the soil–wheel interaction is considered a highly complex and sophisticated problem to be modeled and therefore, diverse methodologies of artificial intelligence are advised [7–9].

As far as our literature review is concerned, there is no study dedicated to the prognostication of the wheel–soil contact pressure by employing wavelet neural network. Furthermore, the experimental dataset are obtained from series of tests in controlled soil bin facility environment. The hypotheses below are outlined in the present study as following.

i. Wheel load, velocity and slippage, as tire parameters, affect the contact area and thus contact pressure.
ii. Artificial neural network and wavelet neural network, as stochastic modeling tools, are suitable candidates to perform the modeling of contact pressure of driven wheel under the effect of input parameters.

2. Materials and methods

A soil bin facility was used due to provision of a controlled condition for carrying out the experiments. A single-wheel tester was used in the soil bin facility. The holistic system consists of the bin frame which accommodates the other components added with the soil mass. A 220/65R21 driven tire is situated in a U-shaped chassis that is connected to the L-shaped frame through four horizontal arms. This configuration improves the dynamic stability of the wheel while traversing. The wheel tester is attached to the carriage as a significant part in the soil bin facilities. The carriage is powered for pulling the single-wheel by an electromotor with the power of 22 kW at the nominal rotational speed of 1457 rpm was applied. Furthermore, a SV 220IS5-2 NO, 380 V model of LG inverter (brand LS) for rotational speed of the engine was applied that gave speed control for the carriage with application of chain system. An induction motor of 5 kW, 3-phase, 1430 sync rev/min was applied to provide driving power for the wheel. The difference between the velocity imposed to the single-wheel tester and the carriage velocity denoted various and desired slippage levels. The load cell was vertically positioned between the wheel U-shaped chassis and L-shaped frame in a series with a power bolt. Rotation of the power bolt applied the desired wheel load and the load cell transmitted data to a separated Bongshin digital indicator BS722 model connected to a data logger thorough a RS232 port where data were simultaneously stored in a laptop computer. In this study, a clay loam soil texture was selected as the predominant soil type of test location, Urmia city, Iran. General soil bin system is depicted in Fig. 1 where the experiment framework and soil constituent properties are detailed in Table 1 and Table 2, respectively.

Fig. 1 – The general soil bin facility used for the experiments.

A new method was performed to calculate contact pressure in this study by application of image processing method. A white color powder was used at soil–tire interface for each treatment and the images were taken simultaneously. A Panasonic LUMIX DMC TZ25 camera was used for this purpose at a constant distance while a 4×4 cm index was used for calibration. The images were taken in RGB environment where illumination is combined with color that a small change in color space could change the color of image remarkably. Therefore, it is necessary to use a space that color and illumination are separated. Using s (saturation) component in HSV color space and b component in LAB space, a preferred separation of tire track and background was achieved. First, the components were normalized in the range between 0 and 1. For improving the separation, the Gamma transform was applied as following.

$$x_1 = (s + v) \quad (1)$$

Table 1 – Summary of experiment conducted.

Independent parameters			Dependent Parameter
Wheel load (kN)	Slippage (%)	Velocity (m/s)	
2	8	0.8	
3	12	1	
4	15	1.2	Contact pressure (kPa)

Table 2 – Soil constituents and its measured properties.

Item	Value
Sand (%)	34.3
Silt (%)	22.2
Clay (%)	43.5
Bulk density (kg/m^3)	2360
Frictional angle (°)	32
Cone index (kPa)	700

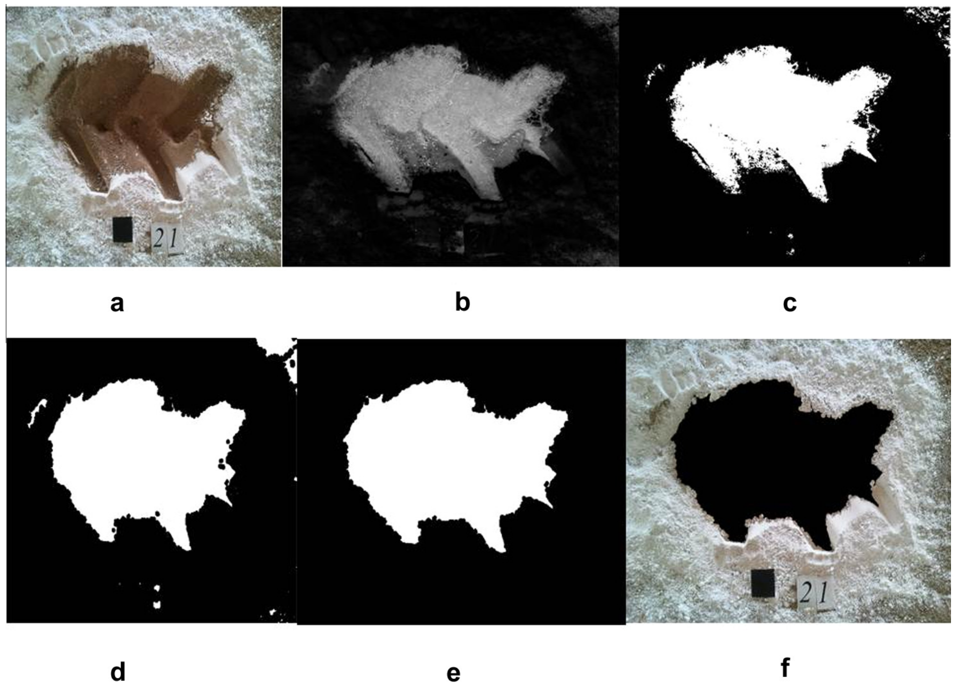

Fig. 2 – The taken to processed images during the various steps from RGB space to binary image.

$$x_2 = x_1^{\alpha} \quad (2)$$

where $\alpha = 2$ was found as an optimal degree for separations. Furthermore, dilation was performed with structural elements equivalent to *ball*. Otsu method was applied to achieve the desired thresholding level and the binary images were obtained. Structural element closing was also used for deletion of noise effects on the images. Subsequently, connected components which had pixels lower than a definite level were removed and the connected region was filled. A sample of the taken and processed images is shown in Fig. 2. Wheel load at each treatment divided by contact area, yielded the corresponding contact pressure value.

3. Modeling phase

3.1. *Artificial neural network*

Artificial neural network (ANN) has been encouraged from the inception that human brain computes similar to a highly complex and nonlinear computer [10]. ANN is a technology that is rooted in diverse contexts of pattern recognition, signal processing, machine learning, and data clustering that has recently found attractiveness in soil–wheel interaction domain [11–13]. An ANN operates by making interconnections between processing elements, each of which are demonstrative of a single neuron in a biological nervous system. The procedure is that a typical neuron accommodates as various input signals and subsequently forms an individual output that is transmitted as input to another neuron. The neurons are tightly interconnected and organized into different layers. In the input layer, neurons as many as input parameters are formed and the output layer is formed by neurons as many as output parameters. Depending on the size of data and requirement of ANN implementation, one or more hidden layers with varying neurons are sandwiched between the input and output layers. Where neurons receive random weights at initiation of ANN development, back-propagation works as an optimization tool and data are subsequently feed forward again. This would recur to reach the adjusted value of error goal or predefined number of iterations (epochs). This type is normally used for cognitive exploration and for stochastic-problem-solving applications.

A total of 27 dataset were obtained from three levels of wheel load, three levels of velocity and three levels of slippage. Data were split into three shares of training, validation and testing with 60%, 10% and 30%, respectively. Data were normalized and scaled in the range of between −1 and 1 to make sure that each input variable has the equal impact on the ANN model. Number of hidden layers and neurons in each hidden layer of ANN is structured based on the size of data and complexity of the problem. Hence, one hidden layer with varying number of neurons in the hidden layer was employed. Among transfer functions, sigmoid transfer function was applied in the hidden layer to be in compliance with the normalization range. This results in the certainty that each input variable provides an equal contribution in the ANN. Levenberg–Marquardt training algorithm as the first choice in ANN implementations was selected in the modeling trials.

3.2. *Wavelet neural network*

Wavelets are a category of functions used to localize a definite function in both position and scaling. Wavelet is also a significant step of the Fourier Transform. Wavelet neural network (WNN) combines the concepts of wavelet and neural network

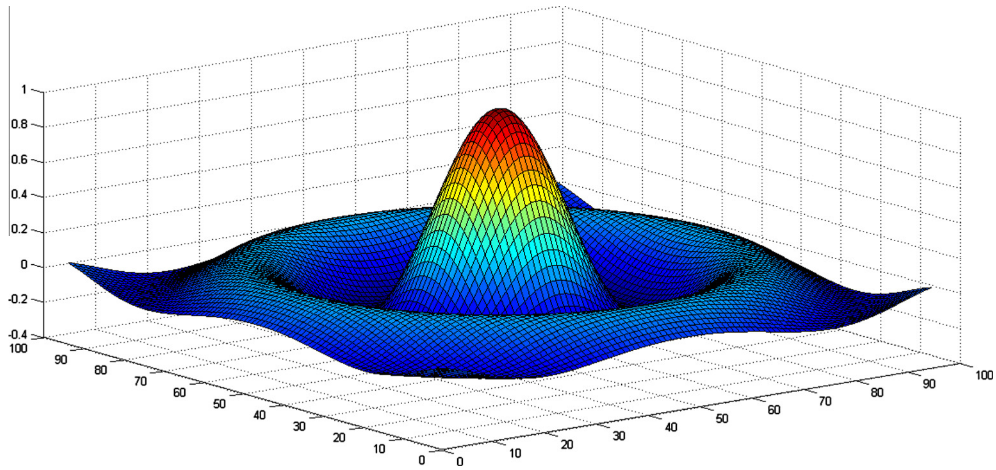

Fig. 3 – An example of a Mexican hat wavelet function.

theories. A WNN is a feed-forward neural network with a single hidden layer with orthonormal wavelet type transfer functions. For a function estimation purpose, WNN is trained to learn the composition of the objective function. Wavelet functions for the transfer function are selected from the mother wavelet functions. While there are J wavelet neurons in the hidden layer, the output as a weighted sum of the wavelet neuron outputs is presented as following.

$$y(u) = \sum_{i=1}^{J} \omega_i \psi_{\lambda_i t_i}(u) + \bar{y} \tag{3}$$

where the parameters t and λ are translation and dilation of the mother wavelet ψ, respectively, and J is the number of wavelet neurons in the hidden layer. Furthermore, ω is the corresponding weight of the wavelet neuron, while $\bar{y}$ is a substitution for the scaling function. In WNN hidden layer, the neurons are with transfer functions from mother wavelet functions. Hence, Mexican hat, Battle–Lémaire Scaling, and Haar wavelet functions were replaced instead of the sigmoid transfer functions of ANN to conjunct WNN. As an example, a Mexican hat wavelet function is defined in Eq. (4) and depicted in Fig. 3.

$$\psi(t) = (1 - t^2)e^{-\frac{1}{2}t^2}, \quad t = \sqrt{x_2 + y_2} \tag{4}$$

In modeling disciplines, it is essential to assess the quality of the trained model. Among diversity of statistical performance parameters, the root mean square error (RMSE) and coefficient of determination (R^2) were selected as the performance criteria to evaluate the accuracy of the developed models as following.

$$\mathrm{RMSE} = \frac{1}{n}\sqrt{\sum\nolimits_{i=1}^{n} (Y_{predicted} - Y_{actual})^2}. \tag{5}$$

$$R^2 = \frac{\sum_{i=1}^{n} (Y_{predicted} - Y_{actual})^2}{\sum_{i=1}^{n} (Y_{predicted} - Y_{mean})^2} \tag{6}$$

where Y_{actual} and $Y_{predicted}$ are measured and predicted values by the developed models, respectively, and n is the number of dataset.

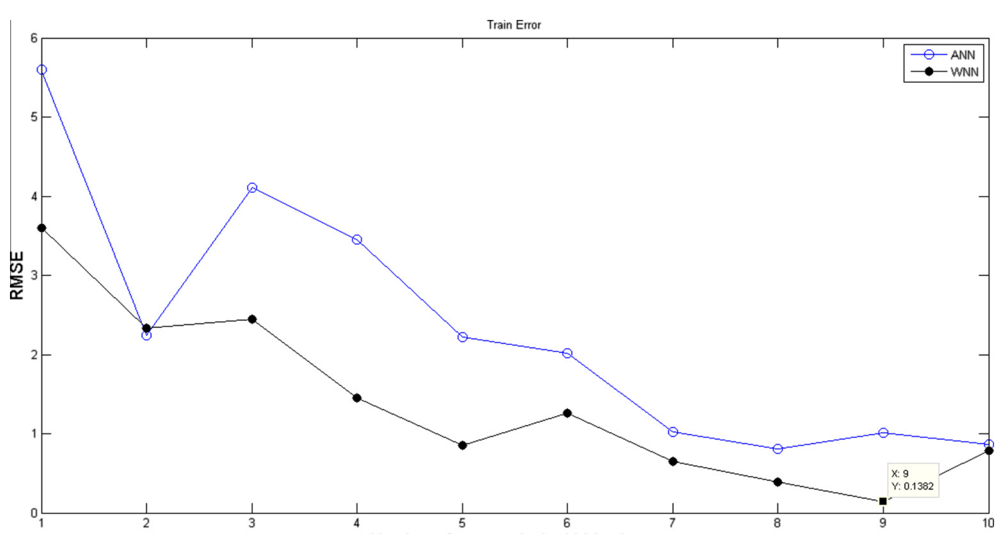

Fig. 4 – The variations of RMSE with respect to number of neurons in the hidden layer for two cases of ANN and WNN.

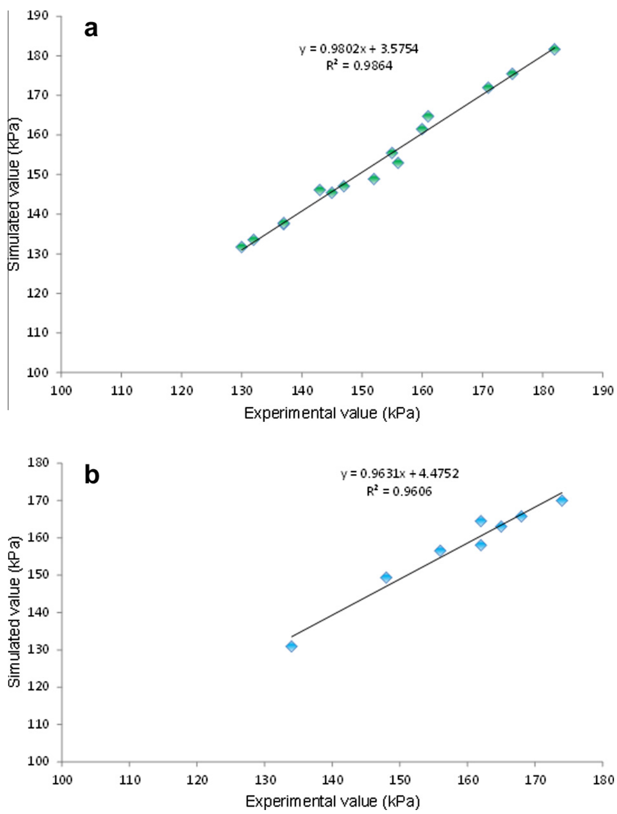

Fig. 5 – The scatterplots for (a) training and (b) testing shares of WNN at optimal configuration.

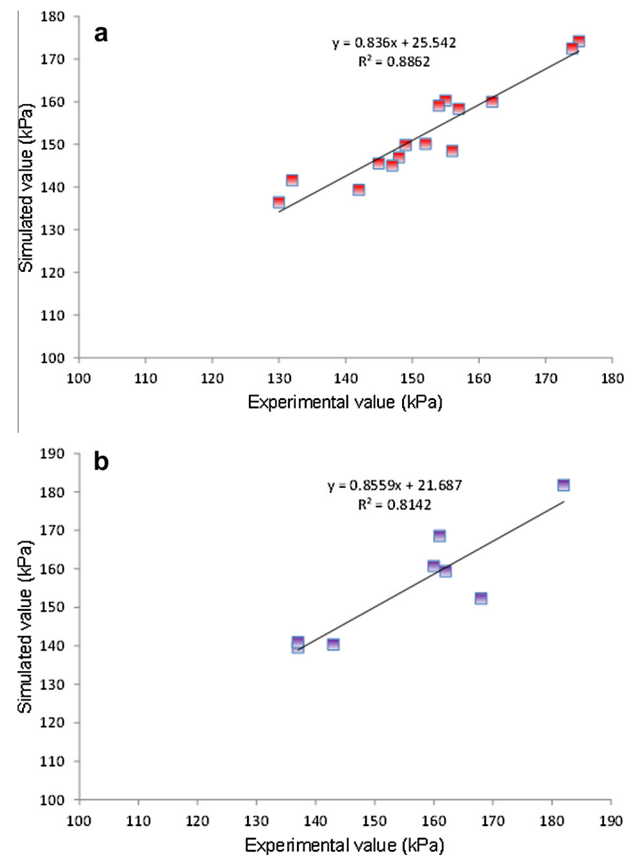

Fig. 6 – The scatterplots for (a) training and (b) testing shares of ANN at optimal configuration.

4. Results and discussion

The initial tests were performed to determine the best mother wavelet function among Mexican hat, Battle–Lémaire Scaling, and Haar wavelet functions. For a feed-forward with back propagation algorithm neural network with one hidden layer, the wavelons (wavelet neurons) were used where the above-mentioned wavelet functions were replaced by sigmoid activation functions. Due to superior performance of Mexican hat wavelet function when compared to the other tested functions, Mexican hat wavelet function was applied in the implementations. The milestone, however, was to assess the accuracy potential of WNN over ANN technique. Hence, in one hidden layer, number of neurons varied between 1 and 10 for both WNN and ANN algorithms (Fig. 4). It is appreciated from Fig. 4 that increased number on neurons in the hidden layer caused the reduction of modeling error for both WNN and ANN, although further reduction is observed for WNN than that of ANN. The lowest RMSE value was observed for WNN at 9 neurons with 0.1382. The scatterplots for training and testing shares of WNN at optimal configuration are illustrated in Fig. 5. Similarly, the scatterplots for training and testing shares of ANN with feed-forward BP algorithm at optimal configuration are illustrated in Fig. 6. The closeness of scattered data around unity slope line is the indication of higher accuracy. Therefore, it can be seen that WNN has further capability in prognosticating the contact pressure than that of ANN. The closer mapping of experimental and

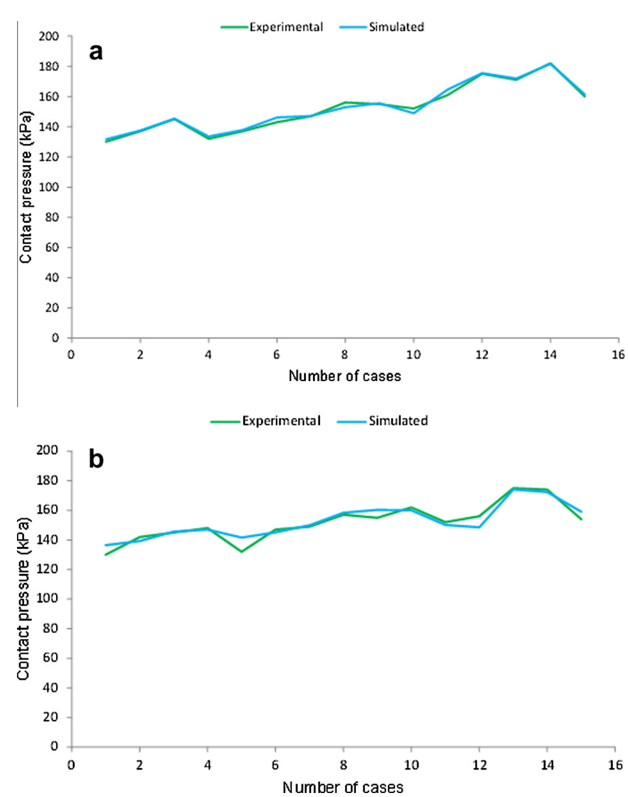

Fig. 7 – The mapping of experimental and simulated values for (a) WNN algorithm and (b) ANN.

simulated values for WNN algorithm in comparison with ANN also approves the aforementioned aspects in concern with the supremacy of WNN (Fig. 7).

5. Concluding remarks

Wavelet concept was hybridized with artificial neural network theory to predict contact pressure of driven wheel at soil–tire interface. Experimental data were obtained from series of tests in a soil bin facility utilizing a single-wheel tester device. Data were under the effect of wheel load at three levels of 2, 3 and 4 kN, slippage at three levels of 8%, 10% and 15%, and velocity at three levels of 0.8, 1 and 1.2 m/s. Image processing technique was also employed to determine contact area as affected by the combination of input parameters forming a total of 21 experiments. Ordinary ANNs with varying number of neurons in the hidden layer were developed and compared to WNN with Mexican hat, Battle–Lémaire Scaling, and Haar wavelet functions. It was found that root mean square error and coefficient of determination values of 0.1382 and 0.9864 achieved by the optimal wavelet neural network are better than that of BP neural network. The proposed model typifies a high learning speed, enhanced predicting accuracy, and strong robustness.

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