A supervised neural computing representation predicts obstacle induced force incitement in off-road vehicles

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Abstract

In this paper an attempt has been made to evaluate and predict obstacle induced force incitement in off-road vehicles affected by inflation pressure, wheel load, obstacle type and height, soil texture, tire type, slippage and velocity using artificial neural network (ANN) technique trained by back propagation algorithms from readily available data obtained from experiments conducted in soil bin facility and a single wheel-tester. A total of 6912 samples were available for training, validating and testing the neural networks. Evaluating a three layered architecture with a four layered one, the optimal topology to yield better performance on the criteria of lower root mean squared error (MSE), $T$ value and coefficient of determination ($R^2$) was a four-layered one. Then among 2 hidden layers, each of layers was increased from 0 to 40 to determine the best number of neurons by the best performance. It was divulged that 8-12-10-2 provided the best performance of MSE and $T$ were 0.027, 0.977, and $R^2$ with, respectively.

Keywords: ANN; Force; Obstacle; Single-wheel tester; Soil bin

1. Introduction

The Obstacle-wheel interaction particularly in the case of off-road vehicles is generally inevitable during traversing through uneven passes. The complex nature of dynamic phenomena through obstruct crossing aggravated by nonlinear and unpredicted behavior of soil has disillusioned researchers to propose general models in off-road wheeled machines. In spite of that, Harth et al. [1] could simulate force incitement induced by wheel-obstacle interactions based on air volume optimization inside tire utilizing various obstacles and tires. The obstacle impact on cable-towed vehicles was investigated by Gao et al. [2] about the force required pulling wheeled vehicles over idealized terrain obstacle and the peak forces of single-axle vehicles equipped with rigid wheels and pneumatic tires. The findings divulged that a vehicle with rigid wheels traversing on a 50 percent slope can cross an obstacle no larger than 1/10 of the wheel diameter. Wherein the shared purpose of researchers is to model soil-wheel interactions, the stochastic nature of soil-wheel interactions and their dependence to a great deal of interdependent parameters hinders developing a unique, general and precise mathematical, analytical, numerical and conventional model. However, this difficulty can be solved by use of nonlinear-complex calculating method of artificial neural networks (ANN).

An artificial neural network (ANN) is adapted to mimic natural neural networks utilizing a computational procedure [3]. ANN benefits over conventional modeling solutions due to their potential in learning linear, nonlinear and complex questions that other methods fail. Further affirmation is their capability in exploring multivariate input/output interrelations wherein statistical solutions are unable. As of higher privilege, ANNs are applicable auxiliaries for fitting a function, generalization, data clustering, robustness and model recognizing. ANN models and their predicting ability depend on training experimental data followed by validating and testing the model by independent dataset.

ANN can be classified as either concurrent or feed forward. Multilayer perceptron feed forward models are chief category of ANNs comprising one or more inputs, hidden layers and outputs each including neurons known as nodes. A very highly useful algorithm known as back propagation has extensively been employed with multilayer perceptron in a supervised way to compute output errors and modification of the synaptic weights of nodes [4]. Determination of a neural network structure is a primary stage in ANN representation. Appropriate ANN topology is significant to achieve simple models with lower mean squared error (MSE), root mean squared error (RMSE), $T$ value the scattering around the line (1:1), high coefficient of determination ($R^2$), and reliable performance during training, validation and test partitions. Each input to the artificial neural network is multiplied by the synaptic weight, added together and dealt with an activation function while ANNs are trained by frequently exploring the best algorithm known as back propagation.

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on the network structure (topology, connections, neurons number) and their operational parameters (learning rate, momentum, etc). The form in which the network architecture is defined affects significantly its performance that can be classified in: learning speed, generalization capacity, fault tolerance and accuracy in the learning.

To the best knowledge of authors, there is no study dealt with application of ANNs to model obstacle induced force incitement in wheeled vehicles. The readily available data yielded from experimental testes were used for development of an ANN representation.

2. Materials and Method

2.1 Data Collecting

A soil bin with 23 m length, 2 m width and 1 m depth was utilized in experiments [6]. The soil bin consisted of a wheel carriage, a single-wheel tester and bin frame. A vertical Bongshin Model DBBP load cell with the capacity of 200 kg, sensitivity of 0.1 kg and frequency of 50 Hz was calibrated and interfaced to data acquisition system including Bongshin digital indicator BS7220 model connected to RS232 port of a Data Logger, enabled monitoring the data on a screen and transmitting to a computer, simultaneously. A three phase electromotor (MOTOGEN Corporation, 30 hp) generated the power of the carriage and single wheel-tester movement along the length of soil bin. The carriage could traverse the length of soil bin in both forward and reverse directions by means of a SV 220 IS5-2NO, 380V Model (LG Corporation) inverter providing various velocities. A single-wheel tester was assembled to the carriage system (Fig. 1). The utilized tires were 220/655R21 and 9.5L-14, 6 radial ply agricultural tractor tire.

This study was conducted at four velocities of 0.5, 1, 1.5 and 2 m/s, four slippages of 5, 10, 15 and 20%, three inflation pressures of 100, 200, and 300 kPa, four wheel loads of 1, 2, 3, and 4 kN as test of principles using two types of triangular and semicircular each with 2, 3 and 4 cm height. Summary of treatments being tested is shown in Table 1.

The soil bin was filled with two soil textures of clay-loam and sandy clay-loam soil. Particular equipment were used to organize soil bed including leveler and harrow given that it’s very imperative to have well-prepared soil inside soil bin for acquiring reliable and precise results from this experiment. Soil constituents and its properties are defined in Table 2.

<table>
<thead>
<tr>
<th>Soil texture</th>
<th>Tire type</th>
<th>Obstacle</th>
<th>Slip</th>
<th>Pressure(kPa)</th>
<th>Wheel Load (kN)</th>
<th>Velocity (m/s)</th>
<th>Dependent Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>220/65R21</td>
<td>2t,s</td>
<td>5</td>
<td>100</td>
<td>1</td>
<td>0.5</td>
<td>Force Incitement</td>
</tr>
<tr>
<td>2</td>
<td>9.5L-14</td>
<td>3 t,s</td>
<td>10</td>
<td>200</td>
<td>2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 t,s</td>
<td>15</td>
<td>300</td>
<td>3</td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>20</td>
<td></td>
<td>4</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

* t: triangular and s: semicircular
2.2. Artificial Neural Networks

A total of 6912 data were used with 9 input components and output component for training, verification and testing the neural networks. Therefore 6912 arrays were produced and then were randomly allocated into three different sets; i.e. training, validation, and testing. In training, validation, and testing step, 65%, 15%, and 20% of these arrays were used, respectively.

A feed-forward artificial neural network with BP algorithm was selected for prediction because of its documented ability for modeling. Structure of network was an important issue. Increasing number of hidden layers may increase efficiency of system, yet roots more computational intricacy. Thus, MLP neural network with 9-N1-N2-1 architecture was considered at first. Defining the number of neurons in hidden layer (N1) is important stage in MLP neural network scheme. So as to choose the number of neurons in hidden layer, N1 was augmented from 1 to 20. Since initial weights and biases of neurons were taken randomly, for each number of hidden neurons (each network structure), network was trained for 100 times to succeed this problem. In each system training network was trained for 1000 epochs. Then, network with minimum value of MSE was considered for that structure. Of the several numerical indicators, the important ones selected for the present study were MSE and T statics given in equations 1 and 2. T value computes the scattering around the line (1:1), a T value close to 1 is prevailed (Weiss et al., 2000).

\[
MSE = \frac{1}{n} \sum(Y_i - \bar{Y})^2
\]  

(1)

\[
T = (\frac{\sum(Y_i - Y)}{\sum(Y_i - Y)})^2
\]  

(2)

where \(Y_i\) and \(Y_{ip}\) are \(i\)th output variables that obtained by experiment and neural network, respectively. \(\bar{Y}\) is the average over \(N\) samples, and \(N\) is number of samples that used in each step. Since the range of input variables were 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.

\[
X_n = 2 \frac{X_i - X_{r,\text{min}}}{X_{r,\text{max}} - X_{r,\text{min}}} - 1
\]  

(3)

where \(X_n\) denotes normalized input variable, \(X_i\) is raw input variable, and \(X_{r,\text{min}}\) and \(X_{r,\text{max}}\) denote minimum and maximum of input variable, respectively. Since better presentation (higher \(R^2\) value, T value close to 1, and lower MSE) was decision parameter, MLP neural network with 9-N1-N2-1 (i.e. two hidden layers) was established.

Preliminary attempts disclosed the learning and training capacity of two hidden layer networks was superior to one hidden layer ones.

For training function, \textit{trainlm} was implemented that updates weight and bias values according to LM optimization and is often considered the fastest back propagation algorithm recommended as a highest preference supervised algorithm. LM is a very predominant curve-fitting algorithm applied in many software presentations for solving generic curve-fitting problems. The LM algorithm provides a numerical explanation to the problem of minimizing a (generally nonlinear) function and is a popular option to the Gauss-Newton technique of discovering the minimum of a function.

\textit{trainbfg} is a network training function that updates weight and bias values according to the BFGS quasi-Newton method. \textit{trainbfg} can train any network as long as its weight, net input, and transfer functions have derivative functions.

Backpropagation is used to calculate derivatives of performance perf with respect to the weight and bias variables \(X\). Each variable is adjusted according to the following:

\[
X = X + \alpha dX
\]  

(4)

where \(dX\) is the search direction, and \(a\) is selected to minimize the performance along the search direction. The line search function \textit{searchFcn} is used to locate the minimum point. The first search direction is the negative of the gradient of performance. In succeeding iterations the search direction is computed according to the following:

\[
dX = -H/gX
\]  

(5)

Where \(gX\) is the gradient and \(H\) is an approximate Hessian matrix.

\textit{trainbfg} was used with Backpropagation to calculate derivatives of performance perf with respect to the weight and bias variables \(X\). Each variable is adjusted according to gradient
descent with momentum,
\[ dX = mc \times dX_{\text{prev}} + lr \times (1 - mc) \times d\text{perf}/dX \] (6)
where \( dX_{\text{prev}} \) is the previous change to the weight or bias. The training and testing performance (MSE) was selected to be the error criterion. Afterwards, a regression analysis between the predicted values and the measured values was performed to assess the network performance. Where various training functions were firstly developed, \textit{trainlm}, \textit{trainbfg}, and \textit{traingdm} were opted. Amongst transfer functions, \textit{hardlim} and \textit{tansig} functions were selected. MATLAB software (version 7.6, 2008, Mathworks Company) was used to develop ANN predictive representations.

![Graph](image1)

**Fig. 2.** RMSE of the a) training and b) testing, it was attained that compared to 3 layered ANN

![Graph](image2)

**Fig. 3.** Effect of learning rate and momentum on RMSE

![Graph](image3)

**Fig. 4.** Mapping between the predicted and actual values.

3. **Results and Discussion**

Established upon first calculations of the RMSE of the
training and testing, it was attained that compared to 3 layered ANN, 4-layer structure arranged better performance (Fig. 2). Based on performance criteria a neural representation with 4-layer architecture was developed. Levenberg-Marquardt back-propagation algorithm with hardlim transfer function for hidden neurons and linear transfer function for output layer neuron provided better performance. Effect of number of neurons/layers on training performance of ANN models is presented in Fig. 2a. Consequently, minimum value of MSE was obtained for 6-12-10-2 structure with RMSE equal to 0.027 for training and 0.041 for test partitions (Fig. 2). As it is inferred from Fig. 2a one hidden layer had the highest MSE value where the figure indicates that increasing the number of hidden layers increased the model capability and reduced the prediction problems. Other network structures such as 6-14-11-2 (MSE of 0.075), 6-17-10-2 (MSE of 0.047) and 6-15-19-2 (MSE of 0.080) achieved low MSE values. The same procedures for computation of satisfactory performance were taken in the case of other training and transfer functions with $R^2$, $T$ and MSE values. However, it discloses that the 6-12-10-2 structure with RMSE equal to 0.027 had the best performance. Though it may seem that the simpler topologies could be utilized, however, in the case of soil-tool interactions due to unidentified behavior of soil and elastic-plastic reactions, nonlinear and complex relations are generally obtained. Complicated structure with higher performance is prior to a simple network structure with lower performance. Ideally MSE close to zero shows that there is no difference between actual and predicted values and $T$ close to 1 demonstrates the better fitting.

The learning rate balances the level of downing the error after each epoch. The learning rate applies a larger or smaller portion of the respective adjustment to the old weight. If the factor is set to a large value, then the neural network may learn more quickly, however if there is a large changeability 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 counter-productive to learning. Typically, it is better to set the factor to a small value and edge it upward if the learning rate seems slow. Momentum runs as a low pass filter to settle sudden changes in the progress. Momentum basically allows a change to the weights to persist for a number of adjustment cycles. The magnitude of the persistence is controlled by the momentum factor. If the momentum factor is set to nonzero value, then increasingly greater persistence of former adjustments is permitted in modifying the current adjustment. This can improve the learning rate in some situations, by helping to smooth out unusual conditions in the training set.

Fig. 3 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. 3 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 0.4 and 0.5, respectively. To demonstrate the good fitting of predicted values versus actual data, Fig. 4 is presented.

4. Conclusions

The study showed that the ANN model could applicably be adopted to solve a wide range of vehicle dynamics problems such as tire-obstacle collision which is of a great field of studying interests for researchers and engineers. In this paper an attempt has been made to evaluate and predict obstacle induced force incitement in off-road vehicles affected by inflation pressure, wheel load, obstacle type and height, soil texture, tire type, slippage and velocity using artificial neural network (ANN) technique trained by back propagation algorithms from readily available data obtained from experiments conducted in soil bin facility and a single wheel-tester. A total of 6912 samples were available for training, validating and testing the neural networks. Evaluating a three layered architecture with a four layered one, the optimal topology to yield better performance on the criteria of lower root mean squared error (MSE), $T$ value and coefficient of determination ($R^2$) was a four-layered one. Then among 2 hidden layers, each of layers was increased from 0 to 40 to determine the best number of neurons by the best performance. It was divulged that 8-12-10-2 provided the best performance of MSE and $T$ were 0.027, 0.977, and $R^2$ with, respectively.

References