PRELIMINARY RESEARCHES REGARDING THE USE OF ANN TO PREDICT THE WHEEL-SOIL INTERACTION

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ABSTRACT. Soil-wheel interactions as a phenomenon in which both components are behaving nonlinearly has been considered a sophisticated and complex relation to be modeled. A well-trained artificial neural networks as a useful tool is widely used in variety of science and engineering fields. We inspired to use this facility for application of some soil-wheel interaction products since nonlinear and complex relationships between wheel and soil necessitate more precise and reliable calculations. A 2-14-2 feed forward neural network with back propagation algorithm was found to have acceptable performance with mean squared error of 0.020. This model was used to predict two output variables of rut depth and contact area with regression correlations of 0.99961 and 0.99996 for rut depth and contact area, respectively. Furthermore, the results were compared with conventional models proposed for predicting the contact area and rut depth. The promising results of ANN model give higher privilege over conventional models. The findings also introduce the potential of ANN for modeling. However, the authors recommend further studies to be conducted in this realm of computing due to its great potential and capability.

Key words: Contact area; Rut depth; ANN; Soil bin.

INTRODUCTION

Contact area is a very role playing factor in determining physical changes occurred in soil causing soil compaction owing to the multitude of load applied to the area of contact. In the case of agricultural wheeled machines, determination of contact area is a factor to decide about amount of stress-strain propagations.

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happening in soil and soil compaction which reduces crop yield. Determination of contact area between tire and soil plays an important role on both the intensity of soil compaction and also in other soil-wheel interactions (Taghavifar and Mardani, 2012). Theoretical models were developed with the intention of contact area determination by many researchers (Komandi, 1990; Godbole et al., 1993; Grecenko 1995). The simplest algorithms were developed assuming contact area as circular, rectangular or ellipsoidal. Komandi (1990) developed a model for determination of contact area in terms of a constant regarding soil type, tire inflation pressure and wheel load as following:

$$A = \frac{C \cdot W^{0.7} \cdot \sqrt{\frac{b}{d}}}{P^{0.45}} \quad (1),$$

where \(A\) is tire contact area \((m^2)\), \(C\) is soil constant, \(W\) is wheel load (kN), \(b\) is tire width (m), \(d\) is wheel diameter (m) and \(P\) is tire inflation pressure (kPa), respectively.

In order to define rut depth, Anttila proposed an empirical model based on WES-models as below:

$$R = \frac{0.248}{N} \cdot d \quad (2),$$

where \(d\) is tire diameter (m), \(N\) is wheel numeric and obtained from eq.3 and \(\delta\) is tire deflection as eq.4:

$$N = \frac{C \cdot b \cdot d}{W} \cdot \sqrt{\frac{\delta \cdot \frac{1}{h}}{1 + \frac{b}{2 \cdot d}}} \quad (3)$$

$$\delta = 0.001 \left(0.365 + \frac{170}{P}\right) \cdot W \quad (4)$$

Broad tires increase the contact area resulting in reduced loading area. Therefore tires should be controlled to have high contact area with soil surface. This attitude reduces the pressure applied by the tire on the ground. This pressure relies on tire inflation pressure and wheel load on the wheel. Therefore, contact area is needed to be estimated precisely.

As a later sign of soil compaction, the induced rut depth can be a reliable representative. Soil compaction which is the result of soil volumetric reduction due to forcing has reasonable relation with soil strain. Soil deformation, definitely, is a method to investigate soil compaction. Thus, rut depth is a major factor to be verified.

Artificial neural networks (ANNs) are extensively used in a large range of issues in scientific fields particularly wherein the mathematical, conventional, analytical and statistical methods fail to succeed. ANNs perform reliably in nonlinear and complex phenomena that are hard to be verified and interpreted. ANNs are appropriate means for fitting a function, data clustering and discerning the model samples. As well, they have been used in different applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing. ANNs have successfully been applied in the fields of pattern, recognition, modeling, and control (Haykin, 1999). A supervised trained ANN is capable of predicting and
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modeling inspired by human being biological neural system. The predictability of a well-trained ANN is yielded from training the experimental data and later to validating and testing by independent data. Unlike many methodologies, ANN models are able to hold multivariate input variables and predict multiple output parameters. A simple topological model can be achieved with high accuracy and reliable performance where the model is achieved fast compared with lengthy iterative calculations of numerical methods and tedious computations of analytical techniques. Furthermore, it is optioned to add or remove any input or output variable where required.

In this paper the authors aimed to investigate the application of ANNs in predicting and modeling induced rut depth and contact area as affected by wheel load and tire inflation pressure from readily available data. Since soil unpredictability is conspicuous feature due to elastic-plastic of soil and its unknown nature, application of ANNs with their potential ability for complicated problems is intended.

MATERIALS AND METHODS

A laboratory intended long soil bin facility and a single wheel-tester were manufactured in the Faculty of Agriculture, Urmia University, Iran (Mardani et al., 2010). The soil bin was consisted of a wheel carriage, a single-wheel tester and bin frame. The single wheel-tester was equipped with a vertical load cell as shown in Fig. 1. In order to provide the desired wheel load, a power bolt was used to impose the objective load. The load cell was interfaced to data acquisition system included a digital indicator and a data logger for monitoring the data on a screen and at the same time for sending the data to a laptop.

Figure 1 - Soil bin set up and its equipments
The experimental phase was carried out on the basis of two important tire parameters: 1) tire inflation pressure, and 2) wheel load. The experiments were conducted at each of tire inflation pressures with variety of wheel loads. The measurements of contact area and rut depth were performed. For measuring the rut depth, as shown in Fig. 2, a digital caliper was used with an index to measure the soil deformation under wheel. Detailed information for measuring the contact area is given in the previous paper of authors (Taghavifar and Mardani, 2012). The soil which was used inside the soil bin was a clay-loam soil and the utilized tire was a towed Good year 9.5L-14, 6 radial ply agricultural tractor tire. The summary of conducted experiments is given in Table 1. Furthermore the soil properties and its constituents are given in Table 2.

![Figure 2 - Measuring rut depth created by tire](image)

**Table 1 - Summary of experiment conducted for a tire width of 0.2 m and wheel diameter of 0.7 m**

<table>
<thead>
<tr>
<th>Independent parameters</th>
<th>Dependent parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertical load (N)</td>
<td>Inflation pressure (kP)</td>
</tr>
<tr>
<td>2000</td>
<td>100</td>
</tr>
<tr>
<td>3000</td>
<td>150</td>
</tr>
<tr>
<td>4000</td>
<td>200</td>
</tr>
<tr>
<td>5000</td>
<td>300</td>
</tr>
</tbody>
</table>
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Table 2 - Soil constituents and its measured properties

<table>
<thead>
<tr>
<th>Item</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand (%)</td>
<td>34.3</td>
</tr>
<tr>
<td>Silt (%)</td>
<td>22.2</td>
</tr>
<tr>
<td>Clay (%)</td>
<td>43.5</td>
</tr>
<tr>
<td>Bulk density (kg/m³)</td>
<td>2360</td>
</tr>
<tr>
<td>Frictional angle (°)</td>
<td>32</td>
</tr>
<tr>
<td>Cone Index (kPa)</td>
<td>700</td>
</tr>
</tbody>
</table>

Table 3 - The results obtained from experiments conducted based on outlined process shown in Table 1

<table>
<thead>
<tr>
<th>Inflation pressure (kPa)</th>
<th>Wheel load (kN)</th>
<th>Contact area (cm²)</th>
<th>Rut depth (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.96</td>
<td>392.03</td>
<td>16.73</td>
</tr>
<tr>
<td>100</td>
<td>2.94</td>
<td>455.08</td>
<td>17.47</td>
</tr>
<tr>
<td>100</td>
<td>3.92</td>
<td>532.22</td>
<td>21.67</td>
</tr>
<tr>
<td>100</td>
<td>4.97</td>
<td>640.62</td>
<td>26.31</td>
</tr>
<tr>
<td>150</td>
<td>1.96</td>
<td>219.65</td>
<td>14.52</td>
</tr>
<tr>
<td>150</td>
<td>2.94</td>
<td>239.97</td>
<td>16.02</td>
</tr>
<tr>
<td>150</td>
<td>3.92</td>
<td>336.15</td>
<td>18.33</td>
</tr>
<tr>
<td>150</td>
<td>4.97</td>
<td>572.62</td>
<td>20.48</td>
</tr>
<tr>
<td>190</td>
<td>1.96</td>
<td>200.83</td>
<td>12.04</td>
</tr>
<tr>
<td>190</td>
<td>2.94</td>
<td>220.89</td>
<td>13.45</td>
</tr>
<tr>
<td>190</td>
<td>3.92</td>
<td>259.09</td>
<td>14.98</td>
</tr>
<tr>
<td>190</td>
<td>4.97</td>
<td>279.5</td>
<td>16.74</td>
</tr>
</tbody>
</table>

Figure 3 - The schematic structure of Multi-Layer Perceptron Neural Networks model
A total of 32 samples were used with two input components (wheel load, and tire inflation pressure) and two output parameters of rut depth and contact area for training, verification and testing the neural networks. Therefore 32 patterns were generated. These patterns are randomly divided into three different sets; i.e. training, validation, and testing. In training, validation, and testing step, 65%, 15%, and 20% of these patterns were used, respectively. A Multi-Layer Perceptron feed forward neural network with back propagation algorithm was used in MATLAB software; trainlm as default training function of MATLAB software with tansig transfer function were used. The schematic structure of Multi-Layer Perceptron Neural Networks model is shown in Fig. 3. The obtained experimental results are presented in Table 3.

RESULTS AND DISCUSSION

The results revealed that a neural topology with one hidden layer is able for predicting and modeling output variables under the effects of input variables. Hence, number of neurons in hidden layer was developed from 1 to 20. The training process was conducted for 1000 epochs or until the cross-validation of data on the basis of mean squared error (MSE). The decreasing rate of MSE is shown in Fig. 4. Furthermore, errors in prediction using ANN with different numbers of neurons in single hidden layer is shown in Table 4. The predicted values by the optimal neural network shown in Table 4 for rut depth and contact area are depicted in Figs. 5 and 6, respectively. The high regressions for rut depth and contact area were yielded 0.99961 and 0.99996, respectively.

Table 4 - Errors in prediction using ANN with different numbers of neurons in single hidden layer

<table>
<thead>
<tr>
<th>Neurons</th>
<th>MSETrain</th>
<th>MSETest</th>
<th>Epoch</th>
<th>Neurons</th>
<th>MSETrain</th>
<th>MSETest</th>
<th>Epoch</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.032</td>
<td>0.031</td>
<td>111</td>
<td>11</td>
<td>0.032</td>
<td>0.031</td>
<td>54</td>
</tr>
<tr>
<td>2</td>
<td>0.038</td>
<td>0.033</td>
<td>319</td>
<td>12</td>
<td>0.032</td>
<td>0.024</td>
<td>59</td>
</tr>
<tr>
<td>3</td>
<td>0.038</td>
<td>0.034</td>
<td>26</td>
<td>13</td>
<td>0.031</td>
<td>0.028</td>
<td>68</td>
</tr>
<tr>
<td>4</td>
<td>0.038</td>
<td>0.028</td>
<td>136</td>
<td>14</td>
<td>0.031</td>
<td>0.02</td>
<td>55</td>
</tr>
<tr>
<td>5</td>
<td>0.038</td>
<td>0.03</td>
<td>129</td>
<td>15</td>
<td>0.033</td>
<td>0.023</td>
<td>87</td>
</tr>
<tr>
<td>6</td>
<td>0.038</td>
<td>0.027</td>
<td>98</td>
<td>16</td>
<td>0.033</td>
<td>0.024</td>
<td>64</td>
</tr>
<tr>
<td>7</td>
<td>0.038</td>
<td>0.027</td>
<td>107</td>
<td>17</td>
<td>0.033</td>
<td>0.023</td>
<td>71</td>
</tr>
<tr>
<td>8</td>
<td>0.038</td>
<td>0.028</td>
<td>74</td>
<td>18</td>
<td>0.033</td>
<td>0.025</td>
<td>69</td>
</tr>
<tr>
<td>9</td>
<td>0.038</td>
<td>0.026</td>
<td>74</td>
<td>19</td>
<td>0.038</td>
<td>0.027</td>
<td>81</td>
</tr>
<tr>
<td>10</td>
<td>0.038</td>
<td>0.029</td>
<td>79</td>
<td>20</td>
<td>0.034</td>
<td>0.028</td>
<td>78</td>
</tr>
</tbody>
</table>
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These rewarding results show that a well-trained supervised ANN can predict soil wheel interactions which are highly nonlinear and complex owing to unknown nature of soil. The lowest MSE was obtained 0.020 with 2-14-2 topology. The findings of this study for more validation were, however, compared with conventional models proposed for predicting contact area and rut depth. The models were contact area by Komandi (1990) eq. 1 and for rut depth Anttila (1998), eq. 4. A comparison of the mean squared errors and $R^2$ values are shown in Table 5.

![Figure 4 - The decreasing rate of MSE](image)

<table>
<thead>
<tr>
<th>Model</th>
<th>$R^2$</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN (rut depth)</td>
<td>0.9992</td>
<td>0.02</td>
</tr>
<tr>
<td>ANN (contact area)</td>
<td>0.9999</td>
<td>0.02</td>
</tr>
<tr>
<td>Komandi</td>
<td>0.9417</td>
<td>59.71</td>
</tr>
<tr>
<td>Anttila</td>
<td>0.9651</td>
<td>7.81</td>
</tr>
</tbody>
</table>

Table 5 - A comparison of the mean squared errors and $R^2$ values
Figure 5 - Predicted values of rut depth obtained by ANN model versus measured values

Figure 6 - Predicted values of contact area obtained by ANN model versus measured values
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CONCLUSIONS

A 2-14-2 neural network provided the best performance index (MSE) for predicting and modeling rut depth and contact area as affected by inflation pressure, and wheel load on clay-loam soil. The value of MSE was 0.020 with regression correlations of 0.99961 and 0.99996 for rut depth and contact area, respectively.

The low variability between the measured and predicted values implied that a feed-forward BP neural network was able to suitably model complex soil-wheel interactions under the selected experiment tests. The results generally validate the dependability of the network in predicting the output in a clay loam soil. Nevertheless, more studies are essential for other soils to make it a generalized ANN model.

REFERENCES


