Real-time neural network system for non-destructive control of asphalt mixtures compaction

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Abstract. The problem is considered of designing a neural network system for control of road materials compaction in real time. The system is designed to ensure the functioning of non-destructive technology in road construction. A model of an artificial neural network (ANN) for monitoring the quality of compaction of road materials during the operation of vibrating rollers in real time is obtained. The system provides normalization of the input data of the ANN model. For the design of the ANN, the following methods were used: the least mean square deviation method; Levenberg-Marquardt algorithm; backpropagation. The structure of a non-destructive neural network system for monitoring compaction in real time is obtained. The results of numerical simulation of a system with an ANN for predicting the compaction coefficient of road materials are presented.

1. Introduction

In the Russian Federation the most widespread are highways with non-rigid asphalt concrete pavements. When building layers of road surfaces, there are problems with the use of non-destructive technologies for quality control of asphalt concrete mixtures. There is a significant lag in application of automated system of continuous compaction control of road materials by vibrating rollers. This situation is related to the problem of import substitution because foreign-made devices are very expensive.

Taking into account innovative technologies for the construction of road surfaces, requirements for the quality of pavements, the tasks of implementing digital BIM technologies, an important scientific and technical direction is the use of automated road building machines equipped with modern technical means, including "smart" devices, for functioning as elements of cyber-physical systems.

One of the most important technical processes in road construction is the compaction of road materials: soils; asphalt concrete mixtures. High-quality compaction can solve many problems that lead to defects in the road’s operation. These facts have been confirmed in many scientific studies, experience in the construction and operation of road surfaces of highways [1].

There are known achievements in automatic systems of compaction control that implement non-destructive technologies for road rollers. These include equipment installed on vibrating road rollers, equipment for intelligent compaction (IC) systems [2, 3], continuous compaction control (CCC) [4, 5]. Global manufacturers Trimble, Topcon, MOBA, etc. produce ready-made sets of automation equipment for installation on foreign-made rollers. The systems provide measurement of compaction indicators that have a correlation with the compaction coefficient. A significant disadvantage of CCC/IC systems is a poor accuracy in measuring of compaction indicators.
One of the modern directions of development of CCC/IC systems is the use of artificial neural networks. For many years the group of Professor S. Commuri (USA) worked in this direction [6-9]. To train the ANN the authors used the signals of accelerometer sensors installed on the frame of a vibrating roller as input data. Then, the spectral transformation method was used. A similar approach is used for almost all compaction measurement systems of CCC/IC indicators. The disadvantages of the intelligent system developed by the S. Commuri group are large errors due to interference from accelerometer sensors and constant changes in the properties of the asphalt concrete mixture. In the available information sources, there is no data on the implementation of developments based on ANN for real models of vibration rollers.

The long-term development of CCC and IC technologies has created a theoretical and experimental basis for the current stage in the development based on the use of artificial intelligence, intelligent optimization methods. The development of artificial intelligence models for the IC system is the results of scientific research by Xu G. and Chang G. K., who proposed a system including an artificial neural network with a genetic training algorithm [10].

The article is devoted to the creation of a model of a neural network system for quality control of compaction of road materials for installation on vibrating rollers. The paper offers a justification of the input data vector for training the ANN and continuous predicting of the mixture compaction coefficient. The software implementation of the ANN model is provided in the MATLAB program.

2. Methods

Compaction resistance in the asphalt mixture occurs due to the pressure of the rollers on the mixture during the operation of vibration rollers. A complex indicator that characterizes the compressive resistance of an asphalt concrete mixture is the modulus of deformation of the mixture, which has a significant impact on the compaction process at all stages of rolling the pavement by rollers.

The dynamic modulus of deformation $E$ has a strong correlation with the temperature of the mixture, it can be determined by the regression model [1]:

$$E = 691.13 \cdot e^{-0.03t},$$

where $t$ – mixture temperature, °C.

The program code for calculating $E$ in the MATLAB program is defined by the function

```matlab
function E = m_deformation(t)
E = 691.13*(exp(t.*(-0.03)));
return
```

The neural network system consists of the following functional elements (figure 1): a microcontroller with a monitor for entering initial data – machine parameters, process and properties of the compacted material, as well as a system for continuous data collection in real time.

The initial stage of the algorithm includes preliminary processing of input data, which determines the performance of the training process of the ANN, the value of the training error and other properties of the neural network.

Normalization of the input data vector is performed to reduce the negative impact on neurons. In this case, the data is reduced to the interval [0, 1] or [-1, 1]. To equate the quantitative values of the input data, the method of linear shift of the interval value of the characteristic value is usually used.
Figure 1. Functional scheme of intelligent information technology.

Determination of the characteristic value $x$ for the $i$-th example of sample using the formula for representing data in the interval $[a, b]$:

$$y = \frac{(x - x_{\text{min}}) \cdot (b - a)}{(x_{\text{max}} - x_{\text{min}}) + a},$$

where $x$ – the parameter value to be preprocessed; $x_{\text{max}}$, $x_{\text{min}}$ – the maximum and minimum sample value of the parameter $x$.

All input data for training the ANN are preprocessed in order to bring it to the interval from 0 to 1. Data normalization function on the example of the mixture deformation module in the MATLAB program language:

```matlab
function e0_n=m_def_norm(e0,a,b,e0min,e0max)

for j = 1:length(e0)
    e0_n(j)=(e0(j)-e0min)*(b-a))/((e0max-e0min)+a);

end

return
```

Designing a model of a neural network system. The software environment creates the information for the machine learning model. The learning element uses received information to upgrade knowledge database. The functional element from the knowledge base is then used to solve the task. The signals of the measuring transducers transmitted from the external environment are random, so the learning element cannot fill in the gaps correctly or ignore insignificant details. The system functions in an arbitrary way, then it receives an information feedback signal from the functional element. The presence of feedback allows the machine learning system to test operational hypotheses and change them if necessary.

Artificial intelligence consists of two processing stages – the training process and testing. Preliminary studies and analysis of the results led to the conclusions that a multi-layer neural network gives a better result compared to such networks as a generalized regression network, a single-layer Perceptron, an Elman network, a cascade network with direct signal propagation, and others. The first layer of the network is the input data vector of the network, which corresponds to the necessary data for training the neural network – the parameters of the machine, process and asphalt concrete mixture. The second layer is a hidden network layer with ten artificial neurons between the input and output layers. The third layer – the output layer of the network, performs the prediction of the degree of compaction of the asphalt concrete mixture.
Supervised learning is shown in figure 2. This assumes that there is a database of training examples for the network. Each sample of the training set collected from the results of laboratory and field tests is given to the input layer of the network. Then it is processed inside the ANN structure.

![Functional scheme of training an artificial neural network model](image)

**Figure 2.** Functional scheme of training an artificial neural network model.

The coefficient of compaction of the asphalt concrete mixture is one of the most important indicators that determine the quality of the compacted pavement of the road. The obtained value of the compaction coefficient, figure 2, is compared in real time with the corresponding parameters from the prepared samples. Next, the training error of an artificial neural network is calculated based on the mean square error method. If the specified error value is exceeded, the weight coefficients of the connections between the layers (internal and input) of the artificial neural network are changed. The weight coefficients are changed based on the algorithm of the error back propagation method, which is suitable for the network structure. The weights change at each iteration until the network training error reaches a low level.

The sigmoidal function is used as an activation function in the synthesis of ANN, which provides an equalization between linear and nonlinear behavior:

\[ y(j) = \frac{1}{1 + \exp(-\nu_j)}, \]

where \( \nu_j \) – weighted sum of all synaptic inputs with a threshold value; \( y(j) \) – the output of an artificial neuron.

All hidden neurons have 8 local connections, where the input values of hidden neurons \( u_{\text{input}} \) are calculated using the following formula:

\[ u_{\text{input}} = \sum_{i=1}^{8} w_{ij} x_i, j = 1, 2, 3..n, \]

where \( w_{ij} \) – a set of weights that are iterated over for all neurons; \( x_i \) – data of the vector of input neurons.

After calculating the vector of input data of hidden neurons, the output data of hidden neurons is determined by substituting the input values of each neuron into the activation function.

The input value of the output neuron is calculated according to the following dependence:

\[ y_{\text{input}} = u_{\text{output}} \cdot w_h, \]

where \( w_h \) – matrix of weights of the layer of hidden neurons.

To determine the output neuron, the sum of the products of the weighting coefficients and the output values of the hidden neurons is activated using the activation function:
Based on the method of back propagation of the error, gradients are determined that are applied when changing the weight coefficients of the ANN. The concept of this approach is to transmit information error signals from the outputs of the neural network to its inputs towards the reverse of the direct propagation of information signals.

As a result of analytical and experimental studies of the pilot scientific project, an ANN model was built for a system of continuous quality control of compaction of asphalt concrete mixture for use on vibrating rollers. A simulation model of the system is obtained in the MATLAB program. The simulation of the ANN is performed on a test example. The results of the graphical interpretation of the change in the compaction coefficient are shown in figure 3.

![Graph showing compaction coefficient over iterations](image)

**Figure 3.** Results of testing an artificial neural network.

The average error in predicting the compaction coefficient of the asphalt concrete mixture is less than 10%, which indicates a good efficiency of using the compaction control method based on the ANN method.

3. Conclusion
As a result of the work performed, a neural network model of the compaction control system was obtained, which determines the value of the compaction coefficient of the asphalt concrete mixture in real time. Checking the trained ANN on a test sample showed that the maximum deviation of the data of the compaction coefficient of the mixture obtained from the neural network and the training set does not exceed 10%, which is an acceptable result for researchers.

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