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The use of artificial neural networks for modeling air void content in aggregate mixture

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ABSTRACT

A database for various pavement mixtures which were tested at the IGMAT Building Materials Institute, Ljubljana, during the period from 1998 to 2009 was established. This database consists of 17,296 asphalt mixture analyses. Artificial neural networks were used in this work to estimate air void content in aggregate mixture of several stone fractions for 7 types of asphalt concrete mixtures (AC 32, AC 22, AC 16, AC 11, AC 11 PmB, AC 8, AC 8 PmB) produced according to EN 13108-1. The main aim of the paper is to model the relationship between different parameters and air void content in aggregate mixture with artificial neural networks and multiple linear regression. The proposed method uses feed-forward neural networks with error back-propagation algorithm. Two different programs for modeling with artificial neural networks, NTR2003 and WEKA toolkit, were used. Before modeling air void content in aggregate mixture outliers among data were determined. Then, the artificial neural network analysis and multiple linear regression were done for each asphalt mixture and also for all mixtures together. Modeling of air void content in aggregate mixtures in general showed that linear models work better than artificial neural network models in the cases of specific asphalt mixture. In the case of analysis of all asphalt mixtures together, neural networks detected real hidden relationships between data and are therefore more effective than the linear model. Feed-forward neural networks are entirely appropriate models for an effective preliminary estimate of air void content in various aggregate mixtures.

1. Introduction

Asphalt mixture consists of aggregate mixture, binder and air voids. Bitumen, which acts as a binder in asphalt compositions, is a viscoelastic material and is an essential component in the composition of asphalt mixtures. The second component of the asphalt is aggregate which does not show any temperature and time dependent properties and therefore represents the mechanical resistance. Asphalt used for pavement constructions is in general exposed to various external factors. Therefore, with pre-selection of appropriate materials technologists are looking for ways to design such asphalt mixture that would have properties which prevent the negative consequences, e.g. permanent deformations, cracks due to fatigue, and temperature. They deal with different types of modeling, analysis, experimentation and data processing.

During recent years automation in measurements and evolution in computer technology enable the creation of large databases and their analyses. One way of modeling various parameters or properties is artificial neural networks [1,2,3]. In the field of artificial intelligence they are the most widely used method which is also used for solving engineering problems. They are mainly used as forecasting models because they do not require prior knowledge and have high accuracy. In the area of road construction Saltan and Terzi [4] used them for the evaluation of carriage-way deformations. Tusar and Novic [5] used them for data exploration on standard asphalt mix analyses. Sukru and Oruc [6] modeled the relationship between setting time, the quantity of added cement, asphalt content of the waste and the modulus of bituminous emulsions by artificial neural networks. Neural networks have been used for the prediction of the compressive strength of concrete [7,8], for stability prediction of tunnel construction [9], for the prediction the time required to carry out earth works and their cost [10], in planning delivery system for prepared pre-mixed concrete [11], in the manufacture of fresh concrete with addition of rubber [12], for modeling corrosion current of reinforced concrete [13], in the modeling process of building construction [14], for evaluating the force of friction between the wheel and the road [15], for modeling lower bearing unbound pavement layers [16], for modeling permanent deformation of polypropylene modified asphalt mixtures [17] and for many other engineering problems.

Artificial neural networks are less complicated and smaller than biological neural networks. They consist of neurons which are linked with connections described by their weights. The particularity of artificial networks is that they are not programmed but trained. For the training

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of networks two sets of data are required. The first set is a training set and the second one is a testing set which is needed to establish the efficiency of training. An important phase of neural network modeling is the determination of weights applied during network training. There are several methods of training. One of the widely used methods is a generalized delta rule or error back-propagation algorithm which is explained in detail by Rumelhart and McClelland [19]. To estimate the air void content in aggregate mixture feed-forward neural networks with error back-propagation learning algorithm have been used. The learning phase of artificial neural networks is influenced by a variety of parameters, such as maximum number of iterations, learning step size, geometry of the network and, most importantly, data. Considering the geometry of artificial neural networks it cannot be precisely defined which one corresponds to the specific data. We decided to deal with networks with two or three hidden layers. The Fortran program NTR2003 and library of neural networks in the program WEKA toolkit have been used. The algorithms used in both programs are not entirely compatible, primarily due to output functions and the processes in the learning phase.

This paper describes the use of artificial neural networks for the estimation of air void content in aggregate mixture, which is defined as mixture of different stone fractions without bituminous binder. Air void content in aggregate mixture is determined in order to find the optimal composition of the fractions of stone material. With the optimum composition of aggregate fractions the maximum density or the minimum amount of air voids in stone material is achieved.

Initially, we assumed that the sieving curve and the density of aggregate mixture are the most influential factors affecting the air void content in the aggregate mixture. Surprisingly, with preliminary investigation we found out that the content of the bituminous binder as an influential factor always improved models. Air void content in aggregate mixture cannot be exactly calculated from sieve curve, density of stone material and bitumen content. Only a rough estimation has been made. There are two reasons why it cannot be calculated exactly. Firstly, the optimum composition of aggregate fractions can be determined if all grains have the same shape. Because of the irregular shapes of aggregate the optimum composition of aggregate fractions is a nonlinear problem. Secondly, additional disorder represents mastic and causes random turning of aggregate grains, which prevents compounding of grains in the densest composition.

The requirements (standards, specifications, guidelines) lay down the permitted range of air voids in asphalt mixtures. At the same time, also the required bitumen content or the rate of void filling with bitumen is often determined. By considering both restrictions, the required air void content in aggregate mixture can be calculated. Air void content in aggregate mixture is therefore important because it is indirectly specified in the requirements.

2. Data

The collected data are the test results of asphalt mixtures tested at the IGMAT Building Materials Institute [18] during the time period from 1998 to 2009. Data used in the analyses are: binder content, sieve analysis, maximum density of aggregate and air void content in aggregate mixtures (see Table 19 in Appendix A).

Firstly, each asphalt concrete mixture produced according to EN 13108-1 (e.g. AC 32 means asphalt concrete mixture with nominal aggregate size 32 mm) has been analyzed from the database separately; at the end an analysis of all mixtures together was performed as well:

- AC 32 (time period 2006/2009)
- AC 22 (time period 2006/2009)
- AC 16 (time period 2006/2009)
- AC 11 (time period 2006/2009)
- AC 11 PmB (time period 2006/2009)
- AC 8 (time period 2006/2009)
- AC 8 PmB (time period 1998/2005)
- modeling of all seven mixes together.

Input parameters in all cases are: binder content, sieve analysis and maximum density of aggregate; output parameter is: air void content in aggregate mixtures.

A large data base has been available. In the case of AC 22 eleven parameters for modeling air void content in aggregate mixture have been analyzed resulting in 381 input–output data pairs (see Table 19 in Appendix A). The number of parameters and the number of input–output pairs of data depend on the analyzed asphalt concrete mixture.

Firstly, we identified the parameters that had a significant impact on the output data. Then we searched outliers for each such parameter (input data). The exact procedure for the determination of outliers is described below:

1. Randomly mix all input–output data pairs.
2. Determine the coefficients of the linear regression.
3. Set the null hypothesis H_0: single properties or input data have no effect on the output data (air void content in aggregate mixture).
4. Determine the P-value. P-value is the probability of Type I error in statistical test. Here a T-test was implemented. The P-value is evaluated by $2 * F_T(-T) = P$-value, where F_T is CDF of T-distribution.
5. For those coefficients where the P-value is low (<0.01) the value of coefficient is significantly different from zero; therefore, the null hypothesis can be rejected.
6. In such cases the single parameter value (property value) is checked.
7. Assume a normal distribution and determine whether the individual values deviate from these assumptions. If deviation is large or if the probability that such value occurs is very small, then the data are labeled as outliers. The limit probability where the data are labeled as outliers is $p = 1/\text{number of data}/10$ (Fig. 1).

In items 1 to 5 the parameters which contain outliers are identified. In items 6 to 7 the outliers are sought.

3. Feed-forward artificial neural networks

Fig. 2 represents the scheme of an artificial neural network. Neuron u_i is connected with a few neurons which send their output signal $o_{k,j,l}$ to neuron u_i. Output signals are multiplied by weights w_{ij}. A threshold signal b_i is added to the sum of weighted signals. This gives the value of the signal of neuron u_i. Then the output function f copies the value to the output signal o_i of neuron u_i. Connections between neurons and the output function may be regulated in advance.

The symbols in Fig. 2 have the following meaning:

u_i value of neuron i,
u_j value of neuron j,

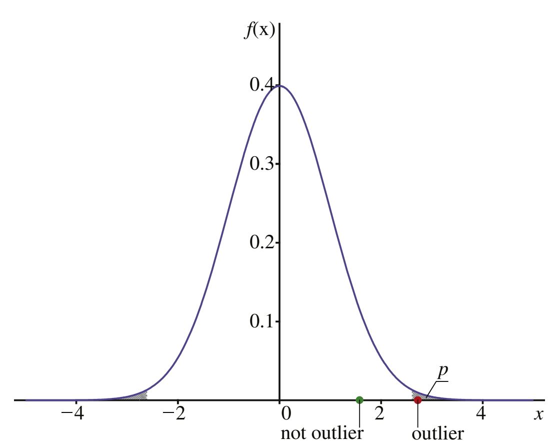

Fig. 1. Determination of the outlier.