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**Development of ANN and MLR models in the prediction
process of the hot mix asphalt (HMA) properties**

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1 **Development of ANN and MLR models in the prediction process of the**
2 **hot mix asphalt (HMA) properties**

3

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9

10 **Abstract:** The oscillation of asphalt mix composition on a daily basis significantly
11 affects the achieved properties of the asphalt during production, thus resulting in
12 conducting expensive laboratory tests in order to determine existing properties and
13 predicting the future results. In order to decrease the amount of such tests, a
14 development of artificial neural network (ANN) and multiple linear regression (MLR)
15 models in the prediction process of predetermined dependent variables air void and
16 soluble binder content is presented. The input data were obtained from a single
17 laboratory and consists of testing 386 mixes of hot mix asphalt (HMA). It was found
18 that it is possible and desirable to apply such models in the prediction process of the
19 HMA properties. The final aim of the research was to compare results of the prediction
20 models on an independent dataset and analyse them through the boundary conditions of
21 technical regulations and the standard EN 13108-21.

22 **Keywords:** hot mix asphalt; artificial neural networks; multiple linear regression;
23 prediction process

24 Introduction

25 Bituminous mixtures contain in its composition mineral mixture, filler, binder and
26 various additives which are mixed at a temperature whose value depends on the
27 properties of used binder. Mostly, they are produced at continuous or cyclic operating
28 mode plants. According to Ramljak et al. (2005), compacted asphalt sample in its
29 composition contains stone skeleton, filler, bitumen, and air voids. Asphalt mixes
30 should contain from 3 to 5% of air void content (Roberts et al. 1991), and any further
31 deviation leads to the appearance of permanent deformations. When installing asphalt
32 mixture, it is necessary to achieve the designed densities because any increase of voids
33 by 1% (more than 6-7%) leads to a 10% reduction in the durability of pavement (Linden
34 et al. 1989) and can significantly decrease a material's projected life span.

35 The asphalt mixture design process can be carried out using different methods,
36 of which the most common are Marshall, Hveem and Superpave. Roberts et al. (1996)
37 stated that in the period from the 1940s through the mid-1990s almost all hot mix
38 asphalt (HMA) mixtures were designed using Marshall or Hveem method. Marshall
39 method is the most frequently used method. In this method, the design process comes
40 down to testing of aggregates, bitumen, making of the Marshall samples, analysis of
41 density and voids, performance of stability and deformation as well as tabular and
42 graphical expression of the achieved results in order to determine the optimal bitumen
43 content. Marshall mix design procedure is suitable only for asphalt mixes with a
44 maximum particle size of aggregate in the amount of 22.4 mm (EN 12697-30,
45 Bituminous mixtures –Test methods for hot mix asphalt – Part 30: Specimen
46 preparation by impact compactor (EN 12697-30:2004+A1:2007). According to
47 Pavement Interactive (2014) "... the Marshall method is used in 38 countries around the
48 world."

49 The main objectives of the research are the following operations:

- 50 • Design and development of the artificial neural network (ANN) model in order
51 to achieve a successful prediction of predetermined dependent variables (air
52 void and soluble binder content) on the basic set of used data,
53 • Design and development of the multiple linear regression (MLR) model in order
54 to achieve a successful prediction of predetermined dependent variables (air
55 void and soluble binder content) on the basic set of used data.

56 The final aim of the research is to compare results of the prediction models on
57 an independent dataset. Obtained values are analysed through the boundary conditions
58 of national technical regulations (Croatian Roads 2013) and the standard EN 13108-21
59 (Bituminous mixtures - Material specifications - Part 21: Factory Production Control
60 (EN 13108-21: 2006)) with the aim of reaching a conclusion on the possible application
61 of the newly proposed models in real conditions of asphalt production.

62 This paper is organized as follows. Section 2 provides a research background of
63 influential factors as well as application of ANN in prediction process of the asphalt
64 mix properties. Section 3 gives an overview of the data sources and data processing
65 from both experimental procedure and development of ANN and MLR models. In
66 Section 4, the results of proposed models are shown and discussed. Finally, the
67 conclusion and recommendations are presented in Section 5.

68 **Research background**

69 *Influential factors*

70 There is significant effect of the composition of asphalt mixtures on the quality
71 properties of asphalt layers. The impact of filler and bitumen content on the asphalt

mixture properties is of crucial importance and is therefore analysed further. Variability of the same ultimately leads to the changes in the air void content and floating durability of a pavement. The purpose of filler is fulfilment of the air voids, to increase stability, to meet the requirements with regard to particle size distribution, and the improvement of connections between binder and aggregate (Roberts et al. 1996). The growth of filler leads to a stiffening or hardening of the asphalt mixture. Mineral dust created by crushing and screening of aggregates (including feedback filler) as well as cement or lime can be used as filler. Certain specifications show that the recommended weight proportion of dust and bitumen in asphalt mixtures range from 0.6 to 1.2 (Roberts et al. 1996).

Air void content is the most measured volumetric feature of hot mix asphalt (HMA) because their share in the total mix affects the durability of the same (Brown and Cross 1989; Ford 1988; Huber and Herman 1987; Roberts and Martin 1996). Air void content (i.e. air voids) less than 3%, could result in the formation of cracks and the emergence of tracks on asphalt pavements (Roberts et al. 1996; Berthelot et al. 2003).

The next observed influential factor in asphalt mixtures is bitumen, which is a mixture of organic compounds and is produced by the distillation of crude oil. Bitumen contains a large number of chemical compounds in its structure whose characteristics have not been separated and identified up to this moment (Transportation Research Circular E-C140 2009). According to the technical specifications, the binder content in HMA mixes can be roughly 3 to 8% and a minimum of 6% for mastic asphalt (Croatian Roads 2013).

Application of artificial neural networks in the predicting process of the asphalt mix properties

Artificial neural networks (ANN) are nowadays used for recognition of patterns,

97 characters, image compression, speech, process control, optimization and more.
98 According to Negnevitsky (2005), the ANNs belongs to machine learning, which
99 involves adaptive mechanisms that enable computers to learn from experience, learn by
100 example and learn by analogy over time. Although a present-day ANN resembles the
101 human brain and there is a certain analogy (Medsker and Liebowitz 1994), the ANNs
102 are capable of learning and observing patterns that human experts fail to recognise. The
103 main structural element of an ANN is the artificial neural node i.e. neuron, which
104 receives signals from its input links, computes new activation level and sends it as an
105 output signal through the output links. The input signal can be raw data or outputs from
106 other neurons, while the output signal can be input to other neurons or a final solution of
107 a problem. The next step in ANN development is the selection of its structure. One of
108 most used structures in data-driven prediction model development is multilayer
109 perceptron (MLP), which is a feedforward neural network consisting of an input layer,
110 one or more hidden layers and an output layer. The MLP architecture was first
111 introduced by Werbos (1974), but its final successful form with prediction,
112 classification and association related to the real problems was presented by Rumelhart
113 et al. (1986).

114 In the study area, ANN were used to study the causes of pavement structures
115 deformation such as potholes, cracking, rutting, roughness, stiffness/elastic modulus and
116 cracks. Significant studies of rutting and roughness began in the mid-1900s when
117 Hoffman and Chou (1994) published the results of the application of ANN in predicting
118 an emergence of cracks, rutting and roughness of pavement. Meier and Rix (1995)
119 published the researches in predicting stiffness and elasticity of pavement by applying
120 neural networks. Over the next decades, they were joined by a number of researchers
121 who applied ANN in predicting the emergence of these deformations in concrete

122 pavements (Eldin et al. 1996; Hsu et al. 1997) and asphalt pavement such as pavements
123 performance prediction (Roberts and Attoh-Okine 1998), pavement crack index and
124 pavement condition rating (Yang and Gunaratne 2003), and pavement serviceability
125 index (Terzi 2006, 2007).

126 Oeser and Freitag (2009) applied ANN in modelling of rheological behaviour of
127 asphalt and showed that they could be used to replace fractional dashpots and
128 rheological models. Raab (2011) concluded that high-quality and large databases are
129 required for successful prediction by applying ANN, because the results obtained
130 indicated to the sufficiently accurate predictions - maximum shear force, deformation at
131 maximum shear stress and maximum shear stiffness of interlayer shear bond properties.
132 Laboratory research performed by Tapkin (2010) predicted the fatigue of bituminous
133 mixture with the addition of fly ash as a filler and concluded that ANN are acceptable in
134 predicting such results. He compared the results by applying single-layer, double-layer,
135 and triple-layer networks and came to the conclusion that one layer of the ANN is
136 sufficient to predict the fatigue of bituminous mixture with the addition of fly ash as a
137 filler.

138 Xiao and Amirkhanian (2009) explored the application of ANN in predicting the
139 stiffness behaviour of rubberized asphalt concrete mixtures with reclaimed asphalt.
140 Achieved results indicate that ANN techniques are more effective in predicting the
141 fatigue life of the modified mixture than traditional models. Ceylan et al. (2007) showed
142 a simplified model of ANN for predicting the value of dynamic modulus. Their research
143 results indicate that the use of ANN allows realization of higher prediction accuracy
144 compared to the existing regression models with fewer inputs. Sing et al. (2013) took
145 into account the impact of shape parameters (angularity, texture, form, and sphericity)
146 in the development of the ANN model for the prediction process of dynamic modulus of

147 HMA, while Gesoglu et al. (2010) modelled mechanical properties of rubberized
148 concrete by applying neural networks and genetic programming. Both methods
149 provided high capacity prediction. However, prediction by statistical regression was
150 relatively low. Ozgan (2011) modelled Marshall Stability of asphalt concrete under
151 various temperatures and exposure time by using ANN.

152 Tušar and Novič (2009) analysed the impact of various factors (444 samples of
153 asphalt) by using several models (multiple linear regression (MLR), partial least squares
154 regression (PLS) and counter-propagation neural network models) in the prediction
155 process of the monitored properties (21 independent variables and 6 dependent
156 variables). The authors conclude that the MLR and PLS models show better predictive
157 ability than the ANN models.

158 Zavrtanik et al. (2016) showed the application of ANN and MLR in the process
159 of forecasting air void content with different used parameters. Overall, they used 17,296
160 Marshall samples of asphalt mixtures (7 types of asphalt concrete, AC 32, 22, 16, 11
161 and 8). The authors conclude that the use of MLR models is better than ANN in the
162 prediction of certain mixtures, but this is not the case for all asphalt mixtures together.

163 In 2014, Ozturk and Emin (2014) presented an ANN model for predicting HMA
164 volumetric at Superpave gyrations levels. They concluded that the application of the
165 ANN model superpave mix design can take approximately 1.5 to 4.5 days. Ozturk et al.
166 (2016) analysed the possible application of ANN for predicting the HMA volumetric
167 properties of mixtures prepared by Marshall Mix design procedures. For modelling
168 purposes, aggregate gradation, bulk specific gravity of aggregates and binder content
169 was used as an input data. One of the main conclusions of their study is that the ANN
170 model could be used as a quality control tool for roadway agencies, which would lead to
171 significant savings in time, cost and labour compared to traditional design processes.

172 Xiao et al. (2010) applied ANN to predict the index of binder penetration after long
173 term aging. Comparing the results obtained by applying neural networks and statistical
174 regression model, they found that neural networks predict more accurately.

175 **Methods and Research**

176 *Experimental procedure*

177 The prediction models development flowchart is shown in Figure 1. The process
178 consists of opening processes, model development processes, and closing processes.
179 Opening processes start with laboratory testing and data gathering. For the purpose of
180 this research, the data were collected from a road construction laboratory that did a total
181 of 386 different compositions of hot mix asphalt (HMA) in 2014 by a single technician.
182 Such gives to the consistency in error, considering the same environmental, equipment
183 and worker. After the model of input and output data were identified, data were divided
184 into samples for the ANN and MLR models development (training, validation and
185 evaluation). From 386 mixes, 336 were used for training and validation and 50 for
186 evaluation purposes.

187 The model development process of the ANN model consists of training,
188 validation and evaluation of the neural network and the MLR model. Both developed
189 prediction models were tested afterwards on an independent dataset followed by
190 performance analysis. The models' performance analysis was done in order to provide
191 insight into functional dependencies among laboratory test results and predicted values
192 of developed ANN and MLR models. During closing processes, the developed models
193 (i.e. results) were analysed and compared towards technical conditions and the standard
194 EN 13108-21. Once the results from the prediction models were verified towards
195 national regulation, the models were adopted as potential applicable prediction models.

Figure 1. The ANN and MLR models development flowchart

From the entire set (386), the 50 mixes were used in the prediction process of the air void and the soluble binder content (i.e. binder content). Figure 2 shows the particle size distribution (minimum, medium and maximum average values of the mineral mixtures passing through the sieves) divided in dependence of the asphalt mix nominal grain size. The determination of particle size distribution was performed according to the standard HRN EN 12697-2 (HRN EN 12697-2: 2003 Bituminous mixtures - Test methods for asphalt produced by the hot process - Part 2: Determination of particle size distribution). From the total number of mixes (386), 6.7% is of the nominal size of 32 mm, 25.5% of nominal size 22 mm, 33.1% of the nominal size of 16 mm, 20.7% - 11 mm, 0.8% - 8 mm, and 13.2% of discontinuous composition (SMA – Stone Mastic Asphalt).

In asphalt mixes, eruptive and dolomite stone aggregates from nearby quarries were used. The dolomite rock has a massive and homogeneous internal texture with a light grey colour. The eruptive rock (amphibolite) has a medium-grained structure with a dark greyish green colour. Densities of the produced asphalt mixes are in range from 2550 to 2700 kg/m³ with air void content ranged from 2.5 to 7% (Androjić & Dolaček-Alduk 2016).

The particle size distribution curve of asphalt mixtures (C_{UM}) is obtained as the sum of the relation of the weight of residue on a specific sieve (R_i) and the total mass of the material (M_{UK}) according to the following formula:

$$C_{UM} = 100 - \sum_{i=1}^n (R_i / M_{UK} \times 100). \quad (1)$$

Figure 2. Particle size distribution curves - 386 mixes during 2014 laboratory tests

Figure 2 shows that the highest cumulative average values of the passing through the sieve 0.063 mm are generated in mixtures with discontinuous composition (SMA) to the amount of 8.3%, mixture of nominal size 8 mm to the amount of 62.2%,

and on the sieve size of 11.2 mm to the amount of 100% (mixture of 8 mm). The lowest average values of the passing are realized by AC 22 on the sieve size of 0.063 mm (4.6%), 4 mm (30.3% disc-SMA) and the percentage of the passing to the amount of 59.9 on the sieve size of 11.2 mm (AC 32).

Tested asphalt mixtures in their composition contain road paving and polymer modified bitumen mined from the local refineries. The soluble binder content is determined according to HRN EN 12697-1 (HRN EN 12697-1: 2003 Bituminous mixtures - Test methods for asphalt produced by hot mix - Part 1: The soluble share of binder). The soluble binder content ($\%_{mas}B_{AM}$) is determined as the difference between the mass of the dry, tested part of the asphalt mixture sample (M_{AM}) and the mass of the separated and dried stone (M_{KM}) in relation to the mass of the dry, tested part of the asphalt mixture (M_{AM}) according to the expression 2:

$$\%_{mas}B_{AM} = \left(\frac{M_{AM} - M_{KM}}{M_{AM}} \right) \times 100 \quad (2)$$

The air void content in the asphalt sample (C_{V-AS}) is determined as the difference between the density of the asphalt mixture (ρ_{AM}) and the asphalt sample (ρ_{AS}) in relation to the density of the asphalt mixture (ρ_{AM}) according to the expression 3:

$$C_{V-AS} = \left(\frac{\rho_{AM} - \rho_{as}}{\rho_{am}} \right) \times 100 \quad (3)$$

The air void content is determined in accordance to the standard HRN EN 12697-8:2003 (Bituminous mixtures - Test methods for asphalt produced by hot process - Part 8: Determination of voids in asphalt specimens).

The soluble binder and air void content of 386 mixes is shown in Table 1. Each mixture consists of 3-4 specimens prepared by the impact compactor as is defined in the

standard HRN EN 12697-30. Table 1 shows the average air void and soluble binder content values in dependence with nominal size of asphalt mixes (8, 11, 11 Disc (SMA – Stone Mastic Asphalt), 16, 22, and 32 mm). The minimum soluble binder content (2.9%) is found in asphalt mixture AC 32, while the maximum content (6.1%) is found is asphalt mixture AC 11. The average air void content ranges between 4.4% and 5.6%, wherein the minimum (individual) share (1.8%) is found in AC 16, and the maximum (individual) share (8.8%) in AC 11 Disc (SMA – Stone Mastic Asphalt).

Table 1. The soluble binder and air void content in laboratory tested asphalt mixtures

		Max mineral size of asphalt mixture (mm)					
		8	11	11 (Disc)	16	22	32
Air Void Content (%)	min	3.4	2.6	2.1	1.8	2.8	3.4
	max	6.3	8.3	8.8	8.0	7.9	7.9
	avg	5.1	4.6	5.4	4.4	5.6	5.5
Soluble binder Content (%)	min	5.6	4.8	4.3	3.9	3.2	2.9
	max	5.7	6.1	5.2	5.6	5.4	4.3
	avg	5.7	5.2	4.9	4.7	3.8	3.6

During the model development process, both the ANN and MLR models were developed and tested using the software RapidMiner v5.3. For the purpose of modelling, the development of the ANN and MLR models was comparatively analysed through two cases (Table 2). Case A predicts the air void content (Dependent variable-Dv) using 14 independent input variables (Iv-gradation, soluble binder content, and density of asphalt mix and mineral mixture), while Case B predicts the soluble binder content (Dv) using 13 independent input variables (Iv-gradation, air void content and mineral mixture density).

Table 2. Case A and Case B variables used in development of ANN and MLR models

Case	USED VARIABLES
------	----------------

	Particle size distribution (0.063, 0.25, 1, 2, 4, 8, 11.2, 16, 22.4, 31.5, 45) – each sieve size separately	Binder content (% mass)	Density of asphalt mix	Air void content	Density of mineral mixture
	[mm]	[%]	kg/m ³	[%]	kg/m ³
A	Iv (1-11)	Iv (12)	Iv (13)	Dv	Iv (14)
B	Iv (1-11)	Dv	-	Iv (12)	Iv (13)

Iv – Independent variable
Dv – Dependent variable

268 **Development of Artificial Neural Network (ANN) Model**

269 The feed forward neuron network was used for the ANN prediction model development.
270 It consists of a minimum of three layers: input, hidden, and output. The numbers of
271 neurons in the input and output layers are defined by a number of selected data, whereas
272 the number of neurons in the hidden layer should be optimized to avoid overfitting the
273 model, defined as the loss of predictive ability (Haykin 2009). Since every layer
274 consists of neurons that are connected by activation functions, the sigmoid function was
275 used. Overall, 288 different types of artificial neural networks were tested, their main
276 properties are shown in Table 3. The backpropagation algorithm was used for the
277 training process.

278 Table 3. Development and training parameters of the ANN
279

TRAINING PARAMETERS OF ANN				
	Number of hidden layers	Training cycles	Learning rate	Hidden layer size
	(layer)	-	-	(piece)
Case A	1, 2 and 3	200, 400, 600 and 800	0.2, 0.4, 0.6 and 0.8	5, 10, 15, 20, 25 and 30
Case B	1, 2 and 3	200, 400, 600 and 800	0.2, 0.4, 0.6 and 0.8	5, 10, 15, 20, 25 and 30

Adopted combination	2	800	0.6	30
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Table 3 demonstrates the two cases (A and B) that were used for the purpose of development and training of ANN. The aim of Case A was to predict as accurately as possible the air void content, while the aim of Case B was to predict the soluble binder content. As the optimum combination of the adopted ANN was the combination with 2 hidden layers, 30 neurons in a single layer, learning rate 0.6 and 800 training cycles. The adopted combination allowed the realization of the highest values of correlation coefficients between the tested and predicted values of the air void content and the amount of bitumen. The configuration of applied neural network is shown in Figure 3.

Figure 3. Configuration of the selected artificial neural network

As previously stated, the prediction of air void content (Case A) was accomplished by using 14 independent input variables (Table 2) by adopted ANN (Table 3). The predicted values of the air void content were then compared to known results, which are achieved in laboratory. The correlation coefficient between the tested and predicted values of the air void content amounts to the high 0.918, 0.507

297 normalized absolute error and 0.842 (coefficient of determination, R^2) for the adopted
298 ANN.

299 The prediction of the soluble binder content (Case B) was accomplished by
300 using 13 independent input variables (Table 2) by adopted ANN (Table 3). The
301 predicted values of the binder content were then compared to known results achieved in
302 laboratory. The correlation coefficient between the tested and predicted values of the
303 binder content amounts to 0.981, 0.179 normalized absolute error and 0.962 (coefficient
304 of determination, R^2) for the adopted ANN.

305 ***Development of Multiple Linear Regression (MLR) Model***

306 The same variables were used for the purposes of developing the MLR model (Table 2).
307 As a result, we tried to get an accurate prediction of air void content (AvC - Case A,
308 equation 4) and soluble binder content (Bc - Case B, equation 5) according to the
309 following terms:

310
$$AvC = x_1b_1 + x_2b_2 + \dots + x_{14}b_{14} + b_0, \quad (4)$$

311
$$Bc = x_1b_1 + x_2b_2 + \dots + x_{13}b_{13} + b_0, \quad (5)$$

312 Where, $x_{1...14}$ represents the independent variables value, $b_{1...14}$ represents the
313 regression coefficient and b_0 deviation in a functional relationship.

314 The correlation coefficient between the tested and predicted values of the air
315 void content amounts to the high 0.815, 0.56 normalized absolute error and 0.664
316 (coefficient of determination, R^2) while the correlation coefficient between the tested
317 and predicted values of the binder content amounts to 0.943.

From the obtained results, achieved from the training and validation of the ANN and MLR model on the base set of 336 mixes, we can conclude that:

- The adopted ANN model predicts the air void content more successfully in comparison to the MLR model (correlation 0.918 against 0.815).
- The adopted ANN model predicts the soluble binder content more successfully in comparison to the MLR (correlation 0.981 against 0.943).

Results and discussion

For model testing purposes, the independent dataset of 50 mixes was used. In the following part of the paper, the testing of the ANN model is shown, followed by the MLR model testing.

Evaluation of Artificial Neural Network (ANN) Model

Figure 4 shows the ratio between the tested and predicted values of the air void content on an independent dataset that was used for evaluation purposes of the ANN model.

Figure 4. Air void content in the tested asphalt mixtures – ANN model

From Figure 4, it can be concluded that the correlation coefficient between the tested and assumed values of the air void content on the additional set of samples (50 independent samples) amounts to the 0.74. Removing 3 mixes (number 29, 41 and 42) that most deviate (ratio of laboratory/predicted values) from the basic dataset (50) increases the correlation coefficient to the amount of 0.8. Such a deviation in the achieved laboratory results can be defined as a rough error.

Figure 5 shows the ratio between the tested and predicted values of the soluble binder content on an independent dataset that was used for evaluation purposes of the ANN model.

Figure 5. Binder content in the tested asphalt mixes – ANN model

From Figure 5, it can be concluded that the correlation coefficient between the tested and assumed values of the binder content on an additional set of samples (50 independent samples) amounts to a high 0.92.

349 *Evaluation of Multiple Linear Regression (MLR) Model*

350 Figure 6 shows the ratio between the tested and predicted values of the air void content
 351 on an independent dataset that was used for evaluation purposes of the MLR model.

352
 353 Figure 6. Air void content in the tested asphalt mixes – MLR model

354
 355 From Figure 6, it can be concluded that the correlation coefficient between the
 356 tested and assumed values of the air void content on the additional set of samples (50
 357 independent samples) amounts to a low of 0.59 compared to the tested set of samples.
 358 Removing 3 mixes (number 29, 41 and 42) from the basic dataset (rough error) leads to
 359 an increase of the correlation coefficient of 0.68.

360 Figure 7 shows the ratio between the tested and predicted values of the soluble
 361 binder content on an independent dataset that was used for evaluation purposes of the
 362 MLR model.

Figure 7. Soluble binder content in the tested asphalt mixtures – MLR model

From Figure 7, it can be concluded that the correlation coefficient between the tested and assumed values of the binder content on an additional set of mixes (50 independent samples) amounts to 0.96 compared to the tested set of mixes.

From the obtained results, achieved from the testing of the ANN and MLR models on the independent dataset, we can conclude that:

- The adopted ANN model predicts the air void content more successfully in comparison to the MLR model (correlation 0.74 against 0.59).
- The adopted MLR model predicts the mass binder content more successfully compared to the ANN model (correlation 0.96 against 0.92).
- Optimizing the basic dataset (removing data with rough error) increases the correlation coefficients in the prediction process of air void content (ANN, from 0.74 to 0.8; MLR, from 0.59 to 0.68).

378 *Model performance analysis*

379 Figure 8a, b (air void content: a – 50 mixes, b – removed 3 mixes (29, 41 and 42)) and
 380 8c (soluble binder content) shows a linear functional relationship between the predicted
 381 values (y) and samples tested in laboratory for ideal situation (tested = predicted), the
 382 ANN and MLR models (for independent set of data) according to the equation 6 (AvC -
 383 air void content) and the equation 7 (Bc - binder content):

$$384 \quad A_v C = ax + b \quad (6)$$

$$385 \quad B_c = ax + b \quad (7)$$

386 From Figure 8a, it is evident that for the observed linear dependencies (ANN
 387 and MLR) are achieved lower values of coefficient R^2 in the amount of 0.3428 and
 388 0.5404 (50 dataset). Due to the forecast of air void content in the amount of 8% (in
 389 laboratory conditions), the ANN model will predict 1.1% lower air void content, which
 390 is less deviation than the MLR model (1.4%). This difference is reduced during the
 391 prediction of lower air void content in the amount of 3%. This difference for the ANN
 392 model is an insignificant amount of 0.1% (0.4% for MLR). From the linear
 393 dependencies (shown in Figure 8a) it can be concluded that the ANN model better
 394 predicts air void content in the asphalt (in relation to the MLR model) for 50 mixes.
 395 From Figure 8b, it is apparent that by removing data with rough error leads to achieving
 396 a higher coefficient R^2 in the amount of 0.4585 and 0.6399 (47 mixes). From the linear
 397 function relationship, it is evident that the air void content (in the range of 3 to 7%) of
 398 the ANN model will be lower by approximately 0.5% (compared to the ideal line $y = x$).
 399 For MLR linear function, it can be seen that the same overlaps with the ideal line at 3%
 400 of air void content and with the ANN model line at 7%.

Figure 8. Functional dependencies among laboratory tested results and predicted values of ANN and MLR models (A and B – air void content; C – binder content)

From Figure 8c, it is evident that for the observed dependencies are achieved high values of coefficient R^2 in the amount of 0.8512 and 0.9222. It can be concluded that the use of the ANN and MLR models results in small variations during individual binder content prediction in the amount of max 1.1% for ANN and 0.7% for MLR. Due to the forecast of binder content in the amount of 8% (in laboratory conditions), the ANN model will predict 1.2% lower binder content, which is higher deviation than the MLR model (0.5%). From the linear dependencies (shown in Figure 8b), it can be concluded that the MLR model better predicts binder content in the asphalt mix (in relation to the ANN model). Table 4 shows the overall view of dependencies between the observed variables (air void and binder content), as well as coefficients of determination R^2 .

Table 4. Dependencies between the observed variables

Items	Model type	Link form	Coefficients		Coefficient of determination R^2
			a	b	
Air Void Content (50)	ANN	$A_v C = ax + b$	0.7953	0.4986	0.5404
	MLR		0.6432	1.491	0.3428
Air Void Content (47)	ANN	$A_v C = ax + b$	0.9963	-0.514	0.6399
	MLR		0.8623	0.3806	0.4585
Binder Content	ANN	$B_c = ax + b$	0.7061	1.1319	0.8512
	MLR		0.8793	0.4394	0.9222

419 **Ratio of the asphalt composition and the boundary conditions**

420 The relation between the observed asphalt mixes and boundary conditions obtained
421 from national technical regulation (The elaboration of the technical characteristics and
422 requirements for construction products for the production of asphalt mixtures and
423 asphalt pavement (2013), Croatian Roads d.o.o, Zagreb) and standard EN 13108-21
424 (Bituminous mixtures – Material specifications – Part 21: Factory Production Control
425 (EN 13108-21:2006)) is presented in following part.

426 Limit values defined by the technical regulations and standard for Factory
427 Production Control were used with the aim of determining the success of predictions
428 models in realistic production conditions. Table 5 shows the boundary voids conditions
429 obtained from technical regulations and the amount of bitumen obtained from standard
430 EN 13108-21. Void limit values for certain mixtures have been adopted for medium
431 traffic load (AC 16 surf/bin use boundary conditions for AC bin). Binder content
432 boundary conditions have been adopted in relation to the value of laboratory results
433 (independent dataset) when the results of the target composition have not been available
434 during the examination. This means that on average laboratory results were
435 added/removed 0.3% of binder content (Table A.1 — Tolerances in absolute percentage
436 for the assessment of conformity of production, small and large aggregate mixes $\pm 0.3\%$
437 (EN 13108-21:2006)).

438 Table 5. Boundary conditions defined by EN 13108-21:2006

439

Items	Asphalt mix				
	Ac 11 surf	SMA 11	Ac 16	Ac 22 base	Ac 32 base
			bin/surf		
Air Void Content	3.0	3.0	4.0	4.0	4.0

	6.0	6.0	7.0	8.0	8.0
Binder	5.1	4.6	4.2	3.5	3.2
Content	5.7	5.2	4.8	4.1	3.8

440

441 Figure 9 shows the relationship between the average asphalt mix air void content

442 (mixes tested in laboratory), results of voids obtained by predicting the independent

443 dataset (ANN and MLR) and the average upper and lower limit values from the

444 Technical Regulations (Table 5).

445

446 Figure 9. Relationship between the asphalt composition and the boundary conditions of

447 air void content

448

449 From Figure 9, it is evident that the average values of air void content obtained

450 by applying the ANN and MLR models for all asphalt compositions satisfy the

451 boundary conditions. The shape of the curves (ANN and MLR) shows that both models

452 predict a similar air void content. It can be seen that the observed models most

453 accurately predict the voids in mixtures AC 22 base (for ANN difference amounts to

454 0.2%, MLR - 0.1%) and AC 16 bin/surf (ANN - 0.5%, MLR - 0.4%). The highest

average deviations between laboratory results and curve model are achieved during the prediction of voids for the asphalt mixture AC 32 base (ANN - 1.5%, MLR - 1.1%).

Figure 10 shows the relationship between the average asphalt mix soluble binder content (mixes tested in laboratory), results of binder obtained by predicting on the independent data set (ANN and MLR) and the limit values from the EN 13108-21:2006 (Table A. 1).

Figure 10. Relationship between the asphalt mix composition and the boundary conditions of binder content

Figure 10 shows that the ANN model prediction line for binder content turns out to be below the lower limit value for the mixture AC 11 surf (0.01% deviation) and SMA 11 (0.06%). The maximum deviation between the respondents and the predicted value ANN model achieves for a mixture AC 11 surf in the amount of 0.4%. This is not the case for the MLR model, whose difference amounts to 0.2% for the same mixture. The ANN model achieves a minimum deviation in the predicting process for the mixture AC 16 bin/surf (0%) and AC 22 base (0.1%), which makes the same model acceptable for use in the binder content forecasting process.

473 In the forecasting process, the MLR model achieves less deviation from the
474 ANN model where the maximum deviation from the set value is 0.2% (AC 11 surf, AC
475 32 base) and the minimum value is negligible 0.01% (AC 16 bin/surf).

476 After the research, we can conclude the following:

- 477 • During the testing of the ANN and MLR models on the base set, we can
478 conclude that the adopted ANN model more successfully predicts the air void
479 content compared to the MLR model (correlation 0.918 and 0.815). On the other
480 hand, the ANN model better predicts the soluble binder content compared to the
481 MLR (correlation 0.981 and 0.943).
- 482 • After the models testing on the independent dataset, it can be concluded that the
483 ANN model more successfully predicts the air void content compared to the
484 MLR model (correlation 0.74 and 0.59). The MLR model better predicts the
485 soluble binder content compared to the ANN (correlation 0.96 and 0.92).
- 486 • Removing data with rough error (from additional dataset) increases the
487 correlation coefficients in the prediction process of air void content (ANN, from
488 0.74 to 0.8; MLR, from 0.59 to 0.68).
- 489 • Achieved are lower values of coefficient R^2 in the amount of 0.3428 and 0.5404
490 between the results obtained from the predictive models and laboratory mixes.
491 From the linear dependences, it can be concluded that the ANN model better
492 predicts air void content in the asphalt (in relation to the MLR model).
- 493 • Removing data (from additional dataset) with rough error leads to achieving a
494 higher coefficient R^2 in the amount of 0.4585 and 0.6399.
- 495 • Observed models most accurately predict the voids in mixtures AC 22 base (for
496 ANN difference amounts to 0.2%, MLR - 0.1%) and AC 16 bin/surf (ANN -
497 0.5%, MLR - 0.4%). The highest average deviations between laboratory results

498 and the curve model is achieved during the prediction of voids for the asphalt
499 mixture AC 32 base (ANN - 1.5%, MLR - 1.1%). The MLR model in
500 forecasting process achieves less deviation than the ANN model where the
501 maximum deviation from the set value is 0.2% (AC 11 surf, AC 32 base), and
502 the minimum value negligible 0.01% (AC 16 bin/surf).

503 **Conclusions**

504 This paper presents an application of artificial neural networks and multiple linear
505 regression in the predicting process of hot mix asphalt properties. The main objective of
506 this research was to the design a model to achieve a successful prediction of
507 predetermined dependent variables (air void and soluble binder content). The final aim
508 of the research was to compare the results of the prediction models on an independent
509 dataset and analyse it through the boundary conditions of national technical regulations
510 and the EN 13108-21:2006.

511 Data of the 386 different types of HMA mixes for the purpose of the research
512 was used while 50 mixes were used in the prediction process of the air void content and
513 the soluble binder content. Although this is a small number of samples, it is of crucial
514 importance because all of them are done by the same laboratory, equipment and
515 technician, which makes the samples consistent. This consistency substantially
516 influences the samples and possible error in their making. The prediction process was
517 divided into Case A (prediction of the air void content using 14 input independent
518 variables) and Case B (prediction of binder content using 13 independent variables).

519 The performed research indicates that it is possible and desirable to apply
520 artificial neural networks in the prediction process of the required properties of hot mix
521 asphalt, wherein it is necessary to use a substantial set of input data. By such

522 application, the time in designing the composition of the asphalt significantly
523 accelerates, while simultaneously the impact of multiple input variables to the required
524 output property is taken into consideration. Further research should be conducted at a
525 higher input, extended database that shall also take into consideration the properties of
526 the used mineral mixtures (angularity and grain shape, wearing, share and composition
527 of the returning and purchasing stone dust, aggregate absorption, and the properties of
528 the binder used).

529 References

- 530 Androjić, I. & Dolaček-Alduk, Z. 2016. Analysis of energy consumption in the
531 production of hot mix asphalt (batch mix plant). Canadian journal of civil
532 engineering, 43 (12), 1044-1051. doi:10.1139/cjce-2016-0277.
- 533 Berthelot, C. F., Allen, D. H., & Searcy, C. R. 2003. Method for performing accelerated
534 characterization of viscoelastic constitutive behaviour of asphaltic concrete.
535 *Journal of Materials in Civil Engineering*, 15(5), 496-505.
- 536 Brown, E. R., & Cross, S. A. 1989. *A Study of In-Place Rutting of Asphalt Pavements*
537 (NCAT Report No. 89-2). Auburn: National Center for Asphalt Technology of
538 Auburn University.
- 539 Ceylan, H., Kim, S., and Gopalakrishnan, K. 2007. "Hot Mix Asphalt Dynamic
540 Modulus Prediction Models Using Neural Networks Approach," ANNIE 2007,
541 ANNs in Engineering Conference, St. Louis, Missouri, November 10-14.
- 542 Croatian Roads 2013. *The elaboration of the technical characteristics and requirements*
543 *for construction products for the production of asphalt mixtures and asphalt*
544 *pavement*. Zagreb: Croatian Roads d.o.o.
- 545 Eldin, N. N., & Senouci, A. B. 1996. Use of Neural Network for Condition rating of
546 Jointed Concrete Pavements. *Advances in Engineering Software*, 23, 133-141.
- 547 Ford, M. 1988. Pavement Densification Related to Asphalt Mix Characteristics.
548 National Research Council, Transportation Research Board.
- 549 Gesoglu, M., Güneyisi, E., Özturan, T., & Özbay, E. 2010. Modelling the mechanical
550 properties of rubberized concretes by neural network and genetic programming.
551 *Material and Structures*, 43, 31-45.

- 552 Haykin, S. O. 2009. *Neural networks and learning machines* (3rd ed.). Upper Saddle
553 River, NJ: Pearson Education.
- 554 Hoffman, P. C., and Chou, K. C. 1994. "Infrastructure assessment: fuzzy regression
555 with neural networks." Proceedings of the First International Joint Conference of
556 the North American Fuzzy Information Processing Society Biannual
557 Conference. The Industrial Fuzzy Control and Intelligent Systems Conference,
558 and the NASA Joint Technology, San Antonio, TX, USA, 273-274.
- 559 Hsu, D. S., and Tsai, C. H. 1997. "Reinforced concrete structural damage diagnosis by
560 using artificial neural network." IASTED International Conference on Intelligent
561 Information Systems (IIS '97), 149.
- 562 Huber, G. A., & Herman, G. H. 1986. Effect of Asphalt Concrete Parameters on Rutting
563 Performance: A Field Investigation. Association of Asphalt Paving
564 Technologists, 56, 33-61.
- 565 Linden, R.N.; Mahoney, J.P. and Jackson, N.C. 1989. The Effect of Compaction on
566 Asphalt Concrete Performance. 1989 Annual Meeting of the Transportation
567 Research Board, Washington, D.C.
- 568 Medsker, L. R., & Liebowitz, J. 1994. *Design and Development of Expert Systems and*
569 *Neural Computing*. New York: Macmillan College Publishing.
- 570 Meier, R. W., & Rix, G. J. 1995. Backcalculation of Flexible Pavement Moduli from
571 Dynamic Deflection Basins Using Artificial Neural Networks. *Transportation*
572 *Research Record*, 1473, 72-81.
- 573 Negnevitsky, M. 2005. *Artificial Intelligence: A Guide to Intelligent Systems* (2nd ed.).
574 Harlow: Pearson Education.
- 575 Oeser, M. and Freitag, S. 2009. Neural networks in rheology: Theory and application.
576 7th International RILEM Symposium ATCBM09 on Advanced Testing and
577 Characterization of Bituminous Materials, Rhodes, Greece, Vol 1, pp 949-958
- 578 Ozgan, E. 2011. Artificial neural network based modelling of the Marshall Stability of
579 asphalt concrete. *Expert Systems with Applications*, 38(5), 6025-6030.
- 580 Ozturk, H. I., & Emin Kutay, M. 2014. An artificial neural network model for virtual
581 Superpave asphalt mixture design. *International Journal of Pavement*
582 *Engineering*, 15(2), 151-162.

- 583 Ozturk, H. I., Saglik, A., Demir, B., & Gungor, A. G. 2016. An artificial neural network
584 base prediction model and sensitivity analysis for marshall mix design, 6th
585 Eurasphalt&Eurobitume Congress, Prague, Czech Republic.
- 586 Pavement interactive, online: [www.pavementinteractive.org/article/marshall-mix-](http://www.pavementinteractive.org/article/marshall-mix-design/seen)
587 [design/seen](http://www.pavementinteractive.org/article/marshall-mix-design/seen). (09.01.2014.)
- 588 Raab, C. 2011. *Development of a Framework for Standardisation of Interlayer Bond of*
589 *Asphalt Pavements* (Doctoral dissertation). Carleton University, Carleton.
- 590 Ramljak, Z., Strineka, A., & Šafran, K. 2005. Dependence of the asphalt sample
591 composition on its tensile strength, *Građevinar*, 57 (3), 141-150.
- 592 Roberts, F. L., Kandhal, P. S., Brown, E. R., Lee, D. Y., & Kennedy, T. W. 1991. Hot
593 Mix Asphalt Materials, Mixture Design, and Construction. National Asphalt
594 Paving Association Education Foundation. Lanham, MD.
- 595 Roberts, F. L., Kanthal, S. P., Brown, E. R., Lee, Y. D., & Kennedy, W. T. 1996. Hot
596 Mix Asphalt materials, mixture design, and construction. NAPA Education
597 Foundation, Lanham Maryland.
- 598 Roberts, F. L., & Martin, A. E. 1996. Hot Mix Asphalt Materials, Mixture Design and
599 Construction, NAPA Education Foundation, Lanham, Maryland, Second
600 Edition.
- 601 Roberts, C. A., & Attoh-Okine, N. O. 1998. Comparative Analysis of Two Artificial
602 Neural Networks using Pavement Performance Prediction. *Computer Aided*
603 *Civil and Infrastructure Engineering*, 13(5), 339-348.
- 604 Rumelhart, D. E., Hinton, G. E., & Williams, R. J. 1986. Learning representations by
605 backpropagating errors. *Nature*, 323(6188), 533-536.
- 606 Singh, D., Zaman, M., & Commuri, S. 2013. Artificial Neural Network Modeling for
607 Dynamic Modulus of Hot Mix Asphalt Using Aggregate Shape Properties.
608 *Journal of Materials in Civil Engineering*, 25(1), 54-62.
- 609 Tapkin, S. 2014. Estimation of Fatigue Lives of Fly Ash Modified Bituminous Mixtures
610 Based on Artificial Neural Networks. *Materials Research*, 17(2), 316-325.
- 611 Terzi, S. 2006. Modeling the Pavement Present Serviceability Index of Flexible
612 Highway Pavements Using Data Mining. *Journal of Applied Science*, 6(1), 193-
613 197.

- 614 Terzi, S. 2007. Modeling the pavement serviceability ratio of flexible highway
615 pavements by artificial neural networks. *Construction and Building Materials*,
616 21(3), 590–593.
- 617 Transportation Research Circular E-C140 2009. *A review of the fundamentals of asphalt*
618 *oxidation*. Washington: Transportation Research Board
- 619 Tušar, M. & Novič, M. 2009. Data exploration on standard asphalt mix analyses.
620 *Journal of Chemometrics*, 23(6), 283–293.
- 621 Werbos, P. J. 1974. *Beyond regression: new tools for prediction and analysis in the*
622 *behavioural sciences* (PhD Thesis). Cambridge: Harvard University.
- 623 Xiao, F. & Amirkhanian, S. N. 2009. Artificial Neural Network Approach to Estimating
624 Stiffness Behavior of Rubberized Asphalt Concrete Containing Reclaimed
625 Asphalt Pavement. *Journal of Transportation Engineering*, 135(8), 580–589.
- 626 Xiao, F., Amirkhanian, S.N. & Juang, H.C. 2010. An Artificial Neural network
627 Approach to Developing Long-Term Aging Models of Asphalt Binders. *Journal*
628 *of Materials in Civil Engineering*, 21(6), 253-261.
- 629 Yang, J., Lu, J. J., & Gunaratne, M. 2003. Application of neural network models for
630 forecasting of pavement crack index and pavement condition rating." Florida
631 Deptment of Transportation, Tampa, Florida.
- 632 Zavrtanik, N., Prosen, J., Tušar, M., & Turk, G. 2016. The use of artificial neural
633 networks for modelling air void content in aggregate mixture. *Automation in*
634 *Construction*, 63, 155-161.