Journal of Cleaner Production 219 (2019) 451–460

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Achieving sustainability through the temperature prediction of aggregate stockpiles

Ivica Androjić [a, b], Ivan Marović [a, *], Jelena Kaluđer [c], Gordana Kaluđer [d]

[a] University of Rijeka, Faculty of Civil Engineering, Radmile Matejčić 3, 51000 Rijeka, Croatia
[b] Asphalt Design d.o.o, A. Starčevića 74, 31220 Višnjevac, Croatia
[c] University of Osijek, Faculty of Civil Engineering, Vladimira Preloga 3, 31000 Osijek, Croatia
[d] Gfk Consulting j.d.o.o, Lj. Posavskog 25, 31551 Belišće, Croatia

A R T I C L E I N F O

Article history:
Received 3 August 2018
Received in revised form
6 February 2019
Accepted 9 February 2019
Available online 12 February 2019

Keywords:
Asphalt production
Mineral mixture
Prediction
Solar aggregate stockpiles
Sustainable management

A B S T R A C T

This paper presents the potential energy savings and how to achieve sustainability by predicting the temperature of aggregate stockpiles in the production process of asphalt mixtures. A possible way to achieve energy efficiency and therefore sustainability is to preheat the mineral mixture, i.e. the aggregate, before it enters the production process in the asphalt mixing plant, thus resulting in lower energy consumption per ton of asphalt. The main objective of the conducted research was to develop and test an artificial neural network (ANN) model and analyse the influence of three independent variables (hour in the day, season, air temperature) on the one dependent variable (temperature of the mineral mixture). The impact of the observed independent variables on the temperature of the mineral mixture is analysed in a standard uncovered aggregate stockpile and in a solar aggregate stockpile. From the obtained modelling results, it can be concluded that it is possible to successfully use ANN in the process of predicting the temperature of aggregate stockpiles in the processes of aggregate production and storage as part of the whole production process of asphalt mixtures.

1. Introduction

The production process of asphalt mixtures is performed at continuous or batch asphalt plants with greatly varying costs depending on the location of the plant as well as the characteristics of the components of the mixture. During the production process, it is necessary to heat the integral components of the mixture to the desired temperature, thus resulting in a significant consumption of thermal energy. The reference mixing temperature for mixtures with paving grade bitumen ranges from 90 to 180 °C depending on the binder penetration (Bituminous mixtures – Test methods for hot mix asphalt – Part 35: Laboratory mixing (EN 12697–35:2004 + A1:2007)). According to the preparation temperature and application technology, asphalt mixtures are divided into hot mix asphalt which is manufactured at temperatures from 135 °C to 170 °C, and cold mix asphalt which is manufactured at an ambient temperature (up to 25 °C). An increasingly popular topic in recent times is warm mix asphalt which is manufactured at temperatures up to 135 °C (warm asphalt mixes, low energy asphalt) (Rukavina et al., 2008). As both mixtures, Warm Mix Asphalt (WMA) and Hot Mix Asphalt (HMA), contain a stone mixture and dust, binder and additives that are mixed at a given equiviscous temperature, it is important to understand that energy consumption is influenced by various significant factors simultaneously. One of the significant differences between WMA and HMA lies in the mixing temperature during the production process, as a lower temperature means lower energy consumption. In order to achieve energy efficiency and therefore sustainability (in the environmental, economic, social and technical domain), it is important to understand the factors influencing energy consumption in the production process of asphalt mixtures and to appropriately manage them.

Knowing that the average production of WMA and HMA in Europe from 2008 to 2013 amounted to 307.1 million tons (ranging from 276.4 to 338 million tons) and 495.2 million tons on average annually in the USA (Asphalt in figures. (2013, 2013), while the world energy consumption is expected to grow by 48% between 2012 and 2040 (Today in energy and independ, 2621), it is important to use resources in a more environmentally friendly manner. Even in areas of small production, such as in the Republic of Croatia,

* Corresponding author.
E-mail address: ivan.marovic@uniri.hr (I. Marović).

https://doi.org/10.1016/j.jclepro.2019.02.099
0959-6526/

with 2.32 million tons produced on average annually (Croatian Asphalt Associat, 2017), it is important to manage the production process of asphalt mixtures more efficiently.

1.1. Achieving sustainability through the production process of asphalt mixtures

Energy consumption in the production process of asphalt mixtures is affected by (Androjić et al., 2017): the conditions of production and storage of the mineral mixture, the moisture content and temperature range of the heated mineral mixture, the quality of the mineral mixture, the asphalt plant, and the type of produced asphalt mixture. As the general technological trend is to lower temperatures in the asphalt production process in order to achieve sustainability, it is important to identify the best possible process to make improvements.

Asphalt mixture production technology is usually defined as the specified sequence of all production processes that depend on the design of the asphalt mixing plant. Sivilevičius and Šukevičius (2009) analysed four different types of asphalt mixing plants (AMP) with no explicitly stated factors that influence energy consumption in the production process of asphalt mixtures, but they concluded that the batch-type AMP plant is the most used in Europe for making asphalt mixtures. Such an AMP type is characterised by the continuous batching of cold mineral materials and the final batching of additionally screened hot fractions by forced blending with other materials. It seems that the weakest link in such a production process is the production and storage of the mineral mixture, i.e. aggregate. Androjić et al. (2017) showed that the conditions and storage of the mineral mixture are directly related to the moisture content and quality of the mixture. In addition, various authors (Airey et al., 2008; Ang et al., 1993; Peinado et al., 2011; Grabovski et al., 2013) show the considerable influence of the moisture content of mineral mixtures on energy demand. Airey et al. (2008) performed laboratory tests to identify the susceptibility of asphalt mixtures to moisture damage. Moisture can have a lasting effect on the aggregate not only during the production phase but it can also lead to the loss of stiffness and structural strength of the bound pavement layers of a road and eventually to the costly failure of the road structure. Ang et al. (1993) reported that reducing the moisture content during the production phase by 3% leads to energy savings of up to 60%, while Peinado et al. (2011) showed that 8.21 kWh of energy is required to reduce mineral mixture moisture by 1%. These authors demonstrated that reducing the heating temperature of the mineral mixture helps to lower the energy consumption of the production process. Grabowski et al. (Grabovski et al., 2013) reported that to dry a single ton of mineral mixture with a moisture content of 6%, 4 L of fuel are needed, while an additional 3 L of fuel are necessary to heat a dry mixture. In addition, Jenny (2009) claims that lowering production temperatures from 180 to 115 °C during the asphalt production process will lower the energy consumption of fuel by 1.5 kg per ton. All this confirms that the weakest links in the production of asphalt mixtures are the processes of the production and storage of the mineral mixture, i.e. the management of aggregate stockpiles. Thives and Ghisi (2017) provide a literature review of the emission and energy consumption of asphalt mixtures, stating that the moisture content of aggregates is an important parameter that influences energy consumption. In addition, they highlighted that WMA technologies can save 20–70% of energy consumption when compared to HMA, mainly due to the reduced temperature in the warm mix processes. Therefore, they see that sustainability would be achieved by switching from HMA to WMA technologies as this would result in a reduction of the carbon footprint generated by the asphalt industry.

In the last few decades, WMA has been a major research challenge in the production of environmentally sustainable asphalt pavements. The primary objective of its implementation during the asphalt technological process is seen in reducing fuel consumption and lowering pollutant emissions in order to improve environmental quality and decrease production costs. EAPA (Environmental guidelines, 2007) stated that energy consumption in the production process can be reduced by 10 kWh/tonne of asphalt if the mix temperature is lowered by 35 °C. Recently, Almeida-Costa and Benta (2016) argue that because the economic and environmental benefits have not always been properly evaluated, WMA technologies are far from being explored to their full potential – mainly due to the idea that additives are expensive. The results of their study show that the incurred costs ensures that the production of the respective warm mixture is economically advantageous. On the other hand, Qiu et al. (2018) propose the use and re-use of various materials in asphalt mixtures and different production techniques in order to preserve the low production temperature of the mixture. They claim that sustainability can be achieved by using porous asphalt (PA) as one of the most critical types of asphalt mixtures, which can be produced in high quality, with a low production temperature and using high percentages of reclaimed materials. Their laboratory results indicate that PA may be produced at 105 °C which is considerably lower than the conventional hot production technique of 170 °C. Zhu et al. (2017) report that the asphalt foaming process, as one of the major WMA technologies, allows lower production and construction temperatures, less greenhouse gas, and other emissions.

Another possible way to achieve energy efficiency and therefore sustainability is to preheat the mineral mixture before it enters the production process in an AMP. As shown in Fig. 1, with a higher accumulated temperature in the mineral mixture, all the above-mentioned problems can be minimised, thus resulting in lower energy consumption per ton of asphalt. One way to do this is by forming solar aggregate stockpiles (Androjić and Kaluđer, 2016; Androjić et al., 2018) that are designed to accumulate thermal energy obtained from solar radiation during exposure to the sun. While solar aggregate stockpiles research showed very good results in energy savings with crushed stone (i.e. aggregate) as stored material (Androjić and Kaluđer, 2016), the set-up stockpiles were used to test various materials (Androjić et al., 2018) such as stone aggregate, waste glass, and recycled asphalt. The research showed potential application of solar aggregate stockpiles in the process of storing recycled materials with effects to additionally improve AMP production process to be more sustainable. Androjić et al. (2017) conducted experimental research to determine the influence of the variable sun exposure surface area of solar aggregate stockpiles on the accumulated heat of the mineral mixture in different seasons. Their experiment shows that solar aggregate stockpiles can be

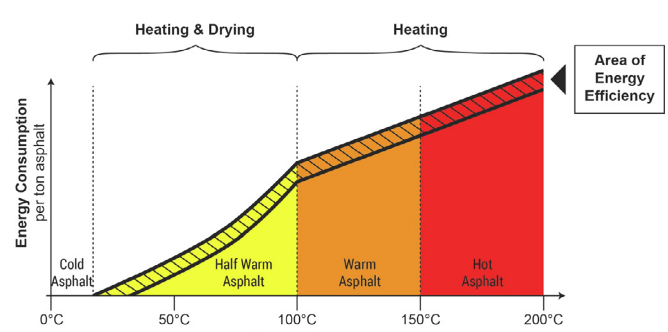


Fig. 1. Classification by temperature range and potential energy savings.

used in industrial applications for the production of HMA.

Based on an analysis of energy consumption in the production of HMA on a batch-type AMP in the Republic of Croatia (Androjić and Dolaček-Alduk, 2016), Androjić and Dolaček-Alduk (2018) developed an artificial neural network (ANN) model for forecasting energy consumption (i.e. gas consumption) in the production of HMA. From the following variables (moisture content, hour capacity, and temperature of the produced asphalt), they concluded that gas consumption can be reduced by 2.8 m^3/t, although it is necessary to increase the amount of overall input data in order to achieve better predictions. The application of ANN in the predicting process of the asphalt mixtures is widely accepted, mostly because of prediction possibilities based on large datasets such as in the prediction of various asphalt mixture properties (Androjić and Marović, 2017; Oeser and Freitag, 2009; Tušar and Novič, 2009; Zavrtanik et al., 2016).

1.2. Objectives of the research

The experimental part of this paper is the continuation of solar aggregate stockpiles research (Androjić et al., 2017, 2018; Androjić and Kaluđer, 2016) and its possible application in the production process of asphalt mixtures. Aforementioned previous researches gave valuable insight into solar aggregate stockpile approach, measurement data of different materials, and possibilities of achieving energy efficiencies and serve as inputs for creating prediction model.

The main objective of the research is to develop and test an ANN model with an analysis of the influence of independent variables (hour in the day, season, air temperature) on the dependent variable (the temperature of the mineral mixture). It is expected that due to different methods of aggregate stockpile deposits (a standard uncovered aggregate stockpile and a solar aggregate stockpile), the influence of external factors will result in different stockpile temperatures. This will help in the processes of aggregate production and storage as part of the whole production process of asphalt mixtures showing possible energy efficiencies due to different kinds of aggregate stockpile deposits. In addition, it is important to understand the factors influencing energy consumption in the production process of asphalt mixtures in order to manage them more efficiently.

2. Experimental part

Fig. 2 shows the schematic view of the conducted research. The research is divided into preliminary activities, modelling, and closing activities. Preliminary activities give an overview of the existing state and goals of the research. The modelling part shows the creation of the solar stockpile test models, the selection of dependent/independent variables, and the execution and making of/testing the ANN model. Closing activities include part of the work showing the final results and conclusions of the research.

After the preparatory work was completed, models of solar/classic stockpiles were created for storing mineral mixtures

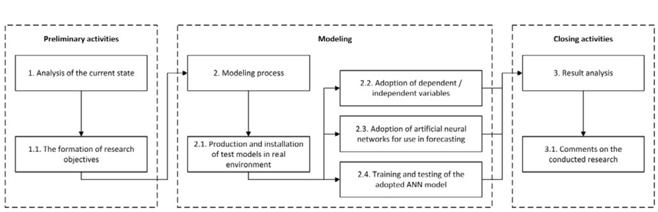


Fig. 2. Schematic view of the conducted research.

intended for the production of the asphalt mixture. The created models were exposed to real-life weather conditions with the goal of collecting information about heat accumulation in the stored mineral mixture. The test was conducted in 2017 (from 12 August to 1 November) and in 2016 (from 18 August to 1 November). After collecting the required data, ANN models were created with the goal of predicting the heat accumulation of the stored mixture.

2.1. Production and installation of test models in a real environment

Androjić and Kaluđer (2016) and Androjić et al., 2017, 2018 have already showed models of solar/classic stockpiles. An analysis was performed for the requirements of the research comparing heat accumulation of the mineral mixture between traditional storage and storage in solar stockpiles.

The observed solar stockpile model (Fig. 3a) was made of 6 cm thick concrete elements of 0.0224 m^3 internal volume, with an internal footprint of 0.4 $\times$ 0.4 m, a ceiling surface slope of 25%, 4 mm glass with a light opening of 0.38 $\times$ 0.38 m, and heat insulation of 5 cm in thickness. In the traditional stockpile, the mineral mixture was stored on an unprepared, exposed surface (polyvinyl chloride base) of approximately 50–60 cm in circumference. Both models were oriented towards the south. For the purpose of storage, a 4/8 grade dolomite stone aggregate was used with a unit mass of 20 kg/model (Fig. 3b).

During data collection, the following effects on the stored mixture temperature were taken into consideration:

- external weather conditions (hourly air temperature);
- season of production;
- part of the day when the temperature measurement was performed.

During the testing period, the solar stockpile model was covered with a layer of mineral wool insulation 5 cm thick in periods without exposure to sunlight and over the course of several days without exposure to sunlight (cloudy and rainy weather). For the purpose of modelling, the temperature of the uncovered mixture was observed during the day from 8 a.m. to 6 p.m. The period when the stockpile was covered is excluded.

2.2. Adoption of dependent/independent variables

In order to perform field measurements and gather actual data a stationary set-up of aggregate stockpiles has been created. The actual layout of the area where set-ups, i.e. stockpile models, were placed is presented in Androjić et al. (2018). Gathered data served for laboratory testings' and development of ANN model in order to predict desired variable i.e. temperature. As the set-ups were placed in the environment and were under its constant influence, it was evident to set such variables as independent ones. As the influence of these external factors results in different stockpile temperatures it gives the opportunity to be used as an input in model development process. The dependent one was the temperature of the stored mineral mixture as stated below.

Fig. 4 shows the adopted independent/dependent variables in the modelling process. It can be seen that the hour of the day, season and hourly air temperature were taken into consideration when measuring the dependent variable. There is a difference between two independent cases in which the temperature accumulation of the stored mixture is predicted (Case A and B). In Case A, the temperature accumulation of the stored mixture is predicted in the solar aggregate stockpile. Case B predicts the temperature accumulation of the mixture stored in the uncovered and unprotected stockpile.

a) b)

Fig. 3. Solar stockpile model (a) and stored mineral mixture (b).

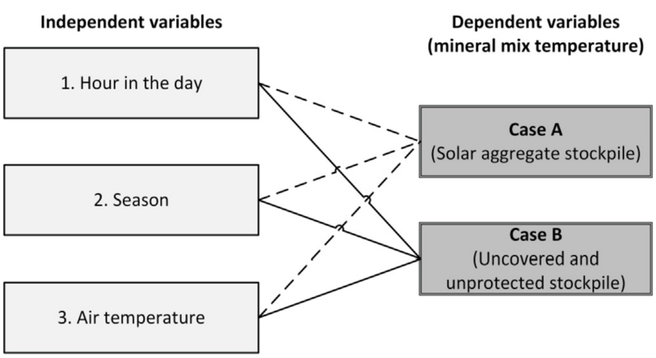


Fig. 4. Used dependent/independent variables in modelling process.

Temperature measurements of the stored mineral mixture (dependent variable) during the day were performed every full hour (24 measurements throughout the day). The measuring was performed using a four-channel digital thermometer equipped with a data logging TC-309 unit connected to 4 k-type thermocouple wires. The hourly air temperature (independent variable 3) was obtained from the local national hydrometeorology station in Čepin, Croatia. For the purpose of modelling, the measurement data are divided into those collected during the summer and autumn seasons.

Table 1 shows the minimum, maximum and average temperature values of the mineral mixture (Cases A and B) and the ambient air temperature. It is evident that the highest expected temperature of the stored mixtures is achieved in the solar models. It can also be seen that all of the observed parameter values (min, max and average) are higher in both models compared to the ambient air temperature.

Table 1
Temperature values of the observed parameters.

Items	Year	Case A	Case B	Air temperature (°C)
		Mineral mix temperature (°C)		
Minimum	2016	8.7	3.1	3.0
	2017	4.8	4.8	3.9
Maximum	2016	45.1	45.8	30.0
	2017	48.9	44.6	36.1
Average	2016	26.4	25.3	19.3
	2017	26.7	24.8	20.7

2.3. Adoption of artificial neural networks for use in forecasting

A feed-forward neural network trained by a back propagation algorithm was used for the purpose of creating the model. A feed-forward neural network is an artificial neural network where the information moves in only one direction, forward. Information is transmitted from the input layer, through the hidden nodes to the output nodes. A back propagation algorithm is a supervised learning method divided into propagation and weight update. These processes are repeated until the performance of the network is acceptable. A multilayer perceptron is a feed-forward artificial neural network model that consists of multiple layers, with each layer fully connected to the next one. In the network itself, apart from input values, each node is a neuron with a nonlinear activation function. In this operator, the usual sigmoid function is used as the activation function.

Fig. 5 shows the schematic view of the conducted modelling procedure. It can be seen that the whole procedure is divided into three parts: data collection and division of data into samples, the model development process (training, validation and evaluation of the ANN model), and the conclusions.

Data collection was performed in 2016 and 2017. Data from 2016 include 45 test days and 495 hourly values (11 hourly values were observed per day), while data from 2017 include 39 test days and 429 hourly values. Values from 2017 were merged and randomly divided into two datasets. First dataset consisted of 70% of collected data from 2017 and served for the development of the ANN model i.e. learning phase, while second dataset consisted of 30% and was used as independent data for validation and evaluation (i.e. testing phase) of adopted ANN model. Additionally, the ANN model was validated and evaluated on the independent data collected during 2016. During testing phase, the performance analysis of the developed ANN model was done (coefficient of determination – r^2

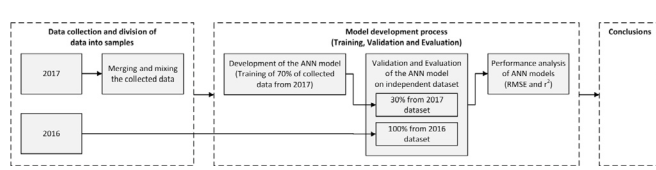


Fig. 5. Schematic view of the modelling procedure.

and root mean square error – RMSE). The whole model development process was done with RapidMiner Studio Version 8.0 software (https://rapidminer.com/products/studio/).

For the purpose of analysing the success rate of the model (Table 2) in the learning and testing phase, a coefficient of determination r^2 (Eq. (1)) and root mean square error (Eq. (2)) were used:where n is the number of data points in the input layer, d_k is the target value, O_k the model response value, d the mean value of the target data, and O the mean value of the network response. In Eq. (2), P_i is the ith predicted value of the mix temperature, O_i is the ith observed value of the mix temperature, and n is the size of the dataset.

2.4. Training and testing of the adopted ANN model

Data from Case A (70% of data from 2017) were used to determine the construction of the ANN model. Altogether, 288 different combinations of neuron networks were analysed with the values shown in Table 3. Performance measures (r^2 and RMSE) were performed on each combination during training phase thus resulting in worst combination ($r^2 = 0.473$) and best combination ($r^2 = 0.927$, RMSE = 2.797). During testing phase (30% of data from 2017) same performance measures were performed on each combination thus resulting in worst combination ($r^2 = 0.486$) and best combination ($r^2 = 0.979$, RMSE = 2.034). Ultimately, the adopted ANN prediction model (i.e. best combination) contained two hidden layers, 10 neurons in the hidden layer, a learning rate of 0.2, a 0.2 momentum and 800 training cycles (Table 3).

The modelling process consisted of 4 individual processes shown in Fig. 6. It can be seen that in Process 1, all the independent variables were used for modelling (Process 1 was also used for determining the architecture of the ANN model). In other processes, certain variables were removed for modelling with the goal of determining the effects on the success rate of prediction (the effects are shown in section 2.1). Finally, an analysis of the observed processes was performed after the modelling procedure.

The modelling process was divided into training, testing and performance analysis of the ANN models. Parallel modelling for Cases A and B was performed with the observed process (Fig. 7).

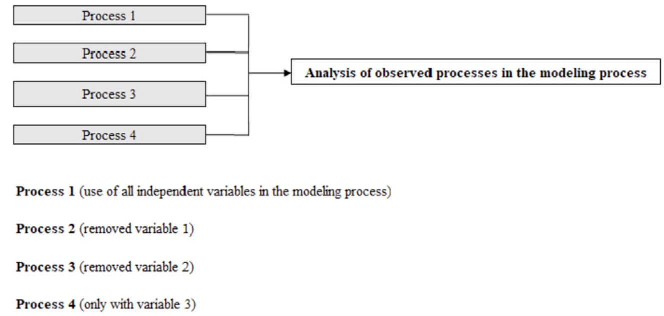


Fig. 6. Analysis of the observed processes.

Table 2
Performance measures.

$$r^2 = \left[\frac{\sum_{k=1}^{n}(d_k - d)(O_k - O)}{\sqrt{\sum_{k=1}^{n}(d_k - d)^2 \sum_{k=1}^{n}(O_k - O)^2}}\right]^2, \quad (1)$$

$$E_{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}, \quad (2)$$

Criterion	Phase	
	Learning	Testing
Coefficient of Determination (r^2)	x	x
Root Mean Square Error (RMSE)	*	x
x - used in evaluation		

Table 3
Development of architecture of ANN model.

Training parameters of ANN			
Number of hidden layers	Training cycles	Learning rate	Hidden layer size
layer	–	–	piece
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
2	**800**	**0.2**	**10**

3. Results analysis and comments on the conducted research

Table 4 shows the completed coefficients of determination and the root mean square error in the construction and testing phases of the ANN models. It can be seen that each process (1–4) is made up of Cases A and B. Each individual case is divided into two parts – one that shows the achieved results for the construction phase of the model (training) and the other showing the testing of the model (testing).

Table 4 shows that in Case A, the highest coefficient of determination was achieved in Process 1 (0.927 in the training phase and 0.971 in the testing phase). It is also visible that the lowest values of the root mean square error amounting to 2.779 °C in the training phase and 2.034 °C in the testing phase were achieved in the same combination. This is the case where all the independent variables were used in the modelling process. In contrast, the lowest value of the observed coefficient of determination (0.756 in the training phase and 0.825 in the testing phase) and the highest value of the root mean square error (5.021 °C in the training phase and 4.937 °C in the testing phase) was achieved in Process 4 where all the independent variables except air temperature were excluded. Case B shows that the highest coefficient of determination values was also achieved in Process 1 (0.962 in the training phase and 0.965 in the testing phase), and the lowest values were also achieved in Process

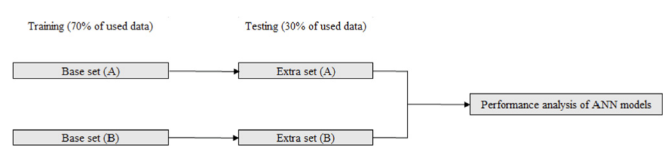


Fig. 7. Construction of individual processes.

Table 4
Achieved modelling results.

Process	Root Mean Square Error (RMSE)/Coefficient of Determination (r^2)			
	Case A (2017)		Case B (2017)	
	Training	Testing	Training	Testing
1	**2.779/0.927**	**2.034/0.971**	**1.738/0.962**	**1.859/0.965**
2	4.738/0.778	4.497/0.858	4.685/0.72	4.59/0.797
3	3.482/0.883	3.456/0.91	2.863/0.925	3.429/0.92
4	5.021/0.756	4.937/0.825	4.771/0.716	4.588/0.79

4 (0.716 in the training phase and 0.79 in the testing phase). In the same way, in Process 1, the lowest values of the root mean square error were achieved (1.738 °C in the training phase and 1.859 °C in the testing phase).

Below a detailed image is given of the relationship between the predicted and real temperature values for Processes 1 and 4 (extremes). The chosen processes were analysed because they represent cases in which the ANN models most/least successfully predict the heat accumulation of the stored mineral mixture.

3.1. Process 1

Fig. 8 shows the linear relationship (y = 0.9364x+1.8041 for Case A and y = 0.9577x+0.9911 for Case B) between the real temperature values (x) and the predicted temperature values (y) in Process 1 of ANN model testing on an independent dataset (30%).

From the shown relationship, it is clear that Case A (compared to Case B) reaches a slightly stronger linear connection between the observed temperature values (r^2 for Case B amounts to 0.9652, and 0.9707 for Case A).

Fig. 9 shows the temperature difference (for the testing phase) between the real and predicted values for Cases A and B (129 processed samples).

In the given Fig. 9, a predominantly higher difference in temperature divergence is visible in Case B compared to Case A. When observing a divergence over 3 °C, 11% of the test samples in Case A exceed this limit which is slightly more than in Case B where this occurs in only 8% of the samples (10 samples). This temperature difference between the two observed cases occurs due to the effects of covering (protection of the stored mixture in model A in periods without or with decreased effects of solar radiation.

3.2. Process 4

Fig. 10 shows the linear relationship (y = 0.825x+5.4273 for Case A and y = 0.8199x+4.9866 for Case B) between the real temperature values (x) and the predicted temperature values (y) in Process 5 of testing the ANN model on an independent dataset (30%).

In the shown relationship, it is visible that Case A (compared to Case B) reaches a stronger linear connection between the observed temperature values (r^2 for Case B amounts to 0.7927, and 0.8252 for Case A) and a significant decrease of the same values in relation to Process 1. It is evident that in this combination a significant increase

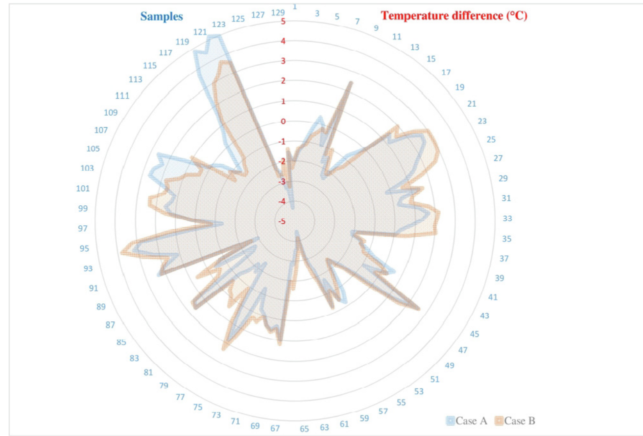


Fig. 9. Temperature differences between the achieved and predicted temperature values – Process 1.

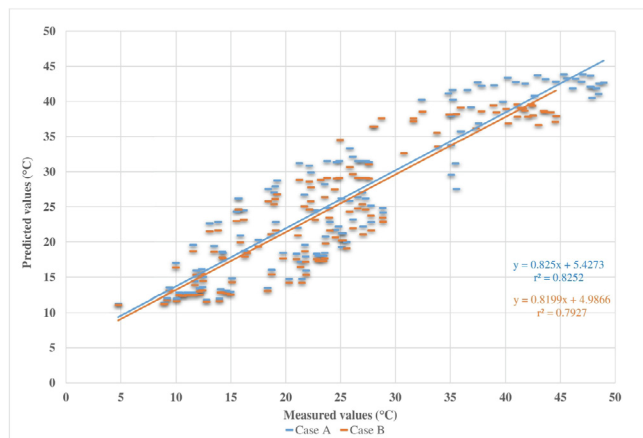


Fig. 10. Functional dependencies between the achieved and predicted values – Process 4.

of values of the root mean square error occurs (Table 4), which ultimately leads to undesirable effects in the model prediction process.

Fig. 11 shows the temperature difference (for the testing phase) between the real and predicted values for Cases A and B (Process 4, 129 samples).

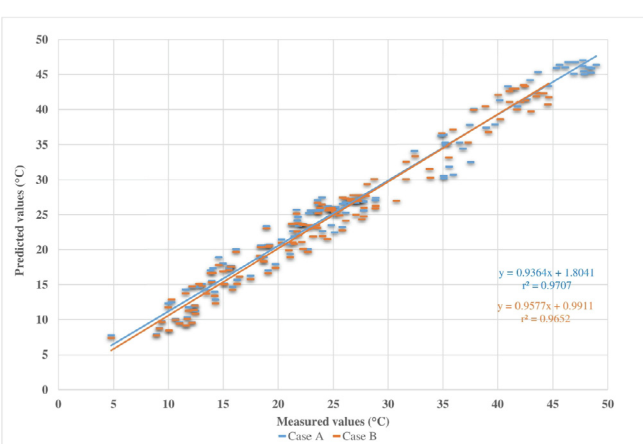


Fig. 8. Functional dependencies between the achieved and predicted values – Process 1.

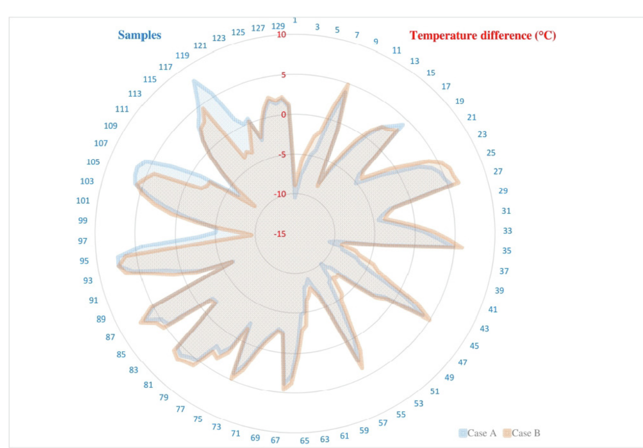


Fig. 11. Temperature difference between the achieved and predicted temperature values – Process 4.

Fig. 11 shows that in both observed cases, a significant increase between the real and predicted temperature values occurs compared to the values in Process 1. In Case B there is an average higher difference in temperature divergence compared to Case B. Case A exceeds the 3 °C temperature divergence in 76 samples (59%) which is a considerable increase compared to 14 samples in Process 1. There is also an increase in the observed temperature difference in Case B with 77 samples (60%) compared to 10 samples from Process 1.

Below, test results are shown of the ANN model on the extra dataset (2016). The ANN model from Process 1 is applied which uses all the independent variables in the learning and testing phases.

3.3. Testing the ANN model - extra dataset (2016)

After the creating and testing phase of the ANN model with data from 2017, testing of the model was performed on an independent set of data collected in 2016. The observed stockpile models (2016/2017) use a similar surface for storage (Case B) and opening size for the effects of sunlight radiation (in 2017 these surfaces were 0.38/0.38 m, and in 2016, 0.36/0.36 m) which was considered an acceptable divergence. Table 5 shows the values of the root mean square error (RMSE) and the coefficient of determination (r^2) for the additional testing process of the adopted ANN model.

The achieved results show that in the process of additional ANN model testing, a lower value of the coefficient of determination (r^2) was reached for Case A (0.8) and an increase of RMSE values (4.655 °C) compared to the initial model testing (30% of dataset). In Case B, the r^2 value amounts to a high 0.944 and RMSE 3.064 °C that are considerably higher values compared to Case A.

Fig. 12a (Case A) and b (Case B) shows the relationship between the average hourly predicted and real temperature differences.

Fig. 12 shows that the highest difference between the real and predicted hourly temperature was reached at 8 a.m. (3.9 °C) which can be attributed to the effects of covering/uncovering the solar models. In addition, it can be seen that at 4 p.m. the predicted temperature falls in the ANN model (extreme) which is not the case with the real data. In Case B this temperature difference is lower between the observed values. The highest difference is reached at 12 a.m. and 5 p.m. (2 °C) which is considered an acceptable tolerance.

Fig. 13 shows the relationship (Process 1, ANN model tested on the extra dataset 2016) between the air temperature and the real/predicted temperature values for Cases A and B. Additionally, it is evident that the observed case includes the relation between the air temperature and the stored mixture (blue colour) whose values are deducted from the predicted values of the relationship between the air and the ANN model temperature (yellow colour). This difference between the observed relationships is shown in red in the diagram.

During the analysis of the final linear relationships for Case A, it can be concluded that somewhat lower values of the coefficient of determination were reached (r^2 for Case A amounts to 0.7667 and 0.821 for the ANN model). By comparing the linear relationships (Fig. 13a, Case A y = 1.1295x+4.6136 and ANN predicted y = 1.3124x+0.9493) it is visible that the ANN model will predict a 3.7 °C lower temperature of the stored mixture at 0 °C air temperature and a 1.8 °C higher value at 30 °C air temperature (compared to the real temperature of the stored mixture).

Table 5
Final modelling results.

Process	Root Mean Square Error (RMSE)/Coefficient of Determination (r^2)	
	Extra dataset (2016)	
	A - Testing	B - Testing
1	**4.644/0.8**	**3.064/0.944**

Case B also reached lower values of the coefficient of determination for the observed relationships (r^2 for Case B amounts to 0.7755 and 0.7797 for the ANN model). From the observed linear relationships (Fig. 13b, Case B y = 1.2994x+0.2029 and ANN predicted y = 1.122x+2.3009), it is clear that the ANN model will predict a 2.1 °C higher temperature of the stored mixture at 0 °C air temperature, and a 3.2 °C higher value at 30 °C air temperature (compared to the real temperature of the stored mixture).

The following conclusions can be drawn from the performed analysis:

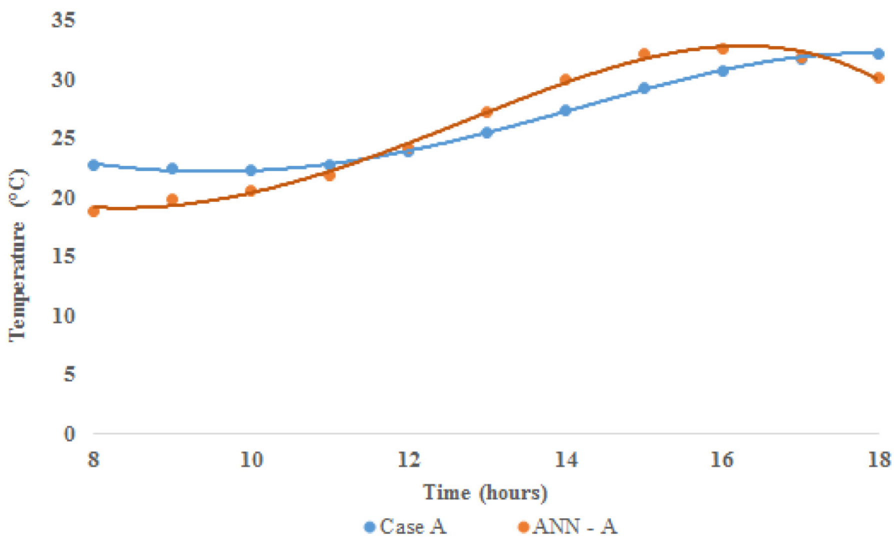
- When creating the ANN model, the calendar season in which the observation is performed, the time of measurement, and the air temperature should be taken into consideration in order to successfully predict the temperature of the stored mixture;
- A modelling process which only uses the air temperature as an independent variable leads to the least accurate results in the prediction process;
- Analysing the relationship between the real and the predicted values for the observed modelling process, high coefficients of determination and root mean square error are reached. The highest difference between the real and predicted hourly temperatures is reached at 8 a.m. which can be attributed to the effects of covering/uncovering the solar models. In Case B, this temperature difference falls in the observed exposure period;
- Analysing the relationship between the air temperature and the real/predicted temperature of the stored mixture, somewhat lower values of the coefficients of determination are reached. It is clear that the ANN model (Case A) will predict a lower temperature of the stored mixture at an air temperature of 0 °C and a higher value at an air temperature of 30 °C.

4. Conclusions

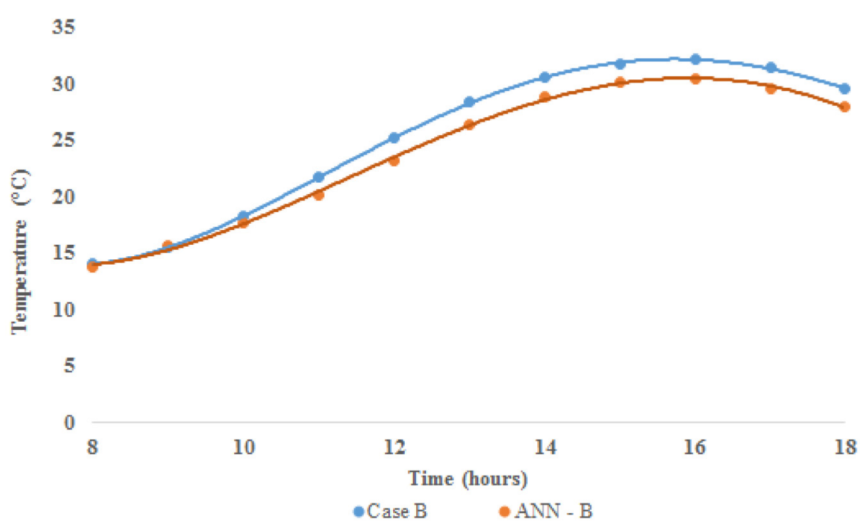
During the production process of asphalt mixtures, it is necessary to heat the integral components of the mixture to the desired temperature, thus leading to significant consumption of thermal energy. As the general technology trend is to lower temperatures in the asphalt production process in order to achieve sustainability, it is important to identify the best possible process to make improvements. In order to achieve energy efficiency and therefore sustainability (in the environmental, economic, social and technical domain) it is important to understand the factors influencing energy consumption in the production process of asphalt mixtures and to appropriately manage them. Based on previous research, we considered the processes of the production and storage of aggregate stockpiles as those where there was the greatest room for improvement.

Therefore, the main objective of the conducted research was to develop and test an ANN model and to analyse the influence of three independent variables (hour in the day, the season, air temperature) on the one dependent variable (the temperature of the mineral mixture). The impact of the observed independent variables on the temperature of the mineral mixture was analysed in a standard uncovered aggregate stockpile and in a solar aggregate stockpile. The tests on the stockpiles were performed during 2016 and 2017. As a result, the following conclusions were reached:

- During the production of the ANN model for Case A, the highest coefficient of determination (r^2) was achieved in Process 1



a) Case A



b) Case B

Fig. 12. The relationship between the real and predicted temperature values - extra dataset (2016).

(0.927 in the training phase and 0.971 in the testing phase) and the lowest values of the root mean square error were attained (2.779 °C in the training phase and 2.034 °C in the testing phase). In Case B, it is evident that the highest coefficient of determination (r^2) was also achieved in Process 1 (0.962 in the training phase and 0.965 in the testing phase) and the lowest values of the root mean square error were attained (1.738 °C in the training phase and 1.859 °C in the testing phase);

- From the analysed relationship between the actual and predicted temperature values, it is apparent that in Case A (in respect of Case B) there was a slightly stronger linear relation (the r^2 for Case B is 0.9652, and 0.9707 for Case A);
- In the process of the subsequent testing of the ANN model (on an extra dataset in 2016), a lower value of the coefficient of determination (r^2) for Case A (0.8) and an increase in the RMSE (4.644 °C) compared to initial model testing (on 30% of the dataset) were achieved. For Case B, the value of r^2 was high (0.944) and the RMSE was 3.064 °C, which was significantly lower than in Case A;
- When analysing the relationship between actual and predicted temperature values (on the extra dataset in 2016) it is evident that the biggest difference is achieved in 8 h (3.9 °C) which can be connected with the effect of uncovering/covering the solar models. In Case B, the temperature difference decreased between the observed values;
- From the achieved linear relationships (between the air temperature and real/predicted temperature values), for Case A it can be established that some lower values of the coefficient of determination were achieved and that the ANN model predicted a 3.7 °C lower temperature of the deposited mixture at 0 °C (air temperature) and 1.8 °C higher value at 30 °C. Case B also yielded lower values of the r^2 for the observed relationships where

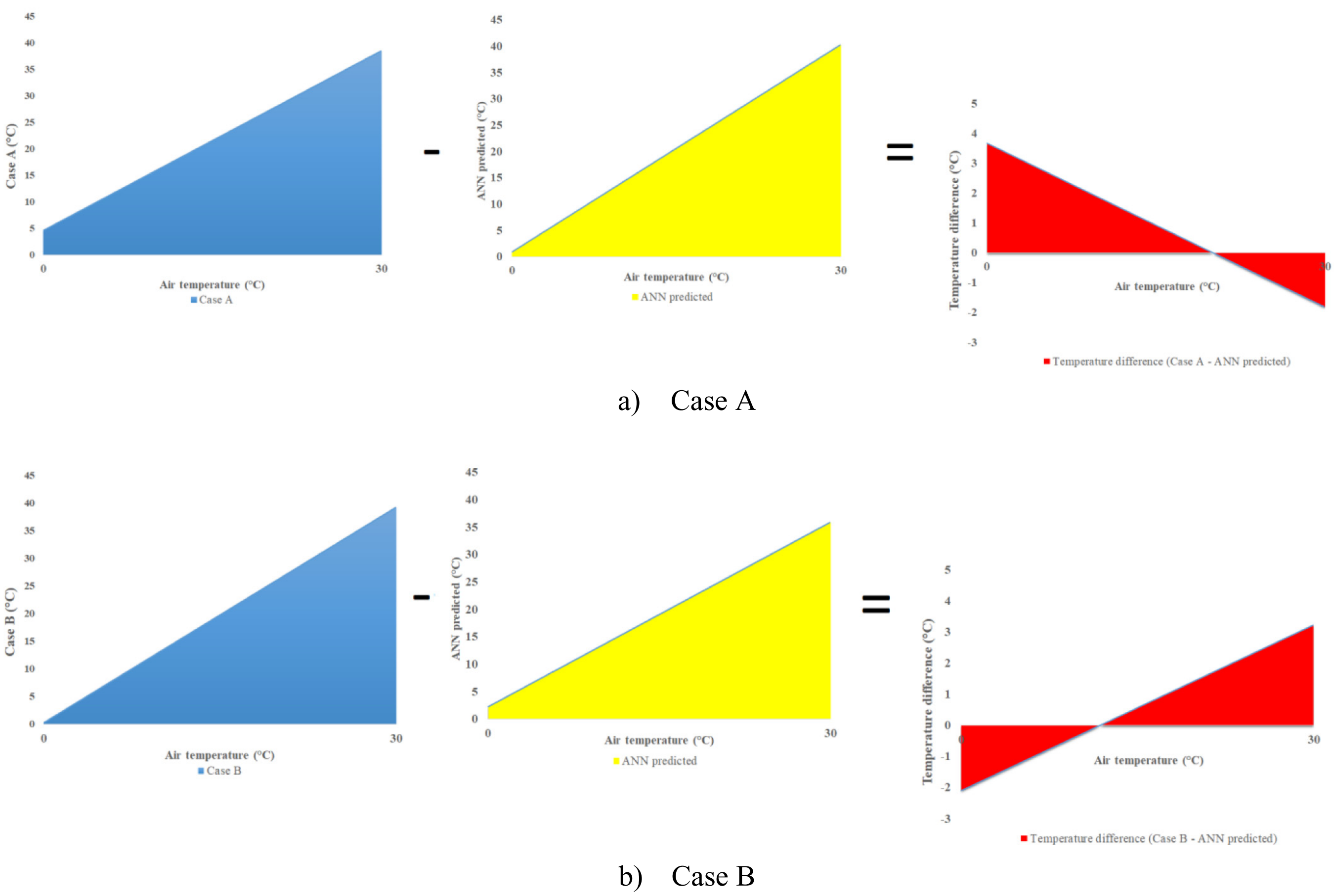


Fig. 13. Relationship between the air temperature and the real/predicted temperatures of the stored mixture.

the ANN model predicted a 2.1 °C higher temperature of the deposited mix at 0 °C air temperature and a 3.2 °C higher value at 30 °C air temperature (relative to the actual temperature of the deposited mix).

The research gives an insight into temperature prediction in the processes of aggregate production and storage as part of the whole production process of asphalt mixtures. In addition, the temperature prediction of different mineral mixture stockpile deposits provides insight into possible ways to achieve energy efficiencies and therefore sustainability by using preheated solar aggregate stockpiles before they enter the production process of asphalt mixtures.

References

Airey, G.D., Collop, A.C., Zoorob, S.E., Elliot, R.C., 2008. The influence of aggregate, filler and bitumen on asphalt mixture moisture damage. Constr. Build. Mater. 22, 2015–2024. https://doi.org/10.1016/j.conbuildmat.2007.07.009.

Almeida-Costa, A., Benta, A., 2016. Economic and environmental impact study of warm mix asphalt compared to hot mix asphalt. J. Clean. Prod. 112, 2308–2317.

Androjić, I., Dolaček-Alduk, Z., 2016. Analysis of energy consumption in the production of hot mix asphalt (batch mix plant). Can. J. Civ. Eng. 43 (12), 1044–1051. https://doi.org/10.1139/cjce-2016-0277.

Androjić, I., Dolaček-Alduk, Z., 2018. Artificial neural network model for forecasting energy consumption in hot mix asphalt (HMA) production. Constr. Build. Mater. 170, 424–432. https://doi.org/10.1016/j.conbuildmat.2018.03.086.

Androjić, I., Kaluđer, G., 2016. Usage of solar aggregate stockpiles in the production of hot mix asphalt. Appl. Therm. Eng. 108 (5), 131–139.

Androjić, I., Marović, I., 2017. Development of artificial neural network and multiple linear regression model sin the prediction process of the hot mix asphalt properties. Can. J. Civ. Eng. 44, 994–1004. https://doi.org/10.1139/cjce-2017.0300.

Androjić, I., Kaluđer, G., Androjić, J., 2017. Influence of the sun exposure surface area of the solar aggregate stockpiles on the accumulated heat of the stored mineral mixture. Energy 135, 75–82. https://doi.org/10.1016/j.energy.2017.06.124.

Androjić, I., Marović, I., Kaluđer, G., Androjić, J., 2018. Application of solar aggregate stockpiles in the process of storing recycled materials. Int. J. Energy Res. 1–14. https://doi.org/10.1002/er.4317.

Ang, B.W., Fwa, T.F., Ng, T.T., 1993. Analysis of process energy use of asphalt-mixing plants. Energy 18 (7), 769–777. https://doi.org/10.1016/0360-5442(93)90035-C.

Asphalt in figures. (2013). EAPA. Online: http://www.eapa.org/userfiles/2/Asphalt%20in%20Figures/AIF_2013.Final.pdf (date).

Croatian Asphalt Association www.h-a-d.hr/proizvodnja-asfalta/2017 (date).

Environmental guidelines on best available techniques (BAT) for production of asphalt paving mixes. (2007). EAPA. Online: http://eapa.org/usr_img/position_paper/bat_update_version2007.pdf (date).

Grabovski, W., Janowski, L., Wilanowicz, J., 2013. Problems of energy reduction during the hot-mix asphalt production. Baltic J. Road Bridge Eng. 8 (1), 40–47. https://doi.org/10.3846/bjrbe.2013.06.

Jenny, R., 2009. CO2 Reduction on Asphalt Mixing Plants Potential and Practical Solutions. Amman-Group, Switzerland.

Oeser, M., Freitag, S., 2009. Neural networks in rheology: theory and application. In: Proceedings of the 7th International RILEM Symposium ATCBM09 on Advanced Testing and Characterization of Bituminious Materials, Rhodes, Greece, pp. 949–958.

Peinado, D., de Vega, M., Garcia-Hernando, N., Marugan-Cruz, C., 2011. Energy and exergy analysis in an asphalt plant's rotary dryer. Appl. Therm. Eng. 31, 1039–1049. https://doi.org/10.1016/j.applthermaleng.2010.11.029.

Qiu, J., Huurman, M., de Bruin, B., Demmink, E.W., Frunt, M.H.T., 2018. Towards 90% warm re-use of porous asphalt using foaming technology. J. Clean. Prod. 190, 251–260.

Rukavina, T., Dragčević, V., Ožbolt, M., 2008. Special Asphalt Mixes. Dani prometnica, Zagreb (Denona).

Sivilevičius, H., Šukevičius, Š., 2009. Manufacturing technologies and dynamics of hot-mix asphalt mixture production. J. Civ. Eng. Manag. 15 (2), 169–179. https://doi.org/10.3846/1392-3730.2009.15.169-179.

Thives, L.P., Ghisi, E., 2017. Asphalt mixtures emission and energy consumption: a review. Renew. Sustain. Energy Rev. 72, 473–484.

Today in energy, independent statistics & analysis, U.S. Energy Information

Administration, Online: http://eia.gov/todayinenergy/detail.php?id=26212 (date).
Tušar, M., Novič, M., 2009. Data exploration on standard asphalt mix analyses. J. Chemometr. 23 (6), 283–293. https://doi.org/10.1002/cem.1229.
Zavrtanik, N., Prosen, J., Tušar, M., Turk, G., 2016. The use of artificial neural networks for modeling air void content in aggregate mixture. Autom. ConStruct. 63, 155–161. https://doi.org/10.1016/j.autcon.2015.12.009.
Zhu, S., Chen, F., Yin, H., 2017. Simulation and validation of asphalt foaming process for virtual experiments and optimisation of WMA production. Road Mater. Pavement Des. 18, 144–164. https://doi.org/10.1080/14680629.2017.1389093.