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Prediction of Optimum Expanded Polystyrene Densities for Best Thermal Insulation Performances of Polystyrene Composite Particleboards by Using Artificial Neural Network

Predviđanje optimalne gustoće ekspandiranog polistirena za najbolje performanse toplinske izolacije polistirenske kompozitne iverice primjenom umjetne neuronske mreže

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ABSTRACT • *The objective of this study is to predict the optimum expanded polystyrene (EPS) densities for the best insulation properties of the particleboards manufactured with waste EPS instead of formaldehyde-based adhesives used in particleboard production with artificial neural network (ANN). For this purpose, the waste EPS particles of five different densities were used in the production of composite particleboards. The experimental data used in the study were obtained from the previous study. Half of the beech, poplar, alder, pine and spruce chips were dried in a drying oven and the other half were naturally conditioned at room temperature, and then 18 mm thick three-layer composite particleboards were produced. The thermal conductivity of panels was determined according to ASTM C 518. The prediction model with the best performance and acceptable deviations was determined by using statistical and graphical comparisons between the experimental data and the prediction values obtained as a result of ANN analysis. Then, using this prediction model, the thermal conductivity coefficient values were estimated for the intermediate EPS densities that were not experimentally tested. According to the analysis findings, the thermal insulation performance for both beech and spruce polystyrene composite particleboards (PCP) panels increased with using of waste EPS foams with a density of 30 kg/m^3. The lowest thermal conductivity values were obtained from the EPS waste foams with the density of 18, 13 and 22 kg/m^3 for the PCP panels produced with poplar, alder and pine in the natural drying, respectively. In the technical drying, these values were found to be 15, 14 and 11-13 kg/m^3, respectively. Technical drying showed much better thermal performance than natural drying while poplar indicated the best performance among the wood species.*

KEYWORDS: *polystyrene composite particleboard; thermal insulation; thermal conductivity; EPS; ANN*

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SAŽETAK • *Cilj je ove studije primjenom umjetne neuronske mreže (ANN) predvidjeti optimalne gustoće ekspandiranog polistirena (EPS) radi postizanja najboljih izolacijskih svojstava iverice proizvedene s otpadnim EPS-om umjesto s ljepilom na bazi formaldehida, kakvo se rabi u proizvodnji iverice. Stoga je za proizvodnju iverice upotrijebljen otpadni EPS pet različitih gustoća. Eksperimentalni podatci primijenjeni u studiji dobiveni su prijašnjim istraživanjem. Jedna je polovica iverja bukovine, topolovine, johovine, borovine i smrekovine osušena u sušioniku, a druga je polovica iverja kondicionirana na sobnoj temperaturi. Od osušenoga i kondicioniranog iverja proizvedene su troslojne kompozitne iverice debljine 18 mm. Toplinska vodljivost ploča određena je metodom ASTM C 518. Predikcijski model najboljih svojstava i prihvatljivih devijacija određen je statističkom i grafičkom usporedbom eksperimentalnih podataka s vrijednostima predviđenima ANN analizom. Potom su primjenom predikcijskog modela procijenjeni koeficijenti toplinske vodljivosti za one gustoće ekspandiranog polistirena koje nisu eksperimentalno ispitane. Prema toj analizi, termoizolacijska svojstva polistirenske kompozitne iverice (PCP) od bukovine i smrekovine poboljšana su pjenom od otpadnog EPS-a gustoće 30 kg/m³. Najniže vrijednosti toplinske vodljivosti za polistirensku kompozitnu ivericu od prirodno osušene topolovine, johovine i borovine dobivene su uz uporabu pjene otpadnog ESP-a gustoće 18, 13 i 22 kg/m³. Za polistirensku kompozitnu ivericu od tehnički osušenog iverja te su vrijednosti bile 15, 14 i 11-13 kg/m³. Tehničkim sušenjem iverja postignuta su znatno bolja toplinska svojstva polistirenske kompozitne iverice nego prirodnim sušenjem, a topolovina je pokazala najbolja svojstva od svih ispitivanih vrsta drva.*

KLJUČNE RIJEČI: *polistirenska kompozitna iverica; termoizolacija; toplinska vodljivost; ESP; ANN*

1 INTRODUCTION
1. UVOD

Thermal insulation is one of the most effective measures to increase energy efficiency by improving the thermal properties of building envelopes (Cetiner and Shea, 2018). At first, it was tried to provide thermal insulation in buildings by using natural materials such as rice straw, rice husk, sawdust, animal fur and wood (Wei *et al.,* 2015). After the industrialization process, chemicals were used in the production of insulation materials to improve their performance (Khoukhi, 2018), and foam insulation materials based on polymer compounds such as polyurethane, polystyrene, and polyethylene have been recently developed (Wi *et al.,* 2021). Expanded polystyrene (EPS) foam, usually called Styrofoam, is widely used in packaging, appliances, building insulations, and decorations because of its outstanding properties, such as superior thermal insulation, excellent dimensional stability, low cost, low density, and low sensitivity to moisture, and it occupies the largest market share in building insulation materials (Li *et al.,* 2020). However, one of the most abundant plastics waste sources comes from various products of EPS foam (Rajak *et al.,* 2020). Global plastic production has exponentially increased in the past decades, and reached 359 million tons in 2018 (Plastics Europe, 2019). Although the amount of plastic waste sent to recycling has doubled in Europe and major industrial countries since 2006, plastic pollution is still a major environmental concern (Geyer *et al.,* 2017; Plastics Europe, 2019; Tokiwa *et al.,* 2009; Xu *et al.,* 2020; Song *et al.,* 2020). The most of EPS wastes come from food packaging and storage, and therefore studies on the recycling of EPS waste have increased recently in more than 30 countries (Koksal *et al.,* 2020). The toxic gases such as carcinogenic polycyclic aromatic hydrocarbons (PAHs) and dioxin, which are released by burning waste EPS foams, cause serious environmental problems (Chaukura *et al.,* 2016; Uttaravalli *et al.,* 2020). In addition, the low density of EPS can rapidly consume the loading capacity of waste storage areas (Chaukura *et al.,* 2016). Due to these problems, recycling methods of EPS wastes need to be both eco-friendly and economical. Demirkir *et al.* (2013a) stated that the production of wood and polystyrene materials as a composite could be an effective solution both in reducing the environmental pollution caused by polystyrene waste and in reducing the emission of formaldehyde released from wood-based panels.

In the previous study, it was determined that the thermal insulation properties of the particleboard panels bonded with different densities of EPS foam wastes were much better than those of the control groups produced with urea formaldehyde (Demirkir *et al.,* 2019). It was observed that the densities of EPS foams used in the production of these panels influenced the thermal conductivity values. Based on this, it is crucial to determine the optimum EPS densities to get the best thermal insulation performance for the building industry. Therefore, it is very important to use the right methods that do not require further experimentation, labour, time, energy and high costs (Demirkir *et al.,* 2013b). Researchers used artificial neural networks (ANN), which are more adaptable than traditional methods, for optimization of wood and wood-based materials because they were faster and more economical (Esteban *et al.,* 2011; Demirkir *et al.,* 2013b; Ozsahin and Aydin, 2014; Tiryaki *et al.,* 2017; Ozsahin and Murat, 2018). Even if the relationships between the experimentally obtained input and output data were complex and meaningless, ANN modelling could be successfully

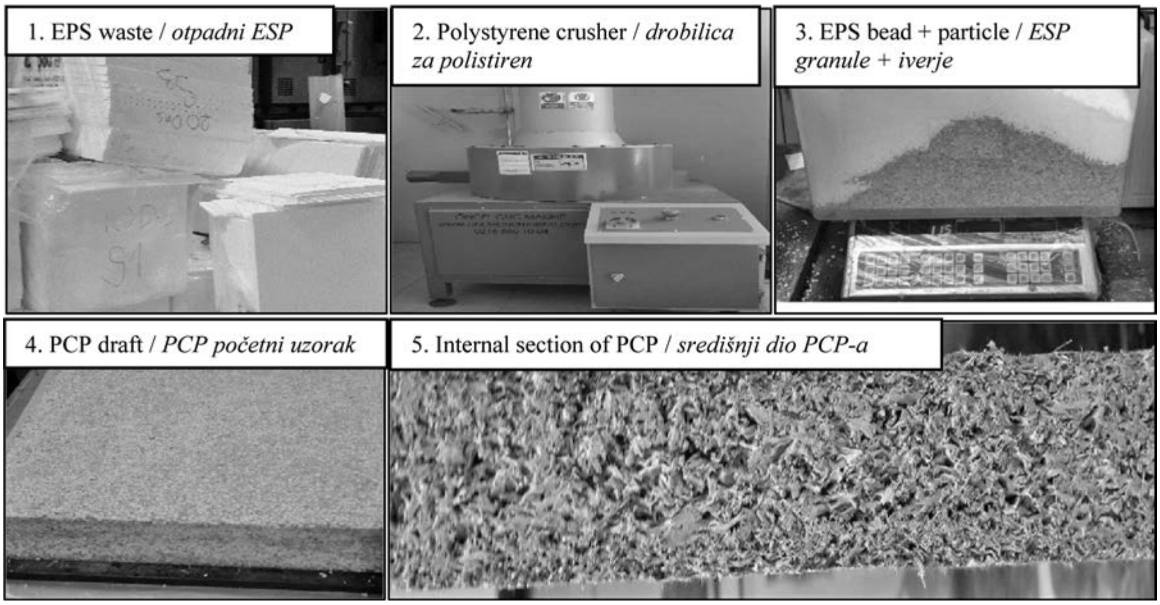

Figure 1 Polystyrene composite particleboards (PCP) production process
Slika 1. Proces proizvodnje polistirenske kompozitne iverice (PCP)

performed to obtain the desired optimum values (Fernandez *et al.,* 2008).

The objective of this study is to predict the optimum EPS density values for the best thermal insulation properties of the particleboards produced with EPS waste instead of formaldehyde-based adhesives via artificial neural network (ANN). For this purpose, the thermal conductivity values of intermediate EPS density values, which were not used in experimental studies, were also predicted by ANN model and the effects of EPS densities for each polystyrene composite particleboard (PCP) group were revealed.

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

2.1 Data collection
2.1. Prikupljanje podataka

The experimental data used in this study were obtained from the previous study by Demirkir *et al.* (2019). Beech (*Fagus orientalis* Lipsky), poplar (*Populus deltoides* I-77/51), alder (*Alnus glutinosa* subsp. *barbata*), pine (*Pinus Sylvestris*) and spruce (*Picea orientalis* L.) woods, widely preferred in the particleboard industry, were used in the production of composites by chipping. Half of these chips were dried in a drying machine at 90 °C until reachng 3 % moisture content (technical drying). The other half were conditioned at room temperature until reaching 12 % moisture content (natural drying). The waste EPS particles of five different densities (10, 16, 20, 24 and 30 kg/m^3) were used as bonding material in the production of composite particleboards. The waste EPS particles, crushed in a polystyrene crusher with a size of 1.5 - 3 mm, were used in the production of polystyrene composite particleboards (PCP). The EPS particles were homogeneously mixed at a rate of 10 % for the surface layer and 8 % for the core layer based on the particle weight (dry weight for technical drying and wet weight for natural drying).

The panel drafts with dimensions of 55 cm × 55 cm × 1.8 cm were pressed for 10 minutes at 150 °C at a pressure of 23-25 kg/cm^2. The ratio of the face thickness to the total thickness of a panel, known as the shelling ratio, was 0.35 for all samples, while the target density was 0.68 g/cm^3. After the panels were conditioned for three weeks, the thermal conductivity test measurements were carried out to determine the thermal properties of the panels. The thermal conductivity coefficients of the panels were determined according to the ASTM C 518 (2004) standard using the Lasercomp Fox-314 thermal conductivity device (Figure 2). Moreover, the thermal conductivity values of waste EPS foams of 10 cm thickness, with a cell content of 98 %

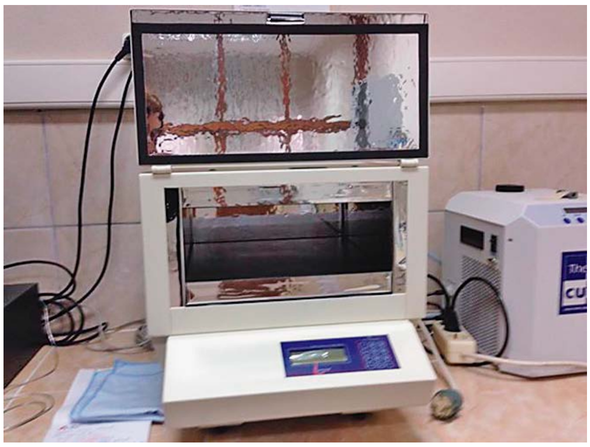

Figure 2 Lasercomp Fox-314 thermal conductivity device
Slika 2. Uređaj za toplinsku vodljivost Lasercomp Fox-314

air and 2 % polystyrene, were calculated as 0.040, 0.039, 0.036, 0.035 and 0.034 W/mK according to their density, respectively.

2.2 Artificial neural network (ANN) analysis
2.2. Analiza umjetnom neuronskom mrežom

ANN analysis, which is one of the algorithms used in nonlinear input and output variables modelling, has started to be preferred in recent years instead of logistic regression analysis, which is one of the most widely used methods in the development of predictive models. ANN, which can successfully model the complex relationships of input and output variables without the need for further statistical training, easily reveals all possible interactions between these variables and enables multiple training algorithms (Tu, 1996; Dumitru and Maria, 2013). ANN was used to predict thermal conductivity values of the EPS densities not used in experimental studies and to predict the optimum EPS densities that gave the best thermal insulating performance for each PCP group. Drying types, wood species and EPS densities were the main variables in ANN modelling of this study. The data obtained from experimental studies were modelled with the MATLAB Neural Network Toolbox. The experimental data were grouped as training data and testing data to determine

Table 1 Training data set used for thermal conductivity prediction model results
Tablica 1. Skup primjera za učenje primijenjen za predikcijski model toplinske vodljivosti

Drying type *Tip sušenja*	**Wood species** *Vrsta drva*	**EPS density, kg/m³** *Gustoća EPS-a,* kg/m³	**Thermal conductivity, W/mK** *Toplinska vodljivost,* W/mK		
			Actual *Stvarna*	**Predicted** *Predviđena*	**Error, %** *Greška, %*
Natural drying *prirodno sušenje*	Beech / *bukovina*	16	0.09891	0.09891	-0.004
	Beech / *bukovina*	24	0.09467	0.09466	0.008
	Beech / *bukovina*	30	0.09245	0.09245	-0.002
	Poplar / *topolovina*	10	0.10040	0.10040	0.005
	Poplar / *topolovina*	16	0.09266	0.09267	-0.011
	Poplar / *topolovina*	20	0.09276	0.09277	-0.010
	Poplar / *topolovina*	30	0.09529	0.09531	-0.025
	Alder / *johovina*	10	0.09674	0.09674	0.005
	Alder / *johovina*	20	0.09668	0.09641	0.282
	Alder / *johovina*	24	0.09664	0.09665	-0.008
	Pine / *borovina*	10	0.09705	0.09705	0.002
	Pine / *borovina*	16	0.09578	0.09661	-0.865
	Pine / *borovina*	24	0.09802	0.09670	1.343
	Pine / *borovina*	30	0.09428	0.09495	-0.714
	Spruce / *smrekovina*	10	0.10110	0.10064	0.452
	Spruce / *smrekovina*	20	0.09794	0.09831	-0.381
	Spruce / *smrekovina*	30	0.09692	0.09705	-0.138
Technical drying *tehničko sušenje*	Beech / *bukovina*	10	0.08995	0.09000	-0.050
	Beech / *bukovina*	20	0.09167	0.09103	0.701
	Beech / *bukovina*	24	0.08866	0.08938	-0.817
	Beech / *bukovina*	30	0.08621	0.08627	-0.074
	Poplar / *topolovina*	16	0.08316	0.08310	0.070
	Poplar / *topolovina*	20	0.08443	0.08604	-1.910
	Poplar / *topolovina*	30	0.08461	0.08414	0.554
	Alder / *johovina*	10	0.08642	0.08357	3.296
	Alder / *johovina*	16	0.08662	0.08665	-0.031
	Alder / *johovina*	20	0.08957	0.08670	3.202
	Alder / *johovina*	24	0.08783	0.08644	1.581
	Pine / *borovina*	10	0.08128	0.08366	-2.928
	Pine / *borovina*	20	0.08602	0.08700	-1.134
	Pine / *borovina*	24	0.08441	0.08691	-2.963
	Spruce / *smrekovina*	16	0.09075	0.09071	0.044
	Spruce / *smrekovina*	20	0.08788	0.08811	-0.263
	Spruce / *smrekovina*	24	0.08783	0.08730	0.604
	Spruce / *smrekovina*	30	0.08673	0.08701	-0.326
Mean absolute percent error (MAPE) training *Srednja apsolutna postotna pogreška (MAPE) na skupu za učenje*			0.70870		
Root Mean Square Error (RMSE) Training *Korijen srednje kvadratne pogreške (RMSE) na skupu za učenje*			0.00110		

Table 2 Testing data set used for thermal conductivity prediction model results
Tablica 2. Testni skup podataka upotrijebljen za predikcijski model toplinske vodljivosti

Drying type Tip sušenja	**Wood species** Vrsta drva	**EPS density,** kg/m³ *Gustoća EPS-a,* kg/m³	**Thermal conductivity, W/mK** *Toplinska vodljivost,* W/mK		
			Actual *Stvarna*	**Predicted** *Predviđena*	**Error, %** *Greška*, %
Natural drying *prirodno sušenje*	Beech / *bukovina*	10	0.10080	0.10071	0.089
	Beech / *bukovina*	20	0.09413	0.09685	-2.884
	Poplar / *topolovina*	24	0.09307	0.09305	0.021
	Alder / *johovina*	16	0.09700	0.09781	-0.836
	Alder / *johovina*	30	0.09385	0.09647	-2.792
	Pine / *borovina*	20	0.09482	0.09491	-0.096
	Spruce / *smrekovina*	16	0.10230	0.09951	2.730
	Spruce / *smrekovina*	24	0.09739	0.10013	-2.816
Technical drying *tehničko sušenje*	Beech / *bukovina*	16	0.08742	0.08882	-1.605
	Poplar / *topolovina*	10	0.08250	0.08335	-1.032
	Poplar / *topolovina*	24	0.08239	0.08546	-3.730
	Alder / *johovina*	30	0.08398	0.08575	-2.106
	Alder / *johovina*	16	0.08679	0.08705	-0.296
	Pine / *borovina*	30	0.08557	0.08668	-1.295
	Spruce / *smrekovina*	10	0.09318	0.09345	-0.289
MAPE testing / *MAPE na testnom skupu*				1.50790	
RMSER testing / *MSE na testnom skupu*				0.00180	

the effects of drying types, wood species and EPS densities on the thermal insulating performance. In order to successfully obtain the ANN prediction model from the experimentally determined thermal conductivity coefficient values, 35 data containing 70 % of the total experimental data were separated for the training set, while the remaining 15 data containing 30 % of the whole data were separated for the test set by considering the homogeneity of the groups. The thermal conductivity coefficient values obtained from both experiments and ANN analyses and the error percentages are shown in Tables 1 and 2 as training and test data sets.

The reliability of a predictive model whose training process has been completed successfully is determined by commonly used performance functions. The root mean square error (RMSE), mean absolute percent error (MAPE) and coefficient of determination (R^2), which are the most important of these functions, were preferred in this study. The equations formed depending on differences between the actual values obtained from the experimental data (t_i) and the predicted values obtained from the ANN model (td_i) in the testing data set are given in Eqs. 1, 2 and 3, respectively (N is the number of objects).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(t_{\mathrm{i}} - td_{\mathrm{i}}\right)^2} \tag{1}$$

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_{\mathrm{i}} - td_{\mathrm{i}}}{t_{\mathrm{i}}}\right|\right]\right)\cdot 100 \tag{2}$$

$$R^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(t_{\mathrm{i}} - td_{\mathrm{i}})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}}(t_{\mathrm{i}} - \bar{t})^2} \tag{3}$$

The network structure of the most reliable prediction model determined using performance functions after numerous trials is shown in Figure 3. This model consists

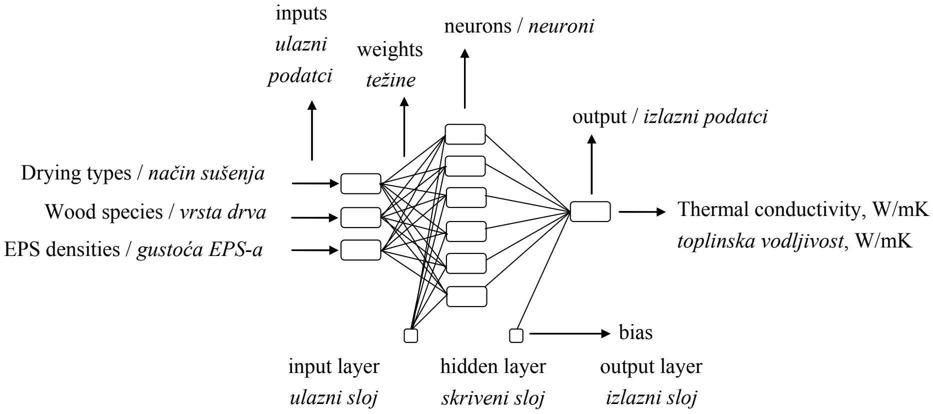

Figure 3 ANN architecture selected as prediction model
Slika 3. Arhiktektura ANN modela odabranoga za predikcijski model

Table 3 Connection weights and biases of thermal conductivity prediction model
Tablica 3. Težine i sistemske pogreške predikcijskog modela toplinske vodljivosti

Hidden layer / *Skriveni sloj*						**Output layer** / *Izlazni sloj*		
Neuron1	Neuron2	Neuron3	Neuron4	Neuron5	Neuron6	Bias1	Neuron1	Bias2
-6.33217	6.21830	12.41869	11.37884	1.17178	-3.39807	6.90932	-0.28800	0.39836
10.34989	10.70420	-14.02956	6.09988	1.16163	-3.28623	0.72941	0.16322	-
-6.15530	25.22297	-1.90658	-0.69203	-0.61331	-1.40521	0.42025	0.57538	-
-	-	-	-	-	-	1.32899	-0.35932	-
-	-	-	-	-	-	0.70403	0.86996	-
-	-	-	-	-	-	-5.91313	0.65224	-

of an input layer containing drying types, wood species and EPS densities, a hidden layer containing 6 neurons, and an output layer containing thermal conductivity coefficients. The connection weights and biases of the thermal conductivity prediction model are given in Table 3.

The feed forward and backpropagation multilayer ANN were used to determine the prediction model. In ANN analysis trials, the transfer (activation) function used the hyperbolic tangent sigmoid function (tansig) in the hidden layer, while the linear transfer function (purelin) was used in the output layer. The Levenberg marquardt algorithm (trainlm) and the momentum gradient reduction backpropagation algorithm (traingdm) were chosen as the training algorithm and the learning rule. The mean square error (MSE) was used for stopping the training phase. The MSE equation, which can be calculated based on the difference between the actual values obtained from the experimental data (t_i) and the predicted values obtained from the ANN model (td_i) in the training data sets, is given in Eq. 4 (N is the total number of training patterns).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(t_{\mathrm{i}} - td_{\mathrm{i}}\right)^2 \tag{4}$$

The data in the training and testing set were normalized (-1, 1 range) since the hyperbolic tangent sigmoid (tansig) function was used to contribute equally to the model for each parameter in the prediction model and then the data were transformed to their original values by reverse normalization so that the results could be evaluated. The processing of normalization was performed by using Eq. 5.

$$X_{\mathrm{norm}} = 2 \cdot \frac{X - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}} - 1 \tag{5}$$

Where, X_{norm} is the normalized value of a variable X (real value of the variable), and X_{max} and X_{min} are the maximum and minimum values of X, respectively.

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

Figure 4 presents the MSE value that gives the best training performance of 0.0099939 in the 500th iteration when the MSE changes based on iteration of the prediction model determined as a result of ANN analysis.

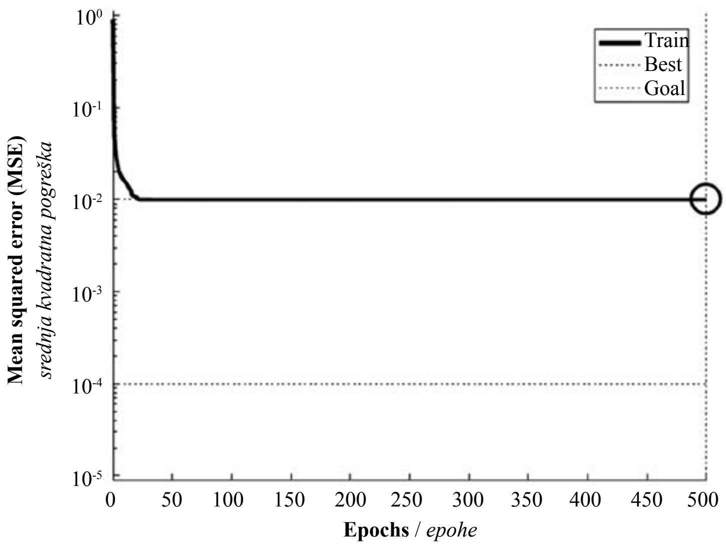

Figure 4 MSE changes at each iteration for training data set of ANN model
Slika 4. Promjene u srednjoj kvadratnoj pogrešci za svaku iteraciju na skupu podataka za učenje modela umjetne neuronske mreže

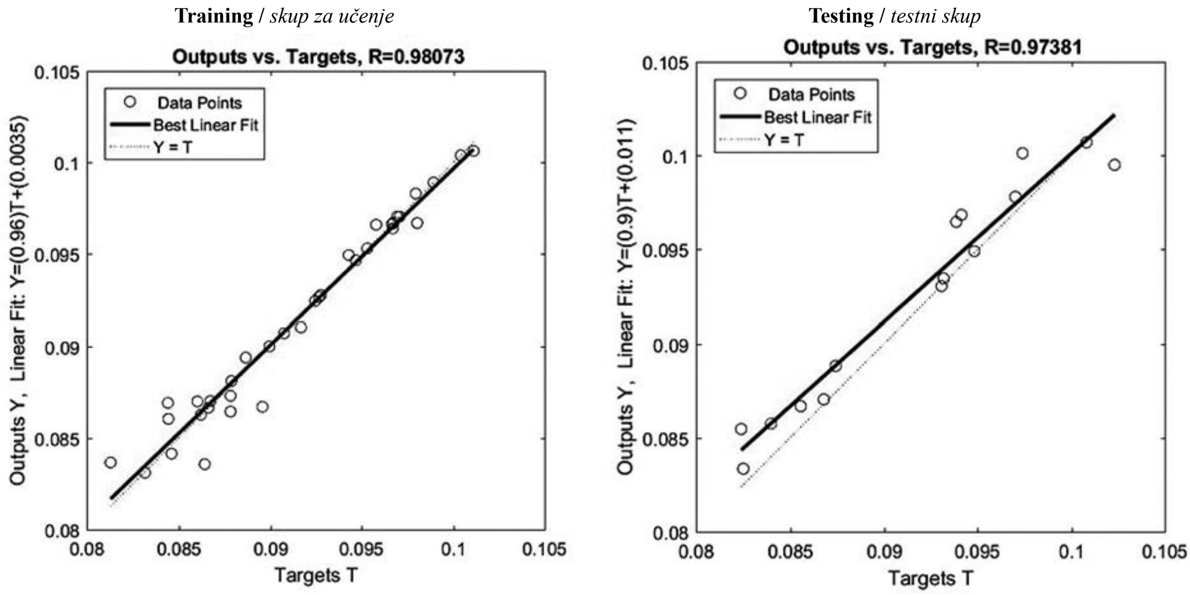

Figure 5 Regression models of thermal conductivity prediction model
Slika 5. Regresijski modeli predikcijskog modela toplinske vodljivosti

The regression analysis results of the thermal conductivity prediction model are given in Figure 5. The correlation coefficient values for training and testing data sets were calculated as 0.98073 and 0.97381, respectively. These values proved the accuracy and validity of the prediction model obtained. Since the reliability of prediction models increases as the correlation coefficients approach 1, a perfect fit between the actual and predicted values can be achieved (Ozsahin, 2012).

The comparison of the thermal conductivity coefficient values obtained from the experiments and the predicted values obtained from the ANN analysis is given graphically in Figure 6. It is seen that the actual values and the predicted values are quite close to each other, and this proves that the predictive ability of the model is quite high.

The MAPE values in the training data sets and testing data sets were calculated as 0.71 % and 1.51 %, respectively (Table 1 and 2). The MAPE value, which is frequently used by researchers to evaluate ANN model performance, is expected to be below 10 % (Antanasijević *et al*., 2013; Tiryaki *et al*., 2016). It is proved that the prediction performance of ANN models is high with these values lower than 10 % (Yadav and Nath, 2017). It is stated in the literature that it is extremely important to calculate RMSE values as well as MAPE values in order to determine the performance of prediction models (Kucukonder *et al*., 2016). In this study, the RMSE values of the thermal conductivity prediction model for training and testing phase were calculated as 0.0011 and 0.0018, respectively. (Table 1 and 2). Taspınar and Bozkurt (2014) stated that the low RMSE values obtained from the ANN analyses are an indicator of the successful performance of the prediction model. The MAPE and RMSE values obtained from the study proved that the ANN model used for prediction and optimization are reliable and can give satisfactory accurate results.

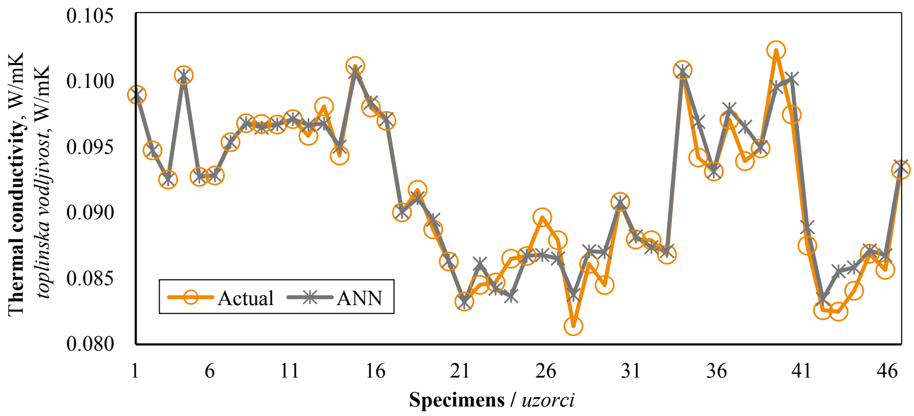

Figure 6 Comparison of measured and predicted values
Slika 6. Usporedba izmjerenih i predviđenih vrijednosti

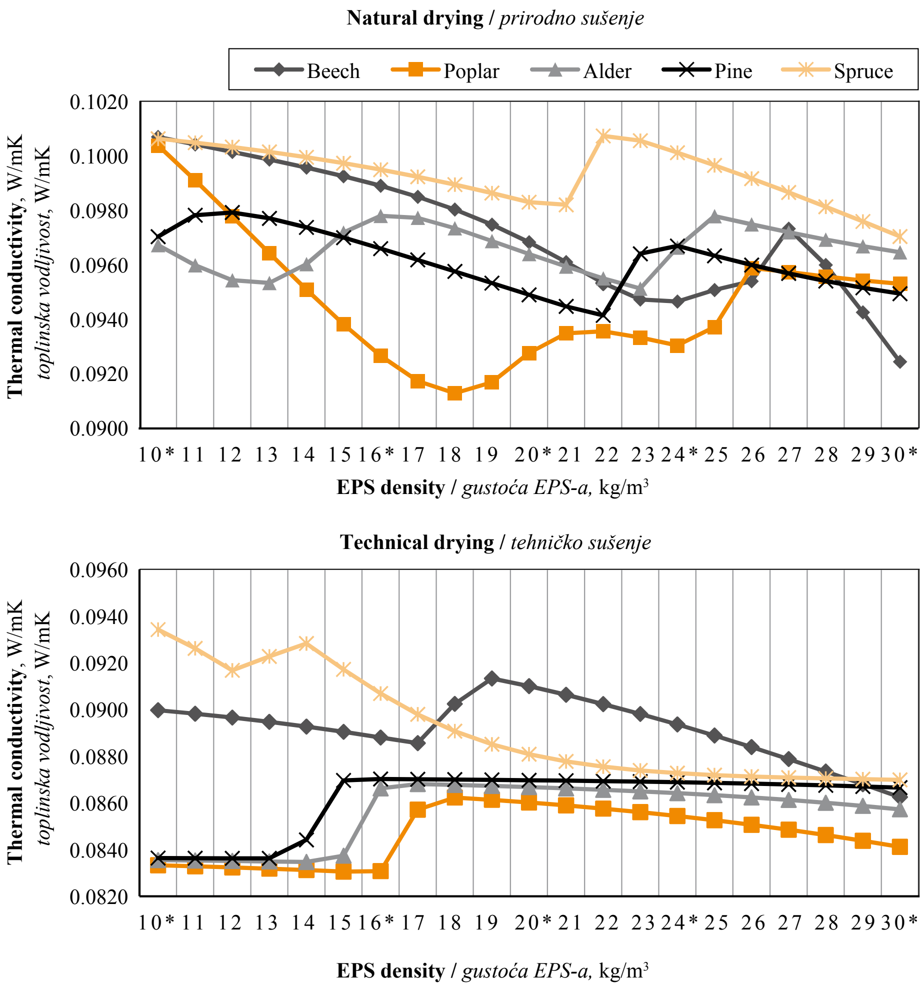

Figure 7 Changes in thermal conductivity values of PCP panels according to increasing EPS densities (*These density values were used both in experiments and ANN analysis. Thermal conductivity results related to these in graphics were obtained from ANN analysis.)
Slika 7. Promjene u toplinskoj vodljivosti PCP ploča s obzirom na povećavanje gustoće EPS-a (*Označene su vrijednosti gustoće korištene i u eksperimentima i u ANN analizi. Rezultati toplinske vodljivosti na grafikonima dobiveni su ANN analizom.)

Thanks to ANN models with low error values (MAPE and RMSE) and high performance, output values can be predicted with high accuracy for intermediate input values that are not used in experiments (Varol *et al.*, 2018). In this study, the thermal conductivity coefficient values were determined by the ANN prediction model for different EPS densities; they are shown in Figure 7 according to the wood species and drying types.

Figure 7 shows the differences in thermal conductivity values among wood species according to the drying type, depending on the density of EPS waste. In the literature, it was stated that the thermal conductivity coefficient values of wooden materials might differ depending on the wood species (Kol and Sefil, 2011; Rice and Shepard, 2004). Furthermore, thermal conductivity values in wood-based panels changed depending on the types and amounts of various binders, fillers and additives (Demir *et al.,* 2016). The lowest thermal conductivity coefficient values of the beech and spruce PCP panels produced by both natural and technical drying were obtained from EPS waste foams with a density of 30 kg/m³. In the natural drying, the thermal conductivity values of PCP panels produced with poplar, alder and pine gave the lowest values by using EPS waste foams with the density of 18, 13 and 22 kg/m³, respectively. In the technical drying, the lowest thermal conductivity values were found in EPS waste boards with the density of 15, 14 and 11-13 kg/m³ for PCP panels produced with poplar, alder and pine, respectively. Density, moisture content, the ratio of early and late wood zones, temperature and heat flow direction of composite materials are some factors that significantly affect the thermal conductivity of the wood-based panels (Suleiman *et al.,* 1999; Bader *et al.,* 2007; Sonderegger and Niemz, 2009; Demirkir *et al.,* 2013a).

While the PCP panels produced with poplar for both types of drying were the group that gave the lowest thermal conductivity values among wood species, spruce and beech PCP panels generally gave the highest values. It has been stated in many studies in the literature that the thermal conductivity coefficient values of wood and wood-based composites are strongly dependent on the density, and in general, the thermal conductivity values increase with the increase in density (Kamke and Zylkowski, 1989; Kol and Altun, 2009; Aydin *et al.,* 2015). Furthermore, the extractive contents in the spruce wood could be shown as a reason for the increase in the thermal conductivity of spruce composite panels. As stated in the literature, the extractive content and a number of checks and knots were other important factors affecting the thermal conductivity (Simpson and Tenwolde, 2007).

The thermal conductivity coefficient values of the composite panels produced with technically dried chips were found to be lower than the boards produced with naturally dried chips. It was known in the literature that the thermal conductivity of the panels varied depending on the temperature changes. Zhou *et al.* (2013) investigated the effect of temperature changes on the thermal conductivity of MDF panels and stated that the thermal conductivity increased with temperature up to 50 ºC and then decreased with increasing temperature between 50 ºC and 100 ºC. The density of the air in the cavities of the wood decreases depending on the increase in temperature, and therefore the heat conduction decreases (Suleiman *et al.,* 1999; Aydin *et al.,* 2015). Moreover, the thermal conductivity values also increased with increasing the moisture content of wood-based panels (Sonderegger and Niemz, 2009). Consequently, it was expected that PCP panels produced from particles dried at 90 ºC to 3 % moisture content gave lower thermal conductivity values than naturally air-conditioned PCP panels at 12 % moisture content.

4 CONCLUSIONS
4. ZAKLJUČAK

In this study, the optimum EPS densities giving the best thermal insulation performances of PCP panels produced with EPS waste foams were determined with ANN analysis. As a results of the ANN analysis, the MAPE and RMSE values of thermal conductivity prediction model in the testing data sets were determined as 1.51 % and 0.0018, respectively. The coefficient of determination (R^2) value was calculated as 0.9483 in the testing data sets. Although there was a complex and non-linear relationship between the input and output variables in the study, the performance of the model was proven with diagnostic tools and accurate, encouraging, and satisfactory results were obtained.

According to the ANN analysis results of the study, the use of EPS waste foams with a density of 30 kg/m^3 increased the thermal insulation performance for both beech and spruce PCP panels. Furthermore, the lowest thermal conductivity values were obtained from the EPS waste foams with the density of 18, 13 and 22 kg/m^3 for the PCP panels produced with poplar, alder and pine in the natural drying, respectively. In the technical drying, these values were found to be 15, 14 and 11-13 kg/m^3, respectively. Poplar species is the wood species that gave the best thermal insulation performance. Technical drying performed much better than natural drying in terms of thermal conductivity. By utilizing the results of this study, PCP panels with the best thermal insulation performance will be produced quickly at low costs, and this will contribute to the recycling of waste EPS foams.

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5 REFERENCES
5. LITERATURA

1. Antanasijević, D. Z.; Pocajt, V. V.; Povrenović, D. S.; Ristić, M. Đ.; Perić-Grujić, A. A., 2013: PM10 emission forecasting using artificial neural networks and genetic algorithm input variable optimization. Science of the Total Environment, 443: 511-519. https://doi.org/10.1016/j.scitotenv.2012.10.110
2. Aydin, I.; Demir, A.; Ozturk, H., 2015: Effect of Veneer Drying Temperature on Thermal Conductivity of Veneer Sheets. Pro Ligno, 11 (4): 351-354.
3. Bader, H.; Niemz, P.; Sonderegger, W., 2007: Untersuchungen zum Einfluss des Plattenaufbaus auf Ausgewählte Eigenschaften von Massivholzplatten. Holz als Roh- und Werkstoff, 65 (3): 173-181. https://doi.org/10.1007/S00107-006-0143-7
4. Cetiner, I.; Shea, A. D., 2018: Wood waste as an alternative thermal insulation for buildings. Energy and Buildings, 168: 374-384. https://doi.org/10.1016/j.enbuild.2018.03.019
5. Chaukura, N.; Gwenzi, W.; Bunhu, T.; Ruziwa, D. T.; Pumure, I., 2016: Potential uses and value-added products derived from waste polystyrene in developing countries: a review. Resources, Conservation and Recycling, 107: 157-165. https://doi.org/10.1016/j.resconrec.2015.10.031
6. Demir, A.; Aydin, İ.; Ozturk, H., 2016: Effect of various fire retardant chemicals in different concentrations on thermal conductivity of plywood. In: Proceedings of International Multidisciplinary Congress of Eurasian, Odessa, Ukraine, 2: 328-332.
7. Demirkir, C.; Colak, S.; Aydin, I., 2013a: Some technological properties of wood-styrofoam composite panels. Composites. Part B: Engineering, 55: 513-517. https://doi.org/10.1016/j.compositesb.2013.07.024
8. Demirkir, C.; Ozturk, H.; Colakoglu, G., 2019: Effect of drying types and polystyrene density on thermal conduc-

tivity of polystyrene composite particleboard. Wood Industry and Engineering, 1 (2): 57-62.
9. Demirkir, C.; Özsahin, S.; Aydin, I.; Colakoglu, G., 2013b: Optimization of some panel manufacturing parameters for the best bonding strength of plywood. International Journal of Adhesion and Adhesives, 46: 14-20. https://doi.org/10.1016/j.ijadhadh.2013.05.007
10. Dumitru, C.; Maria, V., 2013: Advantages and disadvantages of using neural networks for predictions. Ovidius University Annals. Series Economic Sciences, 13 (1): 444-449.
11. Esteban, L. G.; Fernandez, F. G.; Palacios, P., 2011: Prediction of plywood bonding quality using an artificial neural network. Holzforschung, 65 (2): 209-214. https://doi.org/10.1515/hf.2011.003
12. Fernández, F. G.; Esteban, L. G.; Palacios, P.; Navarro, N.; Conde, M., 2008: Prediction of standard particleboard mechanical properties utilizing an artificial neural network and subsequent comparison with a multivariate regression model. Investigación Agraria: Sistemas y Recursos Forestales, 17 (2): 178-187. https://doi.org/10.5424/srf/2008172-01033
13. Geyer, R.; Jambeck, J. R.; Law, K. L., 2017: Production, use, and fate of all plastics ever made. Science Advances, 3 (7): e170078. https://doi.org/10.1126/sciadv.1700782
14. Kamke, A. F.; Zylkowoski, S. C., 1989: Effects of wood-based panel characteristics on thermal conductivity. Forest Products Journal, 39: 19-24.
15. Khoukhi, M., 2018: The combined effect of heat and moisture transfer dependent thermal conductivity of polystyrene insulation material: impact on building energy performance. Energy and Buildings, 169: 228-235. https://doi.org/10.1016/J.enbuild.2018.03.055
16. Koksal, F.; Mutluay, E.; Gencel, O., 2020: Characteristics of isolation mortars produced with expanded vermiculite and waste expanded polystyrene. Construction and Building Materials, 236: 117789. https://doi.org/10.1016/j.conbuildmat.2019.117789
17. Kol, H. S.; Altun, S., 2009: Effect of some chemicals on thermal conductivity of impregnated laminated veneer lumbers bonded with poly (vinyl acetate) and melamine-formaldehyde adhesives. Drying Technology, 27 (9): 1010-1016. https://doi.org/10.1080/07373930902905092
18. Kol, H. S.; Sefil, Y., 2011: The thermal conductivity of fir and beech wood heat treated at 170, 180, 190, 200 and 212 °C. Journal of Applied Polymer Science, 121 (4): 2473-2480. https://doi.org/10.1002/app.33885
19. Kucukonder, H.; Boyaci, S.; Akyüz, A., 2016: A modeling study with an artificial neural network: developing estimation models for the tomato plant leaf area. Turkish Journal of Agriculture and Forestry, 40 (2): 203-212. https://doi.org/10.3906/tar-1408-28
20. Li, M. E.; Yan, Y. W.; Zhao, H. B.; Jian, R. K.; Wang, Y. Z., 2020: A facile and efficient flame-retardant and smoke-suppressant resin coating for expanded polystyrene foams. Composites. Part B: Engineering, 185. https://doi.org/10.1016/j.compositesb.2020.107797
21. Ozşahin, S., 2012: The use of an artificial neural network for modelling the moisture absorption and thickness swelling of oriented strand board. BioResources, 7 (1): 1053-1067.
22. Ozsahin, S.; Aydin, I., 2014: Prediction of the optimum veneer drying temperature for good bonding in plywood manufacturing by means of artificial neural network. Wood Science and Technology, 48 (1): 59-70. https://doi.org/10.1007/s00226-013-0583-2
23. Ozsahin, S.; Murat, M., 2018: Prediction of equilibrium moisture content and specific gravity of heat-treated wood by artificial neural networks. European Journal of Wood and Wood Products, 76 (2): 563-572. https://doi.org/10.1007/s00107-017-1219-2
24. Rajak, A.; Hapidin, D. A.; Iskandar, F.; Munir, M. M.; Khairurrijal, K., 2020: Electrospun nanofiber from various source of expanded polystyrene (EPS) waste and their characterization as potential air filter media. Waste Management, 103: 76-82. https://doi.org/10.1016/j.wasman.2019.12.017
25. Rice, R. W.; Shepard, R., 2004: The thermal conductivity of plantation grown white pine (*Pinus strobus*) and red pine (*Pinus resinosa*) at two moisture content levels. Forest Products Journal, 54 (1): 92-94.
26. Simpson, W.; TenWolde, A., 2007: Physical properties and moisture relation of wood. In: Encyclopedia of Wood. Madison, Wisconsin, FPL, chapter 3.
27. Sonderegger, W.; Niemz, P., 2009: Thermal conductivity and water vapour transmission properties of wood-based materials. European Journal of Wood and Wood Products, 67: 313-321. http://dx.doi.org/10.1007/s00107-008-0304-y
28. Song, Y.; Qui, R.; Hu, J.; Li, X.; Zhang, X.; Chen, Y.; Wu, W. M.; He, D., 2020: Biodegradation and disintegration of expanded polystyrene by land snails Achatina fulica. Science of the Total Environment, 746. https://doi.org/10.1016/j.scitotenv.2020.141289
29. Suleiman, B. M.; Larfeldt, J.; Leckner, B.; Gustavsson, M., 1999: Thermal conductivity and diffusivity of wood. Wood Science and Technology, 33 (6): 465-473.
30. Taspınar, F.; Bozkurt, Z., 2014: Application of artificial neural networks and regression models in the prediction of daily maximum PM10 concentration in Düzce, Turkey. Fresenius Environmental Bulletin, 23 (10): 2450-2459.
31. Tiryaki, S.; Bardak, S.; Aydın, A., 2016: Modeling of wood bonding strength based on soaking temperature and soaking time by means of artificial neural networks. International Journal of Intelligent Systems and Applications in Engineering, 153-157. https://doi.org/10.18201/ijisae.2016Special%20Issue-146964
32. Tiryaki, S.; Özsahin, S.; Aydin, A., 2017: Employing artificial neural networks for minimizing surface roughness and power consumption in abrasive machining of wood. European Journal of Wood and Wood Products, 75(3): 347-358. https://doi.org/10.1007/s00107-016-1050-1
33. Tokiwa, Y.; Calabia, B.; Ugwu, C.; Aiba, S., 2009: Biodegradability of plastics. International Journal of Molecular Sciences, 10 (9): 3722-3742. https://doi.org/10.3390/ijms10093722
34. Tu, J. V., 1996: Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. Journal of Clinical Epidemiology, 49 (11): 1225-1231. https://doi.org/10.1016/S0895-4356(96)00002-9
35. Uttaravalli, A. N.; Dinda, S.; Gidla, B. R., 2020: Scientific and engineering aspects of potential applications of post-consumer (waste) expanded polystyrene: a review. Process Safety and Environmental Protection, 137: 140-148. https://doi.org/10.1016/j.psep.2020.02.023
36. Varol, T.; Canakci, A.; Ozsahin, S., 2018: Prediction of effect of reinforcement content, flake size and flake time on the density and hardness of flake AA2024-SiC nanocomposites using neural networks. Journal of Alloys and Compounds, 739: 1005-1014. https://doi.org/10.1016/j.jallcom.2017.12.256

37. Wei, K.; Lv, C.; Chen, M.; Zhou, X.; Dai, Z.; Shen, D., 2015: Development and performance evaluation of a new thermal insulation material from rice straw using high frequency hot-pressing. Energy and Buildings, 87: 116-122. https://doi.org/10.1016/j.enbuild.2014.11.026
38. Wi, S.; Park, J. H.; Kim, Y. U.; Kim, S., 2021: Evaluation of environmental impact on the formaldehyde emission and flame-retardant performance of thermal insulation materials. Journal of Hazardous Materials, 402. https://doi.org/10.1016/j.jhazmat.2020.123463
39. Xu, Y. Q.; Xiang, J. Y.; Ko, J. H., 2020: Municipal plastic recycling at two areas in China and heavy metal leachability of plastic in municipal solid waste. Environmental Pollution, 260. https://doi.org/10.1016/j.envpol.2020.114074
40. Yadav, V.; Nath, S., 2017: Forecasting of PM 10 Using Autoregressive Models and Exponential Smoothing Technique. Asian Journal of Water, Environment and Pollution, 14 (4): 109-113. https://doi.org/10.3233/AJW-170041
41. Zhou, J.; Zhou, H.; Hu, C.; Hu, S., 2013: Measurement of thermal and dielectric properties of medium density fiberboard with different moisture contents. BioResources, 8 (3): 4185-4192.
42. ***ASTM C 518, 2004: Methods of measuring thermal conductivity, absolute and reference method. American Society for Testing and Materials, West Conshohocken, A, United States.
43. ***Plastics – the Facts, 2019: An Analysis of European Latest Plastics Production, Demand and Waste Data.

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