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STATISTICAL MODELLING IN ECOLOGICAL MANAGEMENT USING THE ARTIFICIAL NEURAL NETWORKS (ANNs)

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Abstract

This paper presents the results of modeling the sulfur dioxide (SO_2) emission in the vicinity of the copper-smelting complex according to the technological and meteorological parameters. As the part of the technological project with an environmental impact, for the prediction of potential SO_2 emission, Artificial Neural Networks (ANNs) were used as the modelling tool. Input parameters of the model included technological data: amount of sulfur introduced to the reverberatory furnace with the charge and the amount of sulfur removed from the process gas in the sulfuric acid factory. Meteorological parameters included: wind speed and wind direction, air temperature, humidity and barometric pressure. Also, the influence of the season was considered as well as the location of the measuring point and its distance from the factory chimneys. The results obtained indicated that the artificial neural networks could be successfully used for prediction of the sulfur dioxide emission according to the known technological and meteorological parameters.

*Keywords:*Neural network, мodelling, пrediction, тechnological process

1. INTRODUCTION

In modern industrial conditions, ecology is treated as vital aspect of almost all new projects. This way, development of the ecology management, as a scientific field, lead to increase in number of methods and techniques that could be applied as tools for improvement of the ecological parameters of each industrial process. In modern approach to technological processes ecological parameters control, modern mathematical methods for prediction are being increasingly used. The reason for such necessity to predict behavior of ecological parameters of a technological process is to forecast potential hazard of the technology. One of the tools that can be used for such purpose is Artificial Neural Network (ANN) (Živković et al., 2009).

This paper presents an attempt to apply ANN methodology for modelling of one aspect of the reverberatory furnace copper production. As the input data for the

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modelling process we used amount of copper concentrate processed and the amount of sulfuric acid produced. The object of modelling was emission of the sulfur dioxide gas which is being continuously monitored at two measuring points in city of Bor (Serbia). Also, for the modelling procedure, we used meteorological parameters: the season, wind speed, wind direction, air temperature, humidity and the barometric pressure measured at the same measuring point as the SO_2 emission. Important input parameter was also the distance from the measuring stations to the smelter plant tall stacks, since two measuring stations are at different distance and the direction from the tall stacks.

Table 1 presents average excess of the SO_2 concentration detected in the air, in the vicinity of this copper smelting complex, during the year 2009. It is obvious that the emission above limited concentration happened almost every month. The problem is even larger because of the fact that the smelter plant is located in the center of the city. Limiting SO_2 concentration, allowed in the air of the urban zones, was prescribed by World Health Organization and it is 350 $\mu g/m^3$ (WHO, 2001). The same limiting concentration was prescribed by EU commission (1999/30/CE), whereby this regulation is obligatory for the EU countries as well as for the countries which are potential candidates for the EU membership. Republic of Serbia also has legal regulative that prescribes the range of maximal allowed concentration of toxic gasses in the air. According to this regulative, maximal allowed SO_2 concentration in the air is also 350 $\mu g/m^3$, in the urban regions.

Considering the danger which is resulting from the increased SO_2 emission, Continuous Operational Real-Time Monitoring System (CORTMS) was establishes in the Bor area, during the year 2003. This system enables continual measuring of the SO_2 content in the air (the values are read out on every 15 minutes). However, this system can only detect the excessive emission of SO_2 when it happens. Until now, this data wasn't applied for prevention or decreasing of the excessive SO_2 emission in the city. The reason for this was lack of adequate mathematical model for such predictions.

Accordingly, this paper presents the attempt to define a model for mathematical prediction of the potential excess of the SO_2 emission above limiting concentration in the air, based on the input parameters of the technological process and meteorological parameters of the region, using Artificial Neural Networks (ANNs). In the previous attempts to resole this problem, analytical approach was used for modelling of the SO_2 emission (Mihajlović et al. 2008). This approach resulted with model equation which can be used for prediction of the SO_2 emission, according to the above mentioned technological and meteorological parameters with accuracy of 78% (R^2 = 0.78).

Also this same topic, concerning the influence of technological and meteorological parameters on air contamination with the SO_2 and heavy metals particle emission (PM10), was analyzed using the multi criteria analysis (Nikolić et al., 2009). As the result, the influence of meteorological parameters on lower or higher presence of toxic components in the air was proved. This paper

Table 1. Descriptive statistics for the SO_2 emission during the year 2009

Month	Measuring point	Minimum, $\mu g/m^3$	Maximum, $\mu g/m^3$	Mean, $\mu g/m^3$	Std. Deviation	Percentile of time over the limiting value, %
January	1	0	4 398	45.78	298.92	2.9
	2	0	2 398	34.56	345.23	15.3
February	1	5	4 989	56.78	234.34	14.4
	2	0	5 367	207.34	342.45	25.3
March	1	10	4 230	67.9	245.45	13.3
	2	0	5 193	203.45	433.34	18.0
April	1	0	3 145	165.45	354.21	16
	2	0	3 678	196.56	324.2	15
May	1	0	4 321	126.45	453.21	11.3
	2	0	4 567	23.45	125.67	1.9
June	1	0	3 453	167.23	345.34	8.05
	2	0	4 876	198.23	457.23	19.58
July	1	0	5 257	106.21	351.627	16.1
	2	0	4 247	194.55	472.985	8.7
August	1	0	2 345	78.92	342.34	8.3
	2	0	3 465	101.23	324.56	16.5
September	1	0	2 345	56.78	234.56	7.3
	2	0	2 435	52.34	256.45	6.5
October	1	10	2 394	206.98	424.851	11.6
	2	0	3 990	86.55	392.172	19.25
November	1	0	3 435	201.23	435.23	16.4
	2	0	4 321	212.23	456.23	18.8
December	1	0	2 879	123.45	345.67	12.3
	2	0	3 245	145.67	345.23	13.45

1-measuring point City park
2-measuring point Jugopetrol

presents one step in front, considering necessity for higher precision of the predictions, which implied approach to mathematical modelling using ANNs.

2. ARTIFICIAL NEURAL NETWORKS (ANN) - SHORT DESCRIPTION OF THE METHODOLOGY

Neural networks constitute a branch of artificial intelligence which has recently undergone rapid evolution and progress (Eldin and Senoucci, 1995). Over the last 10 years, artificial neural networks (ANNs), and particularly feed forward artificial neural networks (FANNs), have been extensively studied to present process models, and their use in industry has been rapidly growing (Ungar et al., 1996). The use of such networks can also be found for number of prediction in environmental management such as modelling the greenhouse effect (Seginer et al., 1994), simulation of the N_2O emission from a temperate grassland ecosystem (Ryan et al., 2004). Also, there is large expansion of General ANNs application in the ecology and the different fields of industrial practice (Lak et al., 1996; Fullana et al., 2000; Chouai et al., 2000; Cilek, 2002; Jorjani et al., 2007).

The main advantage of ANN is the ability to perform the modelling of a problem by the use of examples (i.e. data driven), rather then describing it analytically. ANNs are also very powerful to effectively represent complex non-linear systems. It is also considered as a non-linear statistical identification technique (Demuth and Beale, 2002).

For developing a non-linear ANN model of a system, feed-forward architecture namely MLP is most commonly used. This network usually consists of a hierarchical structure of three type of layers described as input, hidden (may be more then one), and output layers, all comprising certain number of processing nodes. Each node in the input layer is linked to all the nodes in the hidden layer using weighted (w_{ij}) connections. Similar connections exist between hidden and the output layer. The first layer (input layer) has weights coming from the input. Each subsequent layer has a weight coming from the previous layer. All layers have biases. The last layer is the network output (Demuth and Beale, 2002).

A multi/layer, feed-forward neural network is shown in Fig. 1. It has an input layer of six neurons, a hidden layer of three neurons and output layer of one neuron. The input of a neuron in the input layer V_i is experimentally obtained independent variable.

Detailed description of MLP architecture of ANNs is published previously by Živković et al. (2009). This investigation used identical approach to ANN construction

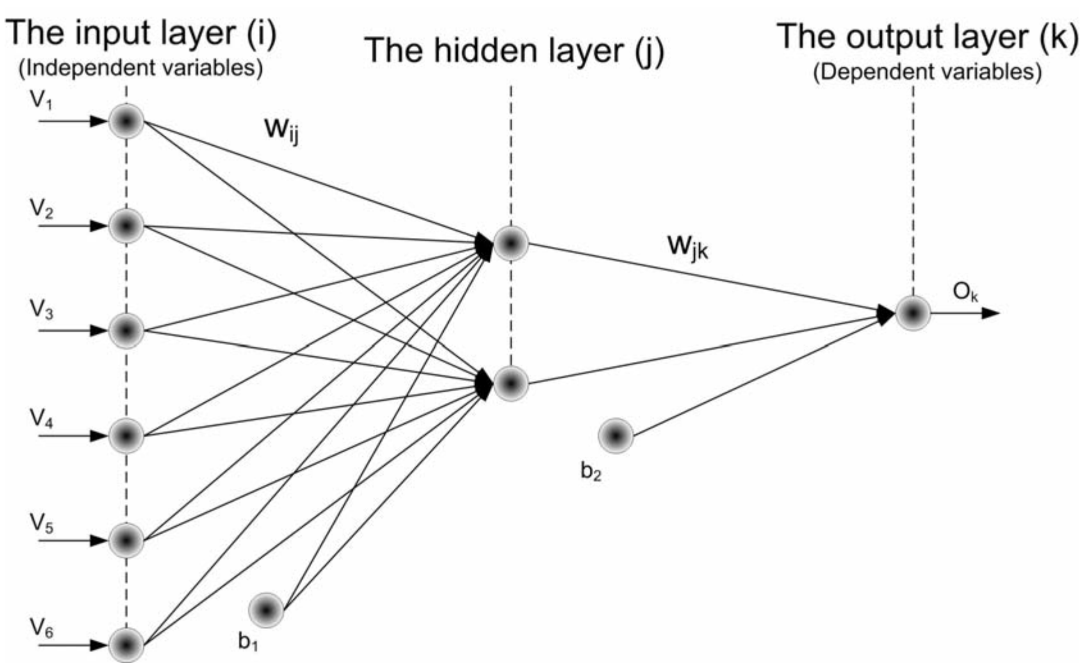

Figure 1. Architecture of a three layer, feed-forward neural network (b_1 and b_2 are bias units). Arrows indicate the flow of information during the prediction.

as well as its Trening/Testing ratio. Namely, neural networks are able to learn because they can change the connection weights between units. After learning, the knowledge is stored in the weights. For the purpose of training, 70% of the staring dataset is usually used. Training of the neural network is terminated when the network has learned to generalize the underlying trends of relationships exemplified by the data. Generalization implies that the neural network can interpolate sensibly at points not contained in its training set. The ability of neural network to do so is typically assessed by means of cross-validation, where the performance of the network is evaluated against a novel set of test data, not used during training. This is also known as the testing stage, where the remaining 30% of the starting dataset is used.

3. STARTING DATASET OF THE MATHEMATICAL MODEL

Technological parameters from the copper smelter plant were collected during July and October 2009, as well as meteorological parameters for the same time periods, to be used as the input data for the mathematical modelling presented in this paper. These two months were selected with the purpose to investigate the influence of the season on the modelling results. Technological parameters included were the amount of processed concentrate, amount of produced sulfuric acid and remaining amount of sulfur from the concentrate which will be emitted in the form of SO_2 gas. This gas is emitted through the smelter plant chimneys presented in the Figure 2. Meteorological parameters incorporated in the modelling procedure as the input data included: the wind direction, wind speed, ambient temperature, air humidity and barometric pressure. These parameters were continuously measured at two measuring stations (City park and Jugopetrol), presented in Figure 2. Also, the object of modelling - SO_2 content in the air - was continuously measured at same two locations. To form adequate data base for mathematical modelling, the data acquisition was performed at 15 minutes intervals. This way, the data base was formed with 5048 data lines.

Figure 3 presents the average percentile of time during which the excessive value of SO_2 emission was recorded (above 350 $\mu g/m^3$). Considering the results presented in Figure 3, it is obvious that the excess value of SO_2 emission was recorded in time intervals during all months of the year 2009, on both measuring points. Maximal excess value was recorded at the measuring station 1 (Jugopetrol) during February 2009. Considering the months which were selected for further modelling of the ecological problem, July and October, there was considerably higher emission of SO_2 recorded at measuring point 1 in July and at measuring point 2 in October. This indicates obvious influence of the wind direction and the season of the year on recorded values of SO_2 emission.

Since the limitations of the analytical modelling of the environmental problem, discussed in this paper, were studied previously (Mihajlović et al., 2008) as well as the possibilities of applying the multicriteria analysis (Nikolić et al., 2009), next step of our investigations involved testing the existence of linear statistical

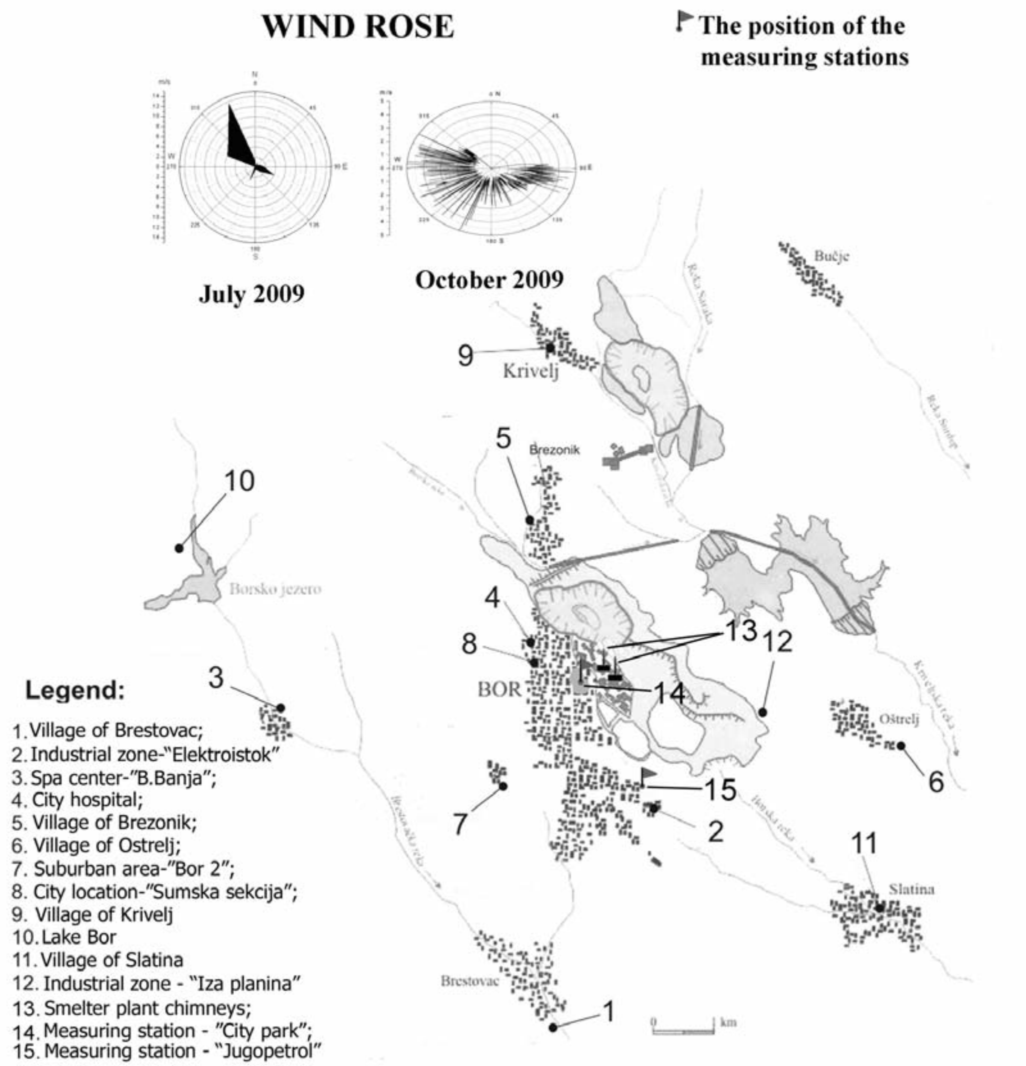

Figure 2. Disposition of the city of Bor with indicated measuring stations (Nikolić et al, 2009)

dependence between dependent (SO_2 content in the air) and the independent variables (technological and meteorological parameters) of the model. Results of calculation of the linear correlations between detected SO_2 emission in the air and all input parameters of the model (both technological and meteorological) are presented in Figure 4.

According to the results presented in Figure 4, there is low statistical significance of the linear correlation between the modelling object (detected SO_2 in the air) and most of the input parameters of the model (R^2 = 0.007). This indicates that investigated system can not be adequately described with linear mathematical model. From this reason, in our further investigations, we decided to apply nonlinear modelling approach such is ANN methodology (Lak et al., 1996; Paruelo and Tomasel, 1997; Demuth and Beale, 2002).

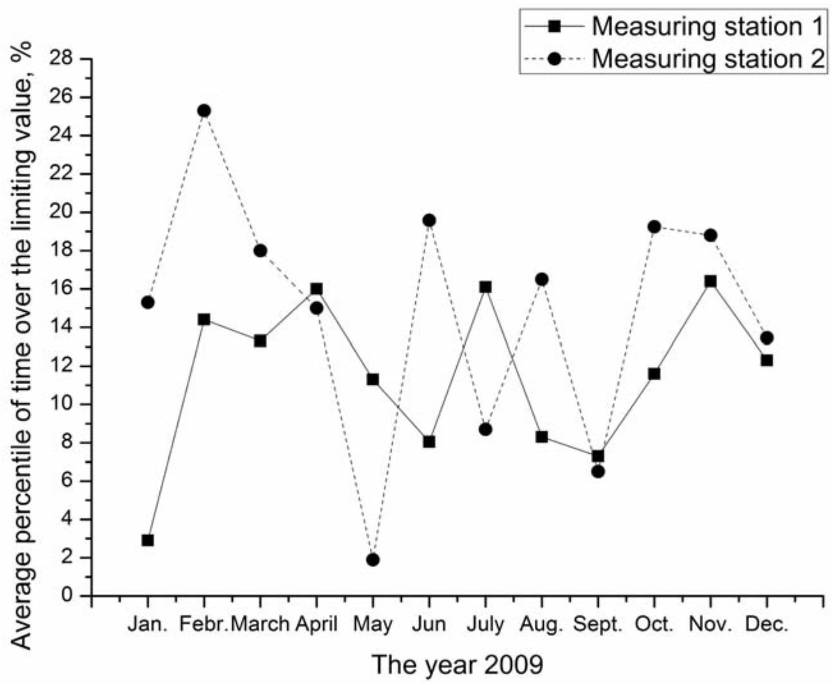

Figure 3. Average percentile of time during which excess emission of SO_2 was recorded at the measuring station 1 (City park) and the measuring station 2 (Jugopetrol)

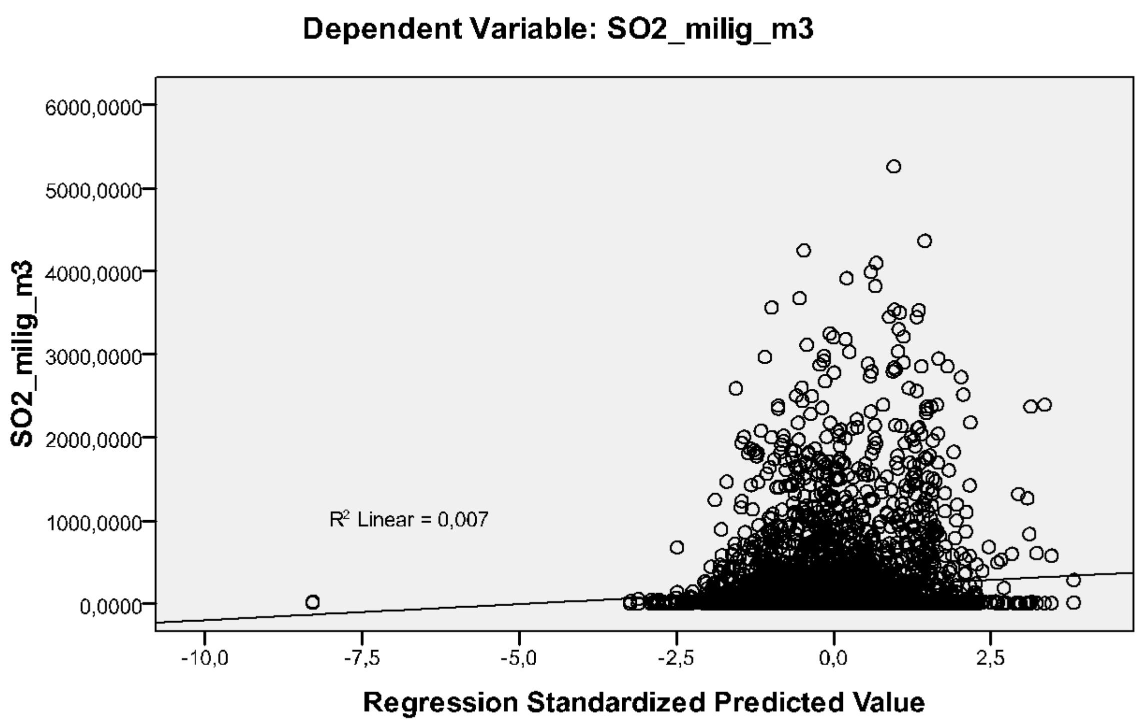

Figure 4. Results of the MLRA analysis of investigated problem

The ANN architecture applied in this work included the input layer with eight neurons (including both the technological and the meteorological parameters), hidden layer included seven and the output layer only one neuron (predicted concentration of SO_2 in the air). Figure 5 presents the architecture of applied neural network.

Total number of collected data samples was 5048. The selected modelling structure consisted of 3534 samples for training (70%) and remaining 1514 samples for testing (30%) of the network. Figure 6 presents the results of modelling obtained using ANN methodology, as the comparison between the values predicted using the network (during

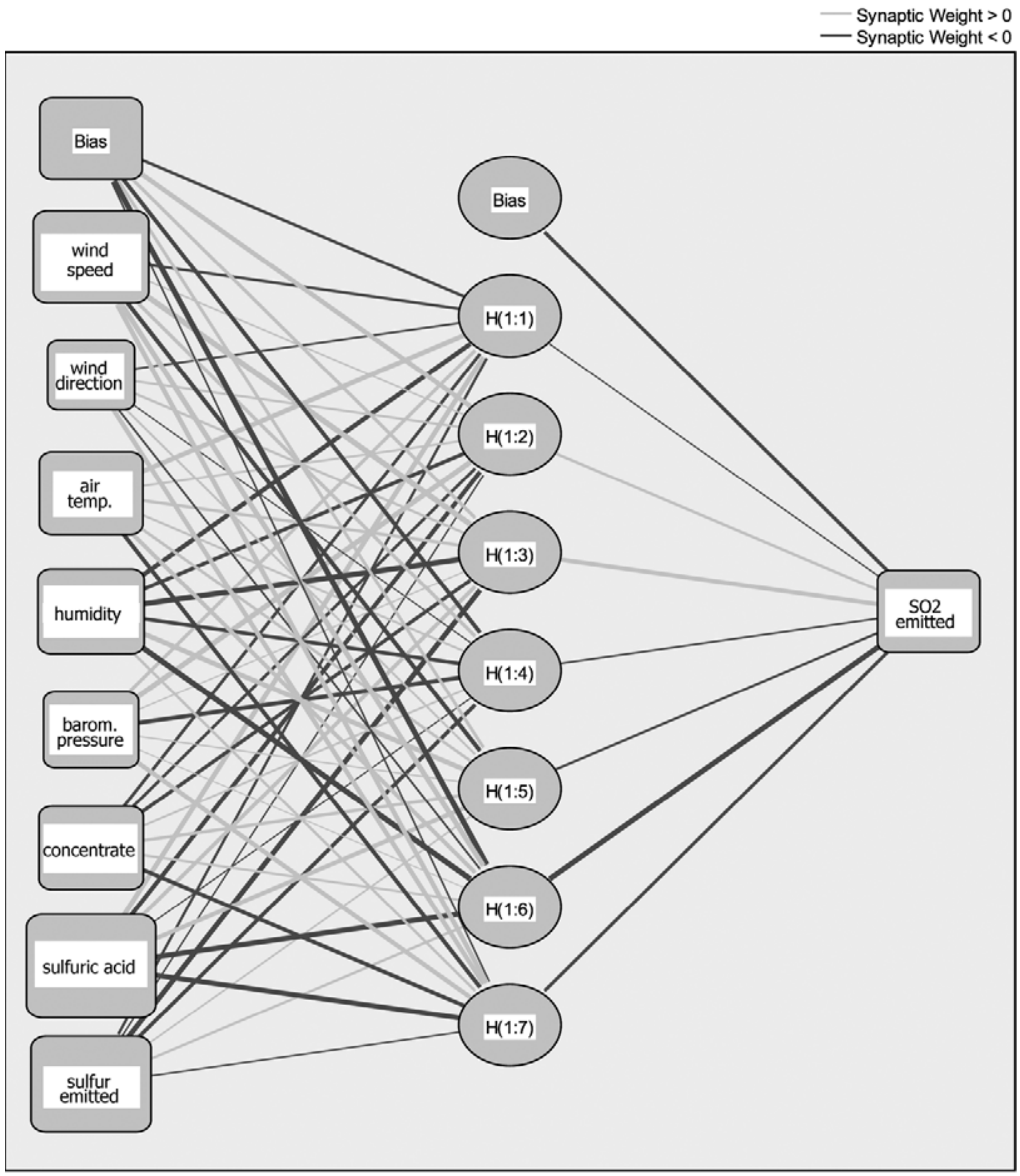

Figure 5. Architecture of the applied neural network

the testing phase) and actually measured values (Kemp et al., 2007). There is obviously large level of fitting obtained (R^2 = 0.999). Figure 7 presents the importance of the individual input parameters on the output of the model. For the model obtained using the above discussed ANN methodology, most influencing input parameter was the amount of produced sulfuric acid, which is logical and expected outcome.

5. CONCLUSIONS

This paper presents the results of the artificial neural network (ANN) application for modelling of the parameters influencing excessive SO_2 emission in the vicinity of copper smelting complex (RTB Bor, Serbia). Considering the fact that this copper smelting complex is positioned in the center of the city, Figure 2, and that this factory still uses the reverberatory furnace as the smelting unit, excessive SO_2 emission is often. For the purpose of continuous measurement of the SO_2 concentration in the ambient air, two measuring stations were installed in the city of Bor. Besides, SO_2 concentration, these stations are continuously measuring the meteorological parameters.

This paper presents the attempt to form mathematical model which will enable prediction of the excessive SO_2 emission with adequate accuracy, based on the recorded meteorological parameters and the technological parameters obtained from the production in investigated copper smelter.

This model, can not be used for improvement of the technological process

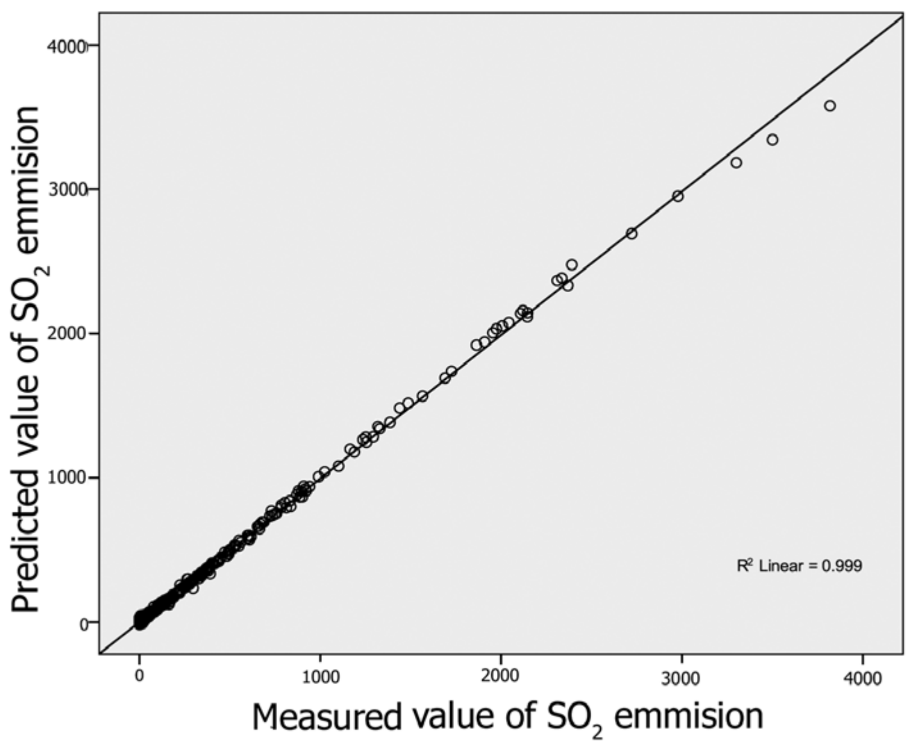

Figure 6. Linear regression of estimated SO_2 *emission versus actual measured emission*

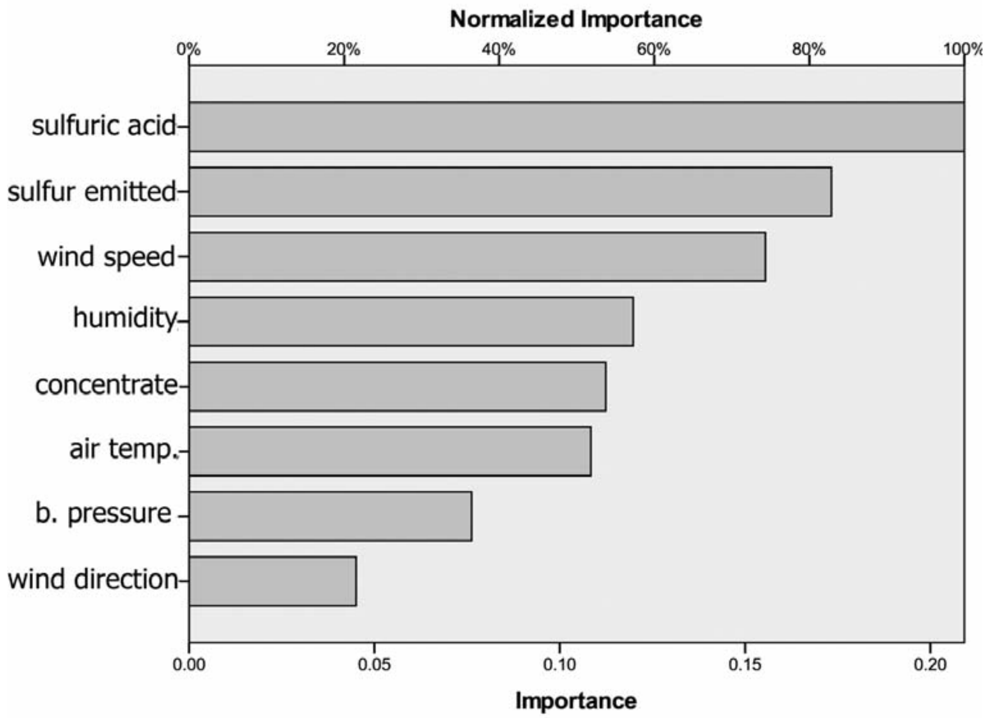

Figure 7. Importance of the individual input parameters influence on output variable of the model

applied in this copper smelting complex, nevertheless, it can be used for indirect protection of the citizens exposure to increased content of the SO2 in air. The essential of this indirect protection can be described as follows. Meteorological parameters such are: wind speed and direction, temperature, air humidity and barometric pressure can be forecasted with adequate precision for limited interval of time in the future. Accordingly mathematical model described in this paper, based on forecasted meteorological parameters and the technological parameters resulting from the production plan of the investigated copper smelting complex can be used for prediction of the potential excessive SO2 emission in the air. This way for these days of the year, when the excessive emission is predicted, correction of the production plan can be performed including decrease of the amount of concentrate to be processed and increase of produced sulfuric acid. These corrections could be performed iteratively until the predicted SO_2 content decreases below the limiting value of 350 $\mu g/m^3$ (WHO, 2001). This way, proper management of the amount of sulfur introduced in the smelting operation with the charge, can facilitate control of the SO_2 emission in the vicinity of investigated copper smelting facility.

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СТАТИСТИЧКО МОДЕЛОВАЊЕ У ЕКОЛОШКОМ МЕНАЏМЕНТУ УПОТРЕБОМ ВЕШТАЧКИХ НЕУРОНСКИХ МРЕЖА

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Извод

Овај рад представља резултате моделовања емисије сумпордиоксид гаса (SO_2), у окружењу топионице бакра, на основу технолошких и метеоролошких параметара. Као део технолошког пројекта са еколошким утицајем, за предвиђање потенцијалне прекомерне емисије SO_2, коришћене су вештачне неуронске мреже, као алат за моделовање. Улазни параметри модела укључују технолошке податке: количину сумпора уведену у пламену пећ са шаржом као и количину сумпора уклоњену из процеса у фабрици сумпорне киселине. Метеоролошки параметри коришћени током моделовања су: брзина и правац ветра, температура ваздуха, влажност и барометарски притисак. Такође, у обзир је узет и утицај годишњег доба као и релативна локација мерне станице и њена удаљеност од топионичких димњака. Добијени резултати показују да вештачке неуронске мреже могу да се успешно користе за предвиђање емисије сумпордиоксида, на основу познатих технолошких и метеоролошких параметара.

Кључне речи: Неуронске мреже, моделовање, предвиђање, технолошки процес

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