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AN ANFIS – BASED AIR QUALITY MODEL FOR PREDICTION OF SO_2 CONCENTRATION IN URBAN AREA

Marija Savić, Ivan Mihajlović*and Živan Živković

University in Belgrade, Technical Faculty in Bor, Vojske Jugoslavije 12, 19210 Bor, Serbia

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Abstract

This paper presents the results of attempt to perform modeling of SO_2 concentration in urban area in vicinity of copper smelter in Bor (Serbia), using ANFIS methodological approach. The aim of obtained model was to develop a prediction tool that will be used to calculate potential SO_2 concentration, above prescribed limitation, based on input parameters. As predictors, both technogenic and meteorological input parameters were considered. Accordingly, the dependence of SO_2 concentration was modeled as the function of wind speed, wind direction, air temperature, humidity and amount sulfur emitted from the pyrometallurgical process of sulfidic copper concentration treatment.

*Keywords:*Mathematical modeling, ANFIS, SO_2 air concentration

1. INTRODUCTION

Sulfur dioxide (SO_2) pollution has long been reported to be associated with many adverse health effects (Herbarth et al., 2001; Brunekreef & Holgate, 2002; Biggeri et al., 2005; WHO, 2006). The control studies have indicated that some respiration problems could appear exposure to increased SO_2 concentrates during period longer than 10 minutes (WHO, 2006). Based on this evidence, it is recommended that a SO_2 concentration of 500 $\mu g/m^3$ should not be exceeded over averaging periods of 10 minutes duration (WHO, 2006). Some evidences of SO_2 harmful effect on human

* *Corresponding author: imihajlovic@tf.bor.ac.rs*

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respiration organs are presented in references (Koren, 1995; Wong et al., 2001; Barnet et al., 2005; Biggeri et al., 2005), this is especially evident with children (Herbnarth et al., 2001). Also, many studies evidenced existence of increased mortality in regions with increased SO_2 concentration in the air (Kan & Chen, 2003; Buringh et al., 2000; Jerrett, 2005).

The European Union (EU) limits the concentration of SO_2 in the air: (1) hourly limit for protection of human health is 350 μgm^{-3} and must not be exceeded more than 24 times in a calendar year; (2) daily limit for protection of human health is 125 μgm^{-3} and must not be exceeded more than three times in a calendar year; (3) annual limit in order to protect ecosystem is 20 μgm^{-3}.

All these measures are the result of high concentrations of SO_2 in many regions of the world which seriously endangers human health and vegetation (WHO, 2006; EU Directive, 2008). In the central region of Chile in the period 1997 – 1999, in the vicinity of copper smelters Caletones, high concentrations of SO_2 were registered. It is thought that there is a possibility of occurrence of acute injuries (in each year), considering that the concentration of SO_2 was in the range of 500 to 50,000 μgm^{-3} (Huidobro-Garcia et al., 2001). In Istanbul, Turkey, SO_2 concentrations were recorded in the range of 50-170 μgm^{-3} (Sahin et al., 2011). In Beijing, during the year 2000, SO_2 concentrations were up to 100 μgm^{-3} (Chak & Yao, 2008). In one of the regions of Spain, in the period 2004 - 2007, SO_2 concentrations ranged up to 100 μgm^{-3} (Santacatalina et al., 2011). In the vicinity of the copper smelter in Bor, Eastern Serbia, in the period 2005-2008, in the urban part of the city, maximum monthly average SO_2 concentrations were recorded in the range of 500-2000 μgm^{-3} (Nikolić et al., 2010). In the period 2000-2008, the episodes occurred with a daily average values in the range of 5000 - 8000 μgm^{-3} in this region (Dimitrijević et al., 2008), when the smelter was stopped after intervention of the state for a few days because of the high toxicity of gas, and then continued to work with the same technical parameters. If the SO_2 > 1000 μgm^{-3} concentrations occur several times a year, it represent a significant risk to human health and vegetation (Garcia-Huidobro et al., 2001). During 2011 and 2012, episodes of SO_2 contrentations up to 10.000 μgm^{-3} were registrated (Djordjević et al., 2013).

In the region of Eastern Serbia, in Bor, within the company RTB Bor, one of the largest copper smelters in Europe operates for over 100 years. In the technology of copper production in this company, since 1975 to date, important improvement at the stage of melting, refining gas and production of H_2SO_4 has not been done. Since 2003, immission of pollutants was monitored at eight measuring points (Nikolić et al., 2010), and after 2010 only at three measuring points, with limited measurement range and transparency of data controlled by the government, and at the two measuring points with the internal character data. In the period 2009-2011, there were episodes of extremely high concentrations of SO_2 with over 9000 μgm^{-3}, with fatal consequences for the bees and agricultural crops. In these cases, the company has paid damages to farmers from the surrounding and penalties for the responsible managers, and then company continued to work with the same technical parameters.

In order to curb the growing harmful effects of air quality, urgent risk assessment and appropriate risk management tools are essential in order to ensure flexible control of high levels of pollution. For this purpose, mathematical models have become essential in the design of business decisions and engineering management of technological processes (Yetilmezsoy et al., 2011). Linear statistical models generally do not produce satisfactory results, which led to the development of nonlinear models of artificial neural networks ANNs (Yilmaz & Kaynar, 2011), and more recently several adaptive neuro-fuzzy techniques - Adaptive Neural-Fuzzy Inference System (ANFIS) are developed, which have been applied successfully to control air pollution (Morabito & Versaci, 2003; Yildrim & Bayramogly, 2006; Ashish & Rashami, 2011). In order to combine the advantages of fuzzy logic methodology and architecture of the neural network, Jang (1993) has proposed a brand new hybrid, adaptive neuro-fuzzy inference system (ANFIS). ANFIS has the advantages of neural networks and fuzzy logic, where the ANN has a better ability to learn, parallel processing, adaptation, fault tolerance, while the strategy of fuzzy logic can deal with higher-level reasoning (Lei & Wan, 2012).

The main objective of this study is to define the appropriate mathematical model for predicting the SO_2 content (imission) at the measuring stations around the copper smelter in Bor, which currently emits the greatest amount of sulfur in the SO_2 in the urban environment smelter. Defined model should allow defining the content of SO_2 in urban areas, with acceptable statistical significance, from the amount of concentrate processed and meteorological parameters, which should enable better management of SO_2 immission in the urban environment around the copper smelter.

1.1. Study area and measuring points

The study area is located in southeastern Serbia, Figure l. City of Bor has about 40,000 inhabitants and is situated at a distance of 30 km from the border with Bulgaria, and about 100 km with Romania. The rivers in this region belong to the basin of the Danube River. The whole region has about 200,000 inhabitants. Near to the Romanian border is a national park Djerdap, representative tourist center of the region.

Locations of measuring stations shown in Figure 1, are representing the system of monitoring of emissions in the city of Bor. Distances between the measuring stations and furnace chimney - the source of pollutant emissions is as follows: measuring station 1 - Jugopetrol, in the south - southeast, is about 2.990 m from the emission source; measuring station 2 – Faculty, in the north - northwest, away from the furnace chimney about 880 m; measuring station 3 - City Park, in the west, from the copper smelter at a distance of about 480 m from the furnace chimney, in the center of the urban part of the city (local government, primary school, hospital, town market, the main shopping areas, promenade); measuring station 4 - Instituit, in the south - southwest of the smelter, in the new town center at a distance of about 2,600 m from the furnace chimney, where there are nearly half of the city's population; measuring station 5 - Brezonik, in the north, at a distance of 2.000 m from furnace chimney on the border of the urban part of the city; and measuring station 6 - Krivelj, located 7,000 m from the furnace chimney in a rural part of the city.

Measuring the concentration of SO_2 at these measuring stations are performed in accordance with standard EN 14212 ISO 10498 : 2004. Accuracy of measuring instruments is at the level of 0.4 μgm^{-3}.

Registered parameters in real time are publicly available on the website of the State Agency for Environmental Protection (http://www.sepa.gov.rs), for measuring stations (3), (4), (5) and (6), and the data from the measuring stations (1) and (2), which are registered by the Institute of Mining and Metallurgy in Bor, are available to local government and RTB company.

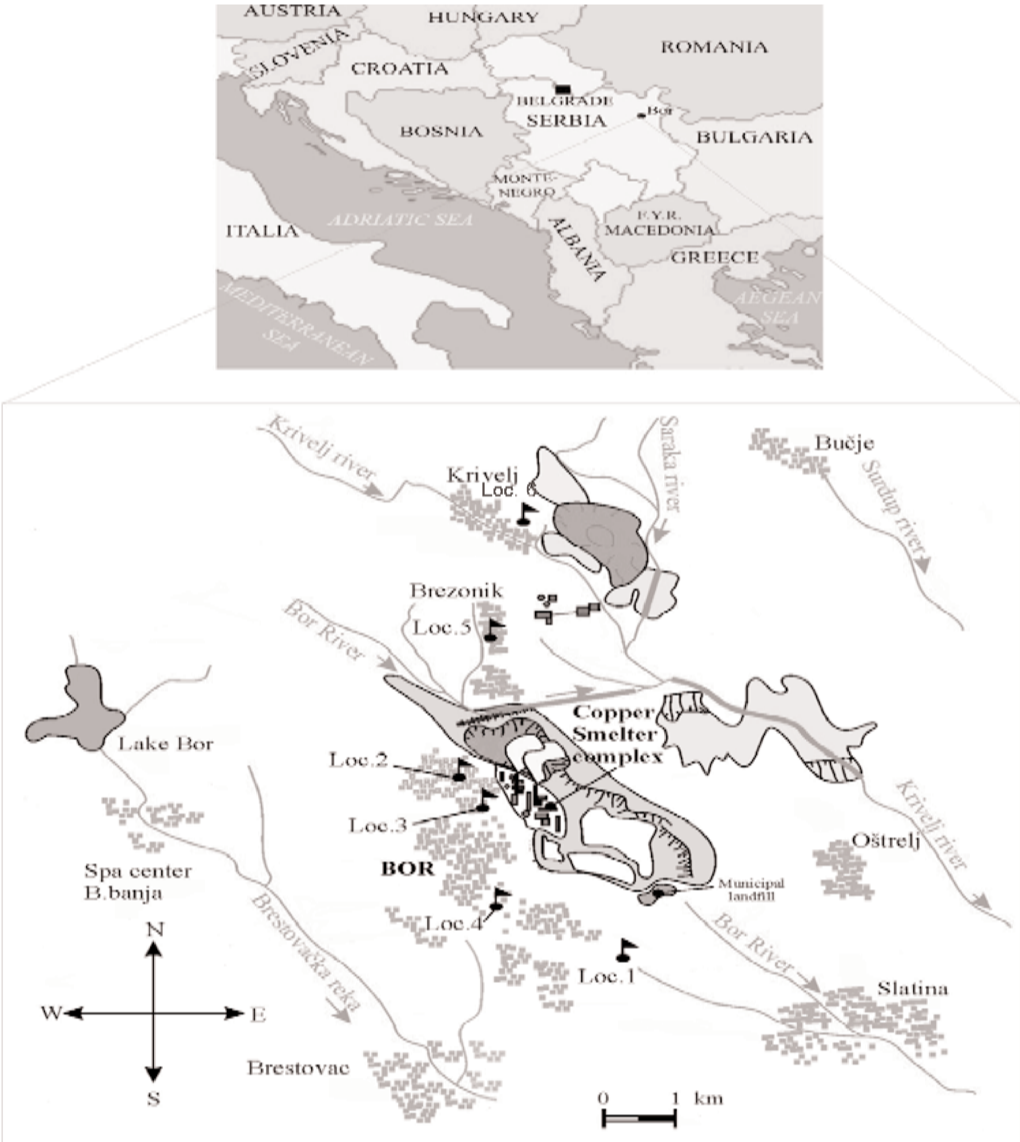

Figure 1. Location of measuring stations in the study area

2. EXPERIMENTAL

In recent years, artificial intelligence (AI) based methods have been proposed as alternatives to traditional linear statistical ones in many scientific disciplines. The literature demonstrates that AI models such as ANN and neuro-fuzzy techniques are successfully used for air pollution modeling (Nunnari et al., 2004; Perez-Roa et al., 2006) and forecasting (Perez et al., 2000; Gautam et al., 2008; Mihajlović et al., 2011).

If observing the measurement series for variables presented in Table 1, it can be concluded that almost all have wide range of relative change (ratio of variance compared to range). This way nonlinear statistic analysis method, based on only one rule describing the behaviour of input variable, such are ANNs, most certainly wouldn't present accurate enough results. From that reason, further modeling approach was based on Adaptive-Network-Based Fuzzy Inference System (ANFIS).

The ANFIS system serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulate input-output pairs. The ANFIS structure is obtained by embedding the fuzzy interference system into the framework of adaptive networks (Jang, 1993). An adaptive network is a network structure consisting of a number of nodes connected through directional links. The outputs of these adaptive nodes depend on modifiable parameters pertaining to these nodes (Guneri et al., 2011). The learning rule specifies how these parameters should be varied through iterations to minimize the final error. On the other hand, according to Takagi and Sugeno (1985) the fuzzy inference system (FIS) is a framework based on fuzzy set theory and fuzzy if-then rules. Three main components of a FIS structure are: a rule base, a database, and a reasoning mechanism. The rule base has adequate number of if-then rules for levels of ranges of input variables. For example, one rule might be "if wind speed is low, than registered SO_2 concentration in the air is high", where low and high are linguistic variables. The database defines the membership functions applied in fuzzy rules and the reasoning mechanism performs the inference procedure (Jang et al., 1997).

This way, for example that there are two input variables (X1 and X2), and assuming that their ranges can be divided in two levels, there would be the rule base with two rules for modeling the value of output variable Y:

Rule 1: If X_1 is in the range A_1 and X_2 is in the range B_1, then $f_1 = p_1x_1 + q_1x_2 + r_1$

Rule 2: If X_1 is in the range A_2 and X_2 is in the range B_2, then $f_2 = p_2x_1 + q_2x_2 + r_2$

In the case $f(x_1, x_2)$ is a first-order polynomial, then the model is called a first-order Sugeno fuzzy model.

The graphical presentation of general ANFIS network is presented in Figure 2. As can be seen in Figure 2, ANFIS architecture can be presented with five layers. Where X_1 and X_2 are inputs to nodes in layer 1, Ai and Bi are the linguistic label of the ranges of input variables (small, large, etc), associated with the node function. Membership functions of nodes located in layer 1 ($O_i^1 = \mu A_i(X_i)$ or $O_i^2 = \mu Bi(Xi)$) specifies the degree to which the given X_i satisfies the quantifier A_i, B_i, etc. Usually, membership functions are either bell-shaped with maximum equal to 1 and minimum equal to 0, or Gaussian function.

Nodes located in the layer 2 are multipliers, which are multiplying the signals exiting the layer 1 nodes. For example $O_i^2 = W_i = \mu A_i(X_i) \times \mu B_i(X_i)$, i = 1, 2, etc. Output of each node is representing the firing strength of a rule. The i-th node of layer 3 calculates the ratio of i-th rules firing strength to sum of all rules firing strengths.

This way $O_i^3 = \overline{W}_i = W_i /(W_1 + W_2 + \ldots)$, i = 1, 2, … Every node i in the layer 4 has a node function of following type: $O_i^4 = \overline{W}_i \cdot f_1 = \overline{W}_i \cdot (p_i x_1 + q_i x_2 + r_i)$, where p_i, q_i and r_i will be referred to as consequent parameters. The single node of layer 5 is the node that computes the overall output as the summation of all incoming signals i.e., $O_i^5 =$

$$\sum_i \overline{W_i f_i} = \frac{\sum_i W_i f_i}{\sum_i W_i}$$

Training of the parameters in the ANFIS structure is accommodated according to the hybrid learning rule algorithm which is the integration of the gradient descent method and the least square methods. In the forward pass of the algorithm, functional signals go forward until layer 4 and the consequent parameters are identified by the least squares method to minimize the measured error. In the back propagation pass, the premise parameters are updated by the gradient descent method (Jang et al., 1997).

3. RESULTS AND DISCUSSION

The main motive for investigations presented in this article was to draw conclusions about the possibilities of predicting the SO_2 concentration in the ambient air, under different environmental conditions and based on the influence of sulphur entering the process with the charge. This way, for modeling the dependence of SO_2 concentration, on different predictors, the data obtained from the automated measuring stations were used in combination with the data obtained from the smelting process. The data were collected during the year 2011, in the period of two months (October and November). Measurement of the four input parameters: wind speed (X_1); wind direction (X_2); air temperature (X_3); relative humidity (X_4) and the one output (Y) parameter – SO_2 concentration in the air, was facilitated using three of above described measuring stations (4, 5 and 6, in Figure 1), with data acquisition in the data base on one hour intervals. The data was collected from three different stations to assess the influence of the wind direction and the distance from the source of emission. The last input parameter (X_5) – amount of sulphur emitted through the chimneys of the smelter plant (Figure 1) was calculated according to the amounts of sulphur entering the process with the concentrate and its utilization in the sulphuric acid production facility. Those values were obtained from the smelter plant. Before the model building phase, all the data points were examined for potential outliers. The measurement intervals, during which some of investigated input parameters were not recorded, from some reasons, were eliminated. After this, 1,800 data sets remained for further analysis.

The values of the measured input parameters (X_i) and the air quality indicator, investigated in this work – output of the

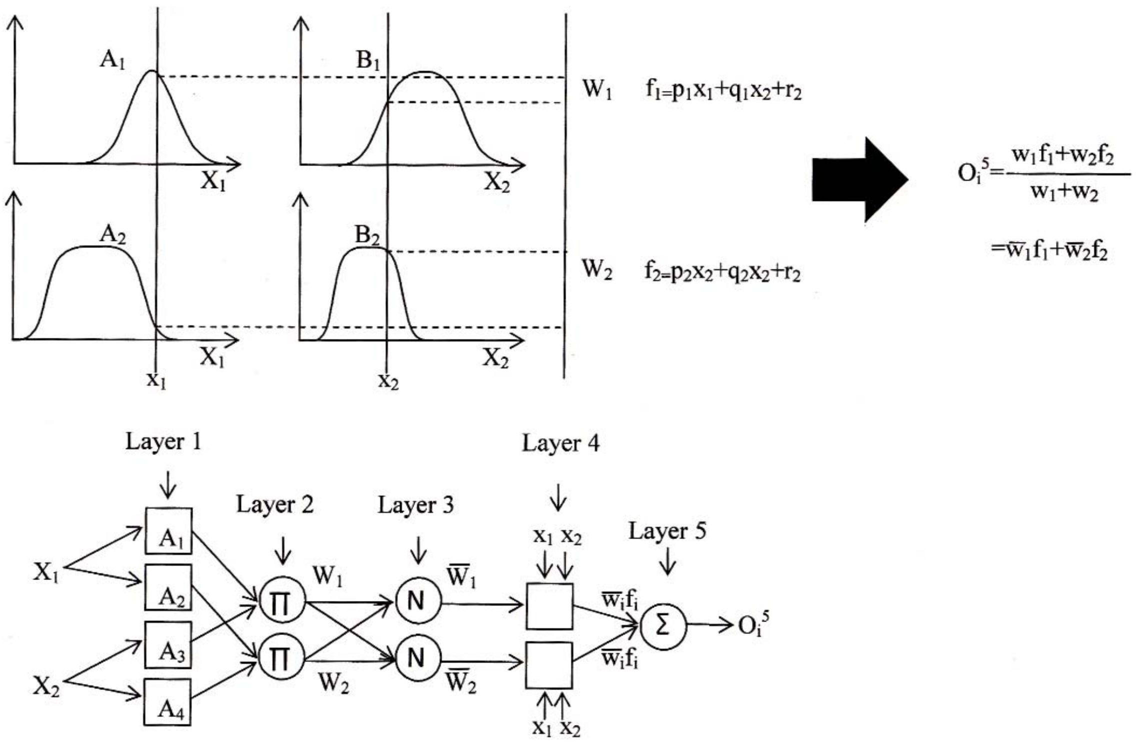

Figure 2. Graphical presentation of ANFIS

process (Y) in the form of descriptive statistics results – are presented in Table 1.

According to the results presented in Table 1, potential risk of the SO_2 pollution in the air is obvious in this region, considering that measured hourly SO_2 concentration is in

Table 1. Values of the Input (X_i) and the Output (Y) Variables of the Model – Descriptive Statistics of 1,800 Data Sets

							Mean			
Io.	**Measured Parameter**	**Unit**	**Model Symbol**	**Range**	**Min**	**Max**	**Statistic**	**Std. Error**	**Std. Deviation**	**Var.**
1.	**Wind speed**	**m/s**	**X_1**	8.6	0	8.6	1.5534	.03174	1.326	1.812
2.	**Wind direction**	**^{O}**	**X_2**	359	0	359	168.9929	2.66976	113.23697	12822.611
3.	**Air temperature**	**^OC**	**X_3**	28.30	-2.30	26.00	11.5628	.11191	4.74520	22.517
4.	**Relative humidity**	**%**	**X_4**	83.30	16.70	100.0	74.7916	.47789	20.26934	410.846
5.	**S emitted from the process**	**t**	**X_5**	149.14	3.36	152.50	59.8323	.83209	35.29299	1245.595
6.	**SO_2 in the air**	**μg/m^3**	**Y**	4624.00	0	4624.00	119.2257	8.49300	360.12739	129691.741

the range up to 4624.7 $\mu g/m^3$, which is above prescribed maximal values.

Defining the linear correlation dependence between the output and the input parameters, with significant value of coefficient of correlation (R^2), provides the possibility of predicting potential excess of SO_2 concentration in the air, in the investigated area, using linear statistical analysis methods such is multiple linear regression analysis (MLRA). MLRA is one of the most widely used methodologies for expressing the dependence of a response variable on several independent variables (Al-Alawi et al., 2008). For defining the linear correlation dependence in the form: output of the model (Y) = f input of the model (X_1 – X_5), a bivariate correlation analysis was performed. As the result of this analysis, Pearson correlation (PC) coefficients with responding statistical significance were calculated (Table 2).

According to values presented in Table 2, it could be concluded that there isn't high linear dependence between SO_2 concentration in the air (Y) and input variables, although statistical significance is recorded for most of correlated pairs. According to these values, it was decided that using MLRA for obtaining the dependence between SO_2 concentration and investigated predictors, wouldn't result with high accuracy.

On the other hand, if the value of correlation between two variables is not high, this doesn't automatically mean that behaviour of one variable do not influence the behaviour of other. This is indicator that their inter correlation cannot be described with linear model, however modeling based on dynamic behaviour of the variables can be used to present their inter dependences (Đorđevic et al., 2010). In such cases, modeling could be facilitated using nonlinear statistic approach such are Artificial Neural Networks (ANNs) - in case that input variables do not have vide range during whole time interval of observation (Abdul-Wahab & Al-Alawi, 2002; Ozdemir et al, 2008; Al-Alawi et al., 2008), or Adaptive-Network-Based Fuzzy Inference System for variables with vide range of change (Noori et al., 2010; Johanyak & Kovacs, 2011).

According to the number of input variables, their ranges and the variations, presented in Table 1, it was decided that two rules ANFIS network should be applied. Selected membership function was Gaussian one. Number of input variables was five (X_1 to X_5), with one output variable (Y).

To apply the ANFIS methodology the assembly of 1,800 input and output samples was divided into two groups. The first group consisted of 1,292 (≈70 %) at random selected samples, and it was used for training of the model, whereas the second group consisted of 508 (≈30 %) remaining samples from the starting data set, and it was used for testing the model. The selection of the variables for these two stages was performed by using random number generator. In the gathering data process for the training and the testing stage, the values for each input variable are normalized by the maximum values. This was done because of different nature and measuring units of input variables.

During the training phase the correction of the weighted parameters (p_i, q_i, r_i, etc) of the connections is achieved through the necessary number of iterations, until the mean squared error between the calculated and measured outputs of the ANFIS network,

Table 2. Correlation Matrix for the Input ($X_1 - X_5$) and the Output (Y) Variables of the Investigated occurrence (Number of Data Points for Each Variable is Equal to 1,800)

	X_1 wind speed	X_2 wind direction	X_3 temperature	X_4 relative humidity	X_5 S emitted from the process	Y SO_2 in the air
X_1	1					
X_2	.339**	1				
X_3	.210**	-.008	1			
X_4	-.345**	-.088**	-.546**	1		
X_5	-.003	.027	.229**	-.088**	1	
Y	-.107**	-.115**	.106**	-.090**	-.005	1

**. Correlation is significant at the 0.01 level (2-tailed).

is minimal. During the second phase, the remaining 30% of the data is used for testing the ”trained” network. In this phase, the network uses the weighted parameters determined during the first phase. These new data, excluded during the network training stage, are now incorporated as the new input values (X_i) which are then transformed into the new outputs (Y). For calculation presented in this paper MATLAB ANFIS editor was used (MathWorks, R2012b).

In the phase of the network training, the necessary number of iterations was performed until the error between the measured output of the SO_2 concentration in the air - Y and the calculated values wasn't minimized and remained constant. In the case of the investigation presented in this paper, optimal number of iterations (epochs) was 10. The obtained results from the training stage can be evaluated by comparison of the calculated values Y with the measured ones (Figure 3). The dependance of the output value (Y) on different predictors is presented in Figure 4.

The ANFIS modeling approach, in the training stage, predicted the SO_2 concentration in the air with a determination coefficient R^2 = 0.526 (Figure 3), which doesn't represent very large significance. The reason for such behaviour of the model is in large dispersion of the starting sample, ranging with SO_2 values from 0 to 4,624.

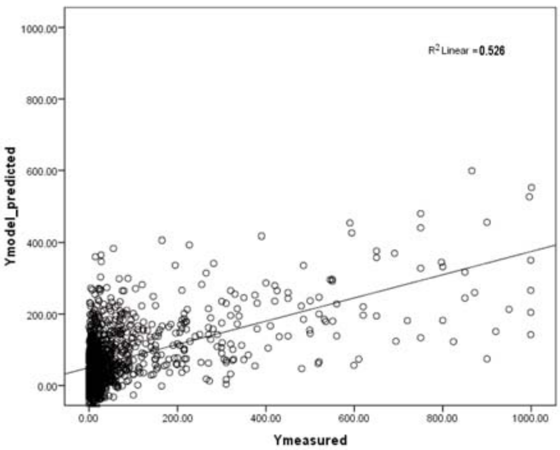

Figure 3. Coefficient of determination between measured and model predicted SO_2 concentration in the training stage

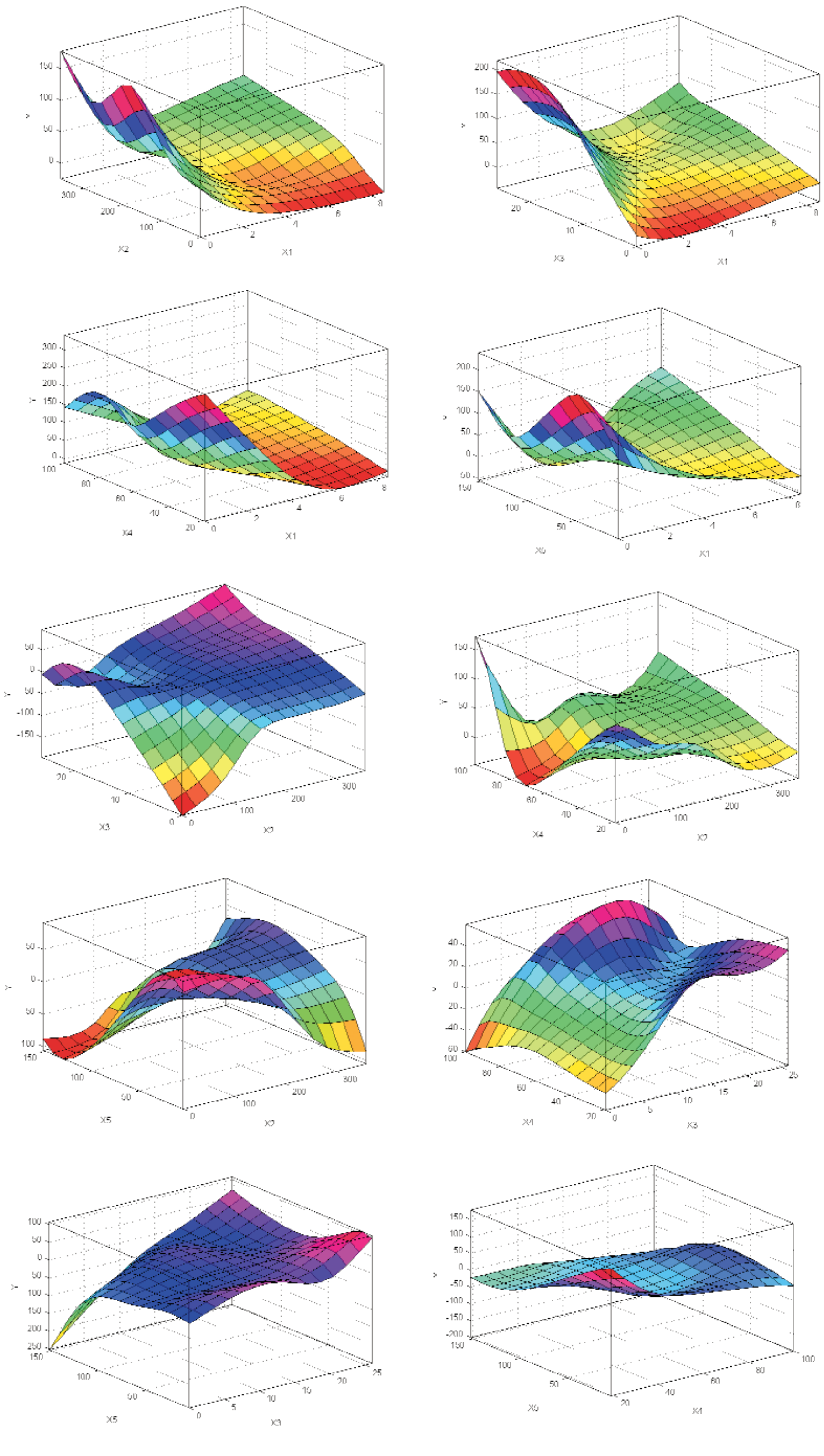

Figure 4. Surface diagrams presenting dependence of SO_2 concentration on input parameters

However, the ANFIS model is largely more accurate than plain ANNs and MLRA approach, which resulted with R^2 below 0.2. Accordingly, using the model described in this paper, SO_2 concentration in the air can be predicted as the function of investigated input variables, with the accuracy above 50%.

Another merit of obtained model is in possibility to assess the influence of single or coupled input variables on values of output variable. Such dependence of SO_2 concentration on different combinations of input variables is presented in Figure 4.

According to results presented in Figure 4, the interrelation of different predictors is obvious. The predictor can influence the output variable in completely different way when paired with one, compared to pairing with another. For example Y is in direct dependence on X_1 (Wind speed) if paired with X_2 (Wind direction). On the other hand, Y becomes indirectly dependant on X_1, when paired with X_3 (Air temperature).

4. CONCLUSION

This paper presents the beginning of investigation of applicability of nonlinear statistical modeling on modeling the SO_2 content in the air dependence on different predictors. It was presented that such approach can be used in general, based on ANFIS method. On the other hand, the model fitting that was obtained was not that high. The reason is in the fact, that the data for only two months were used for analysis. In our future work, the procedure will be repeated with data aquatinted in longer time intervals (a year or more). Also, results of bivariate influence of predictors on output variable will be further studied in subsequent work.

МОДЕЛ ПРЕДВИЂАЊА КВАЛИТЕТА ВАЗДУХА У УРБАНОЈ СРЕДИНИ ЗАСНОВАН НА ПРАЋЕЊУ КОНЦЕНТРАЦИЈЕ SO_2

Марија Савић, Иван Михајловић и Живан Живковић

Извод

Овај рад представља резултате моделовања концентрације сумпордиоксица у урбаној средини, у окружењу топионице бакра у Бору (Србија). Модел се заснива на “ANFIS” методолошком приступу. Циљ самог моделовања је да се развије алат за предвиђање који ће моћи да израчуна потенцијалну концентрацију SO_2 изнад прописаних граничних вредности, засновано на улазним параметрима. Као предиктори, разматрани су како технолошки тако и метеоролошки улази модела. На тај начин, зависност концентрације SO_2 је моделована у функцији брзине ветра, правца ветра, температуре ваздуха, влажности и количине емитованог сумпора током пирометалуршког процеса третмана сулфидних концентрата бакра.

Кључне речи: Математичко моделовање, ANFIS, концентрација SO_2 у ваздуху

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References

Abdul-Wahab, S.A., Al-Alawi, S.M. (2002). Assessment and prediction of tropospheric ozone concentration levels using artificial neural networks. Environmental Modelling & Software, 17, 219-228.

Al-Alawi, S.M., Abdul-Wahab, S.A., Bakheit, C.S. (2008). Combining principal component regression and artificial neural networks for more accurate predictions of ground-level ozone. Environmental Modelling & Software, 23, 396-403.

Ashish, M., Rashmi, B. (2011). Prediction of daily air pollution using wavelet decomposition and adaptive-network-based fuzzy inference system. International Journal of Environmental Sciences, 2 (1), 185-196.

Barnet, A.G., Williams, G.M., Schwartz, J., Neller, A.H., Best, T.L., Petroeschevsky, A.L., Simpson, R.W. (2005). Air pollution and child respiratory health: a case-crossover study in Australia and New Zealand. Amer. Respir. Crit. Care. Med., 171, 1272- 1278.

Biggeri, A., Bellini, P., Terracini, B. (2005). Meta-analysis of the Italian studies of short-term effects of air pollution (MISA). International Journal of Occupational and Environmental Health, 11, 107-122.

Brunekreef, B., & Holgate, S.T. (2002). Air pollution and health. Lancet, 360, 1233-1242.

Buringh, E., Fischer, P., Hoek, G. (2000). Is SO_2 a causative factor for the PM-associated mortality risks in the Netherlands?. Inhalation Toxicology, 12, 55-60.

Chak, K.C., Yao, X. (2008). Air pollution in mega cities in China. Atmospheric Environment, 42, 1-42.

Dimitrijević, A., Michalewski, H.J., Zeng, F.G., Pratt, H., Starr, A. (2008). Frequency Changes in a Continuous Tone: Auditory Cortical Potentials. Clinical Neurophysiology, 119, 2111-2124.

Đorđević, P., Mihajlović, I., Živković, Ž. (2010). Comparison of linear and nonlinear statistics methods applied in industrial process modeling procedure. Serbian Journal of Management, 5 (2), 189-198.

Djordjevic, P., Mitevska, N., Mihajlović, I., Nikolić, D., Živković, Ž. (2013). Effect of the slag basicity on the coefficient of distribution between copper matte and the slag for certain metals. Mineral Processing and Extractive Metallurgy Review, Taylor & Francis, (In press).

EU Directive (2008). Directive 2008/104/EC of the European Parliament and of the Council. Official Journal of the European Union.

Garcia-Huidobro, T., Marshall, F.M., Bell, J.N.B. (2001). A risk assessment of potential agricultural losses due to ambient SO_2 in the central regions of Chile. Atmospheric Environment, 35, 4903-4915.

Gautam, A.K., Chelani, A.B., Jain, V.K., Devotta, S. (2008). A new scheme to predict chaotic time series of air pollutant concentrations using artificial neural network and nearest neighbor searching. Atmospheric Environment, 42, 4409-4417.

Guneri, A.F., Ertay, T., Yucel, A. (2011). An approach based on ANFIS input selection and modeling for supplier selection problem. Expert Systems with Applications, 38, 14907-14917.

Herbarth, O., Fritz, G., Krumbiegel, P., Diez, U., Franck, U., Richter, M. (2001). Effect of sulfur dioxide and particulate pollutions on bronchitis in children – a risk analysis. Environmental Toxicoilogy, 16, 269-276.

Jang, J.S.R. (1993). ANFIS: Adaptive-network-based fuzzy inference system, IEEE Transactions on Systems, Man, and Cybernetics, 23 (03), 665-658.

Jang, M., Cai, L., Udeani, G., Slowing, K., Thomas, K., Beecher, C., Fong, H., Farnsworth, N., Kinghorn, A.D., Mehta, R., Moon, R., Pezzuto, J. (1997). Cancer Chemopreventive Activity of Resveratrol, a Natural Product Derived from Grapes. Science Magazine, 275, 218-220.

Jerrett, M., Burnett, R.T., Ma, R., Pope, C.A. 3rd, Krewski, D., Newbold, K.B., Thurston, G., Shi, Y., Finkelstein, N., Calle, E.E., Thun, M.J. (2005). Spatial analysis of air pollution and mortality in Los Angeles. Epidemiology, 16, 727- 736.

Johanyak, Z.C., Kovacs, J. (2011). Fuzzy model based prediction of ground-level ozone concentration. Acta Technica Jaurinensis, 4 (1), 113-124.

Kan, H., & Chen, B. (2003). Air pollution and daily mortality in Shanghai: a time-series study. Archives of Environmental Health, 58, 360-367.

Koren, H.S. (1995). Associations between criteria air pollution and asthma. Environmental Health Perspectives, 103, 235-242.

Lei, K.S., Wan, F. (2012). Applying ensemble learning techniques to ANFIS for air pollution index prediction in Macau. Advances in Neural Networks, 7367, 509-516.

Morabito, F.C., Versaci, M. (2003). Fuzzy neural identification and forecasting techniques to process experimental urban air pollution data. Neural Networks, 16, 493-506.

Nikolić, Đ., Milošević, N., Mihajlović, I., Živković, Ž., Tasić, V., Kovačević, R., Petrović, N. (2010). Multi-criteria analysis of air pollution with SO_2 and PM_{10} in urban area around the copper smelter in Bor, Serbia. Water Air Soil Pollution, 206, 369-383.

Noori, R., Hoshyaripour, G., Ashrafi, K., Araabi, B.N. (2010). Uncertainty analysis of developed ANN and ANFIS models in prediction of carbon monoxide daily concentration. Atmospheric Environment, 44, 476-482.

Nunnari, G., Dorling, S., Schlink, U., Cawley, G., Foxall, R., Chatterton, T. (2004). Modelling SO_2 concentration at a point with statistical approaches. Environmental Modelling & Software, 19, 887-905.

Ozdemir H., Demir, G., Altay, G., Albayrak, S., and Bayat, C. (2008). Prediction of Tropospheric Ozone Concentration by Employing Artificial Neural Networks. Environmental Engineering Science, 25 (9), 1249-1254.

Perez, P., Trier, A., Reyes, J. (2000). Prediction of $PM_{2.5}$ concentrations several hours in advance using neural networks in Santiago, Chile. Atmospheric Environment, 34, 1189-1196.

Perez-Roa, R., Castro, J., Jorquera, H., Perez-Correa, J.R., Vesovic, V. (2006). Air-pollution modelling in an urban area: Correlating turbulent diffusion coefficients by means of an artificial neural network approach. Atmospheric Environment, 40, 109-125.

Sahin, E., Colla,S., Liesa, M., Moslehi, J., Müller, F.L., Guo, M., Cooper, M., Kotton, D., Fabian, A.J., Walkey, C., Maser, R.S., Tonon, G., Foerster, F., Xiong, R., Wang, Y.A., Shukla, S.A., Jaskelioff, M., Martin, E.S., Heffernan, T.P., Protopopov, A., Ivanova, E., Mahoney, J.E., Kost-Alimova, M., Perry, S.R., Bronson, R., Liao, R., Mulligan, R., Shirihai, O.S., Chin, L., DePinho, R.A. (2011). Telomere dysfunction induces metabolic and mitochondrial compromise. Nature, 470 (7334), 359-365.

Santacatalina , M., Carratala, A., Mantilla, E. (2011). Influence of local and regional Mediterranean meteorology on SO_2 ground-level concentration in SE Spain. Journal of Environmental Monitoring, 13, 1634-1645.

Takagi, T., Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. IEEE Trans., Systems, Man and Cybernetics, 15 (1), 116-132.

WHO (2006). Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide. Summary of risk assessment, Global Update 2005.

Wong, G.W., Ko, F.W., Lau, T.S., Li, S.T., Hui, D., Pang, S.W., Leung, R., Fok, T.F., Lai, C.K. (2001). Temporal relationship between air pollution and hospital admissions for asthmatic children in Hong Kong. Clinical and Experimental Allergy, 31, 565-569.

Web reference: www.sepa.srbija

Yetilmezsoy, K., Ozkaya, B., Cakmakci, M. (2011). Artificial intelligence-based prediction models for environmental engineering. Neural Network World, 3 (11), 193-218.

Yildirim, Y., Bayramoglu, M., (2006). Adaptive neuro-fuzzy based modelling for prediction of air pollution daily levels in city of Zonguldak. Chemosphere, 63, 1575-1582.

Yilmaz, I., Kaynar, O. (2011). Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. Expert Systems with Applications, 38, 5958-5966.