INTELIGENTNI SISTEM ZA PROCENU ZAGAĐENJA VAZDUHA OD SAOBRAĆAJA

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Apstrakt: Tema ovog rada je da se na efikasan način utvrdi emisija zagađenja od saobraćaja u gradu Nišu. Poznato je da je saobraćaj pojedinačno najveći zagađivač. Stoga je potreban njegov odgovarajući tretman kao izvora za tačno određivanje nivoa zagađenja. Na kritičnim lokacijama u gradu su izvršena merenja koncentracije CO_2, frekvence saobraćaja, kao i praćenje smera i pravca kretanja vozila. Ovi eksperimentalni podataci su korišćeni za treniranje hibridnog estimator za procenu nivoa zagađenja. Razvijeni inteligentni sistem je fazi-model optimalno podešen pomoću neuronskih mreža, poznatih kao ANFIS. Testni podaci za neke karakteristične slučajeve prikazani na kraju rada pokazuju dobro slaganje rezultata ANFIS estimatoroa sa eksperimentalnim podacima. Prikazani rezultati su dobar pokazatelj upotrebljivosti ove metode.

Ključne reči: *Emisija CO_2, Fazi- modeliranje, Neuronske mreže, Saobraćaj, Zagađenje vazduha,*

INTELIGENT SYSTEM FOR TRAFFIC INDUCED AIR POLLUTION ESTIMATION

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Abstract: The subject of this paper is to effectively estimate traffic induced pollution emission in the city of Niš. It is well known that the traffic is the single largest pollutant. Therefore, proper treatment of this component of pollution is very important for precise estimation of pollution levels. Measurements of traffic frequency, vehicle direction, CO_2 concentration, were carried out at several critical locations in the city. This experimental data were used as training data for hybrid soft computing estimator of pollution levels is developed. Developed inteligent system estimator is fuzzy model optimally adjusted by artificial neural network, commonly known as ANFIS. Test data for some characteristic cases presented at the end of the paper shows good agreement of ANFIS estimator output with experimental data. Presented results are true indicator of implemented method usability.

Keywords:, *Air polution, CO_2 emission, fuzzy modelling, neural networks, Traffic*

1. INTRODUCTION

The pollutant concentrations in urban areas produced by traffic emissions depend on vehicle characteristics, traffic and weather conditions, and the geographic and built environment characteristics of the local site. Impact of pollutants, as a consequence of a traffic activity (CO, NO_X, CO_2, SO_X, VOC) has been very well documented [1,2]. Recently, since recognizing the problem of global warming, caused by GHG emissions, more attention has been focused on CO_2 emissions. Traffic is representing one of the greatest emitters of pollutants, as well as of carbon dioxide. As it has been estimated, in the overall balance of CO_2 in the City of Niš, traffic participate with 87699.38t per year, or 38.09% from overall anthropogenic emission in the City, followed by individual house hold heating, and district heating emissions, which are presented in tab.1. [3]. The dependence of CO_2 concentration and traffic, in the case of stabile atmosphere has been very documented by [4,5].

Other very important parameters in pollution modeling are wind and atmospheric stability. Wind direction, velocity and amount of turbulence in the ambient atmosphere has a major effect on the dispersion of air pollution plumes. A study done by Kh. Ashrafi and Gh. A. hoshyariopur [6] shows a relation of atmosphere conditions and CO concentration in the City of Teheran. For this reason, wind and his influence on the pollution were carefully studied [5]. Three measuring locations were established in the City. On this measuring sites, wind parameters, temperature, humidity and CO_2 concentration were continuously monitored during 3 year period.

In this paper, artificial neural networks were used for determination of CO_2 concentration at measuring site. The neural networks method was chosen because of his ability to approximate highly nonlinear functions with limited information about the nature of these relationships. This is very suitable, because of stochastic nature of traffic, wind and weather data. In this study, the feed forward neural network was used. As input data traffic intensity in the city, wind speed, wind direction, temperature and atmospheric stability were used, while CO_2 concentration represented an output.

Table 1. CO_2 sources and their share in the City of Niš according to [3]

	Power [TJ]	IPCC emission factor [kgCO_2/TJ]	Emission CO_2 [t]	Emission share
Heating – city heating plant	1284,96	56100	72086.26	31.30%
Ind. heating - wood	315,44	112000	35329.28	15.34%
Ind. heating – brawn coal	249,48	97500	24324.30	10.56%
Ind. heating –lignite	107,25	101000	10832.25	4.70%
Traffic			87699.38	38.09%
Total			230271.47	100.00%

To the contrary to the conventional modelling and estimation approach of traffic induced air pollution, alternative computational intelligence strategy is proposed. Computationally intelligent estimator developed in this paper is based on the hybrid soft computing modelling approach [7].

Estimative model is realised through the implementation of fuzzy systems using artificial neural networks (ANN), which provides for trainable neuro-fuzzy structure. The learning methods of ANNs enable neuro-fuzzy systems to learn from data sets and due to the massive parallelism of the ANNs efficient real-time processing.

2. LITERATURE REVIEW

Artificial neural networks represent an efficient tool in pollution estimation. In the study of Junsub and Prybutok [8], ANN were used to estimate daily maximum ozone concentration in an industrialized urban area. In the research conducted by Tudoroiu *et al.* [9], neural networks have been used to estimate air quality among Romanian coast with regards to identified sources. Kurtulus *et al.* have used ANN to estimate methane emissions at Istanbul landfill site. Many studies have sought to predict pollutant concentrations by traffic and weather data. Among these, Moseholm *et al.* [10] studied the usefulness of neural network to understand the relationships between traffic parameters and CO concentrations measured near an intersection. Dorzdowicz *et al.* [11] developed a dispersion model based on neural network to estimate hourly mean concentrations of CO in the urban area of Rosario City. Gardner and Dorling [12] developed a multilayer perception neural network model to estimate hourly NO_x and NO_2 concentrations by meteorological conditions data of Central London showing that the neural network outperforms the ordinary least squared model developed by Shi and Harrison [13] using the same study site. Similar work was done in Santiago, Chile [14], and in Perugia, Italy [15]. Furthermore, Grivas and Chaloulakou [16] used the neural networks to predict PM10 hourly concentrations in the metropolitan area of Athens comparing their performance with a multivariate regression model, whereas Pelliccioni and Tirabassi [17] showed that the integrated use of dispersion models and neural networks can improve the prediction performance of models. Galatioto and Zito [18] were analyzing the importance of traffic parameters in the urban parts of Palermo city, and they have concluded after a sensitivity analysis, the mostly correlated traffic parameter to pollutant concentration is queue length.

3. INPUT DATA

As it has been stated in the introduction, besides pollution sources, wind has a large influence in pollution concentration. Wind flow enables to pollutants to move through domain. Also turbulent intensity of the wind increases a mixing of fresh and polluted air. It is therefore important to categorize the amount of atmospheric turbulence - atmospheric stability present at any given time. Temperature, wind speed, wind direction, traffic intensity, atmospheric stability and time, were used as input data respectivly.

3.1. Traffic data

The traffic was monitored on critical road intersections. The results of traffic frequency intensity have been shown in Fig. 1. It was shown in the paper [4], that the total variation of passenger vehicles during a day is 4.45%.. In the graph, in Fig. 1 a), two main peaks on a working day are occurring: in the period between 8 AM and 9 AM, and between 3 PM and 4 PM. Those periods correspond to the daily morning and evening rush-hours. On Saturday and Sunday only one peak is occuring (Fig. 1 b)).

3.2. Wind measurements

From the data obtained from the Main meteorological station Niš, shown on the Fig. 2, it is obvious that there almost no other than this two main wind directions. Two main wind directions in the City of Niš are: North-West (~330°, from the Morava river valley), and East (~90°, from the Nišava river valley). Also, measurements were continuously performed, and the measured wind data were used as an input.

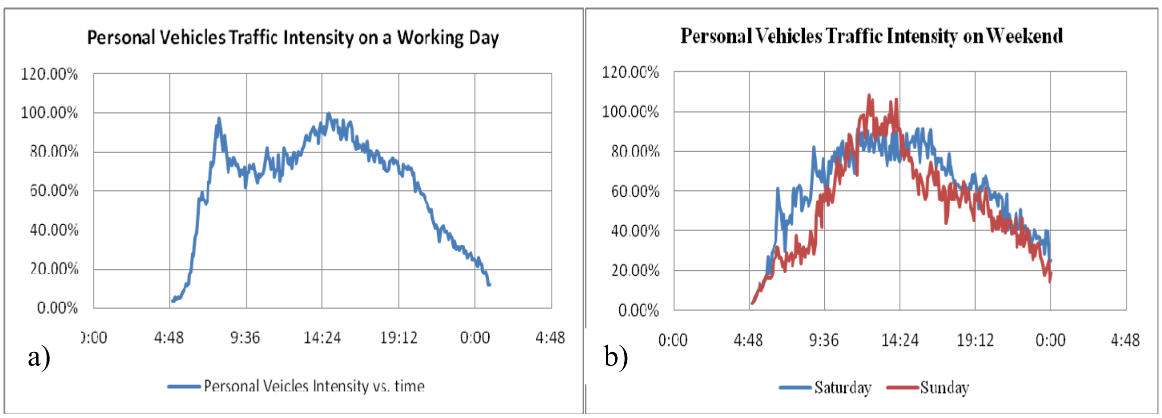

Fig. 1. Traffic in the City of Niš: a) Traffic frequency in Vehicles per 5 min on monitored crossroads; a) Traffic intensity on a Working day; b) Traffic intensity on a weekend

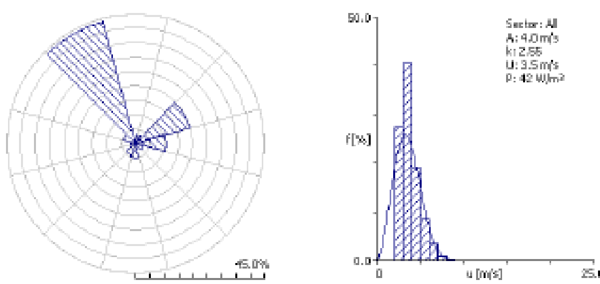

Fig. 2. Wind direction in the City of Niš (left), and wind speed distribution (right)

Sampling rate is 1sec, while the measuring results are being shown as average over the 5 min. period. This technique was used to reduce the influences of wind turbulence on the measurements. The characteristics of the anemometer are presented in the tab. 2.

Table 2. Cup anemometer technical data.

Wind speed measurment		Wind direction measurment	
Measuring range	0.5÷50m/s	Measuring range	0÷360˚
Accuracy	±0.1m/s	Accuracy	±0.1˚
Temperature range	-40÷80˚C	Temperature range	-40÷80˚C
Rel. Humidity	0÷100%RH	Rel. Humidity	0÷100%RH
Acqusition speed	1 sample/sec	Acqusition speed	1 sample/sec

3.3. Temperature measurments

The temperature sensor used is PT 100 element, with precision of 0.50°C. This measurement was added in order to ensure the comparison of the measured data with standard ones.

3.4. Technical data of the CO_2 sensor

The characteristics of the sensor used are shown in the following table. From this data one can notice that the sensor can operate normally in the entire measuring range, since the lowest measured value of CO_2 concentration was 392 ppm, and the higher about 1000 ppm.

3.5. Characterization of atmospheric turbulence

The amount of turbulence in the ambient atmosphere has a major effect on the dispersion of air pollution plumes because turbulence increases the entrainment and mixing of unpolluted air into the plume and thereby acts to reduce the concentration of pollutants in the plume. It is therefore

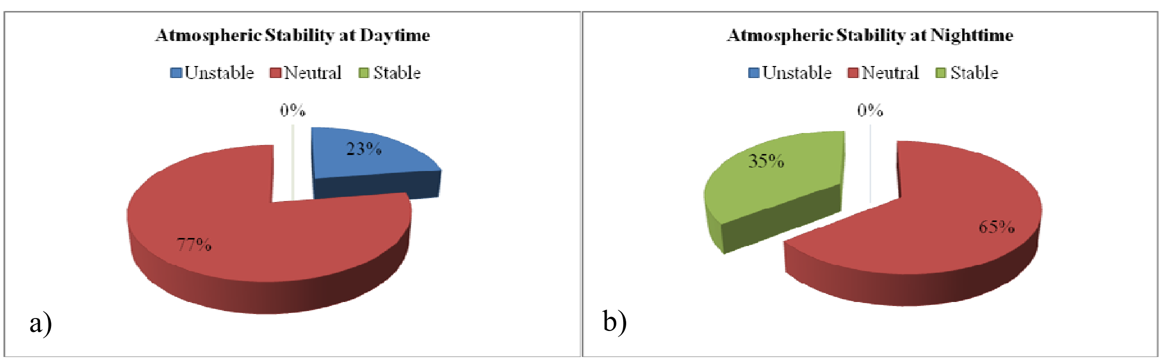

Fig. 3. Stability pattern for a) December 2008. daytime; b) December 2008. nighttime

important to categorize the amount of atmospheric turbulence present at any given time. For the atmospheric stability analysis the Pasquill [19] method was used.

From the diagram on the Fig. 3could be seen that atmosphere was mostly neutral to stable during the period, which is expected for the winter conditions.

4. NEURO-FUZZY AIR POLLUTION LEVEL ESTIMATIVE MODEL

To estimate air pollution level, Takagi–Sugeno–Kang (TSK) fuzzy models [20] have been used having rule structure with fuzzy antecedent and functional consequent parts, which thereby qualify to be treated as mixed fuzzy and non-fuzzy models. TSK fuzzy models have the ability to represent both qualitative knowledge and quantitative information and allow for application of powerful learning techniques for model identification from data.

To develop models, the structure identification and parameter adjustment [21] tasks needed to be solved. The former determines I/O space partition, rule antecedent (i.e., premise) and consequent variables, the number of IF–THEN rules, and the number and initial positions of membership functions. The latter identifies a feasible set of parameters under the given structure. For the problem of structure identification, a clustering technique presented in previous section was used [22]. Exponential potential function was used to rank and select most representative cluster centers from plant I/O data, and these cluster centers are then used to generate an initial TSK fuzzy model. Also another approach was considered - partitioning based on expert process knowledge. Gaussian membership functions have been used. Model parameters adjustment was performed using efficient ANFIS neuro-fuzzy scheme [23] overviewed in previous sections. Using ANFIS initial TSK models obtained from the structure identification phase have been represented as generalized feed forward neural networks and trained with plant I/O data, thereby adjusting the parameters of the antecedent membership functions as well as those of the functional consequents with hybrid learning scheme.

Several versions of the ANFIS model structures were considered. First, versions with three inputs (air temperature, wind speed and wind direction), five inputs (air temperature, wind speed, wind direction, traffic frequency and time of the day), and six inputs (air temperature, wind speed, wind direction, traffic frequency, time of the day and atmospheric stability) were tested, while model output was CO_2 concentration in all considered cases.

It is obvious that some theoretical knowledge can be confirmed from such results, and also rules with trained optimal parameters can be arranged in readable form providing understandable conclusions that were extracted from data by the estimative model.

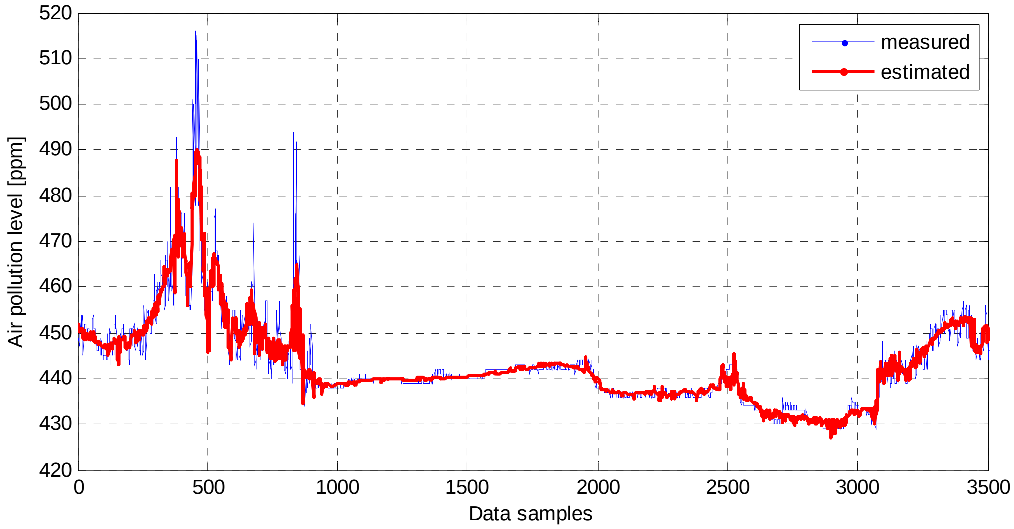

Fig. 4. Experimental verification of accuracy of trained fuzzy model with six inputs

Among several tests performed, one experimental verification of accuracy of the developed estimator with six inputs and 7 rules is presented in Fig. 4, for 3500 experimental data samples not used for model training.

5. CONCLUSION

Modeling problem that was studied in the paper originates from the traffic induced air pollution, which is highly nonlinear and complex process thus making conventional modeling difficult. Estimative models for the CO_2 content were identified using computational intelligence. Concisely recapitulated, applied ANFIS networks were capable of capturing the nonlinearities in process data, the training was efficient and prediction accuracy of the obtained models was good. Proposed hybrid fuzzy estimative model based on the TSK fuzzy reasoning also provides other features, such as interpretability of the models, use of all sources of information on the process, etc.

Based on the results reported in this paper, as well as on previous results published by the autors and others, it could be concluded that application of computational intelligence for air pollution level estimation has both proven its potential and opened interesting directions for future research. Above all, hybrid computational intelligence methodologies could be further explored to provide more efficient and precise estimation by integration of available expert knowledge with other sources of information, such as measured data.

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