AIR QUALITY ESTIMATION BY COMPUTATIONAL INTELLIGENCE METHODOLOGIES

by

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The subject of this study is to compare different computational intelligence methodologies based on artificial neural networks used for forecasting an air quality parameter – the emission of CO_2, in the city of Niš. Firstly, inputs of the CO_2 emission estimator are analyzed and their measurement is explained. It is known that the traffic is the single largest emitter of CO_2 in Europe. Therefore, a proper treatment of this component of pollution is very important for precise estimation of emission levels. With this in mind, measurements of traffic frequency and CO_2 concentration were carried out at critical intersections in the city, as well as the monitoring of a vehicle direction at the crossroad. Finally, based on experimental data, different soft computing estimators were developed, such as feed forward neural network, recurrent neural network, and hybrid neuro-fuzzy estimator of CO_2 emission levels. Test data for some characteristic cases presented at the end of the paper shows good agreement of developed estimator outputs with experimental data. Presented results are a true indicator of the implemented method usability.

Key words: *computational intelligence, CO_2 emission, air quality, neural networks, hybrid neuro-fuzzy systems*

Introduction

Air pollutants exert a wide range of impacts on biological, physical, and economic systems. The high concentration of air pollutants affects human health and may be hazardous. Consequently, it has become a vital task to accurately keep track of the air quality and variation of ambient air pollution levels in urban areas. Natural phenomena are mostly a time series with some degree of randomness. Pollutants in the atmosphere may disperse or concentrate during varied time periods. Recently, since recognizing the problem of global warming, caused by green-house gas (GHG) emissions, more attention has been focused on CO_2 emissions [1, 2].

As it has been estimated, in the overall balance of CO_2 in the city of Niš, traffic participates with 87699.38 t per year, or 38.09% from the overall anthropogenic emission in the city, followed by individual household heating, and district heating emissions, which are presented in tab. 1 [3-5]. The emission concentrations in urban areas produced by traffic emis-

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sions depend on vehicle characteristics, traffic and weather conditions, and the geographic and built environment characteristics of the local site.

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

	Power [TJ]	IPCC emission factor [$kgCO_2\ TJ^{-1}$]	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 – brown 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

Other very important parameters in emission concentration modeling are wind and atmospheric stability. Wind direction, velocity and amount of turbulence in the ambient atmosphere have a major effect on the dispersion of air pollution plumes. A study done by Ashrafi *et al.* [6] shows a relation of atmosphere conditions and CO concentration in the city of Tehran. For this reason, wind and its 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 a 3-year period.

Commonly used conventional methods for air quality and pollution estimation are some of the class of statistical methods; either the time-series methods, which do not use meteorological inputs, or regression or similar methods, which are mostly based on a multivariate linear relationship between meteorological conditions and ambient air pollution concentrations. However, when applying the conventional time-series models to the ambient air pollution forecast, the pollutant level variations are generally not simple autoregressive or moving average models [7]. Contrary to the conventional modeling and estimation approach of air quality, alternative computational intelligence strategies are proposed.

Artificial neural networks (ANN) represent an efficient tool in air quality estimation. In the study of Junsub *et al.* [8], ANN was used to estimate a daily maximum ozone concentration in an industrialized urban area. In the research conducted by Tudoroiu *et al*. [9], neural networks were used to estimate air quality along the Romanian coast with regards to identified sources. Kurtulus *et al.* used ANN to estimate methane emissions at an Istanbul landfill site. Many studies have sought to predict emission concentrations by using 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 *et al.* [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 outperformed the ordinary least squared model developed by Shi *et al.* [13] using the same study site. Similar work was done in Santiago, Chile [14], and in Perugia, Italy [15]. Furthermore, Grivas *et al.* [16] used neural networks to predict PM10 hourly concentrations in the metropolitan area of Athens, comparing their performance with a multivariate regression model, whereas Pelliccioni *et al.* [17] showed that the integrated use of dispersion models and neural networks can improve the prediction performance of models. Galatioto *et al.*

[18] analyzed the importance of traffic parameters in the urban parts of Palermo, and the authors concluded that, after a sensitivity analysis, the most correlated traffic parameter to emission concentration was queue length.

This paper presents a comparison of different soft computing methodologies for the determination of CO_2 concentration at the measuring site. The proposed methodologies are all based on artificial neural networks. The neural networks were chosen because of their ability to approximate highly non-linear functions with limited information about the nature of these relationships. This is very suitable, due to the stochastic nature of traffic, wind and weather data. For this study, different feed forward ANN, a non-linear autoregressive exogenous recurrent neural network (NARX), and an adaptive neuro-fuzzy inference system (ANFIS) were used and their performances were compared. Wind speed, wind direction, temperature, traffic intensity in the city, atmospheric stability, and time of day were used as input data, while CO_2 concentration represented an output.

Input and output data: selection, measuring, and analysis

As stated in the introduction, temperature, wind speed, wind direction, traffic intensity, atmospheric stability and time were used as input data, respectively.

The temperature sensor used was a PT 100 element, with the precision of 0.50 °C. Besides emission sources, wind has the largest influence on emission concentration. Wind flow enables the emissions to move through the domain. Furthermore, turbulent intensity of the wind increases the mixing of fresh and affected air. It is, therefore, important to categorize the amount of atmospheric turbulence (atmospheric stability) at any given time [1].

Time of day was additionally added to estimator inputs, since its use together with temperature can compensate for the lack of information about other sources of emission, like city heating plant and individual households.

As one of the indicators of air quality, CO_2 emission was measured and later estimated. From the data acquired, 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 highest around 1000 ppm.

Traffic data

Živković *et al.* [4] showed that the total variation of passenger vehicles on crossroads presented in fig. 1 during a single day is up to 4.45%. The traffic frequency on the main crossroads in the city of Niš is presented in fig. 2. In the graphs in fig. 1(a), the similarity of curves representing the frequency of traffic on different crossroads, throughout the day, can be noted. In the graphs in fig. 1(a) two peaks on a working day occur: in the period between 8 a. m. and 9 a. m., and between 3 p. m. and 4 p. m. Those periods correspond to the daily morning and evening rush-hours. The traffic frequency during the weekends was measured only on one crossroad, fig. 1(b), but having in mind the similarity of curves during working days, the assumption was made that the measured weekend frequency of traffic only on one crossroad was adequate as an input of an estimative model.

For the analysis presented in this paper, traffic data were averaged for all monitored crossroads and scaled so that 100% represented the highest daily traffic frequency. The obtained data of traffic intensity in the city of Niš during a working day, fig. 1(c), and on Saturdays and Sundays, fig. 1(d), were later used as an input of the estimative model.

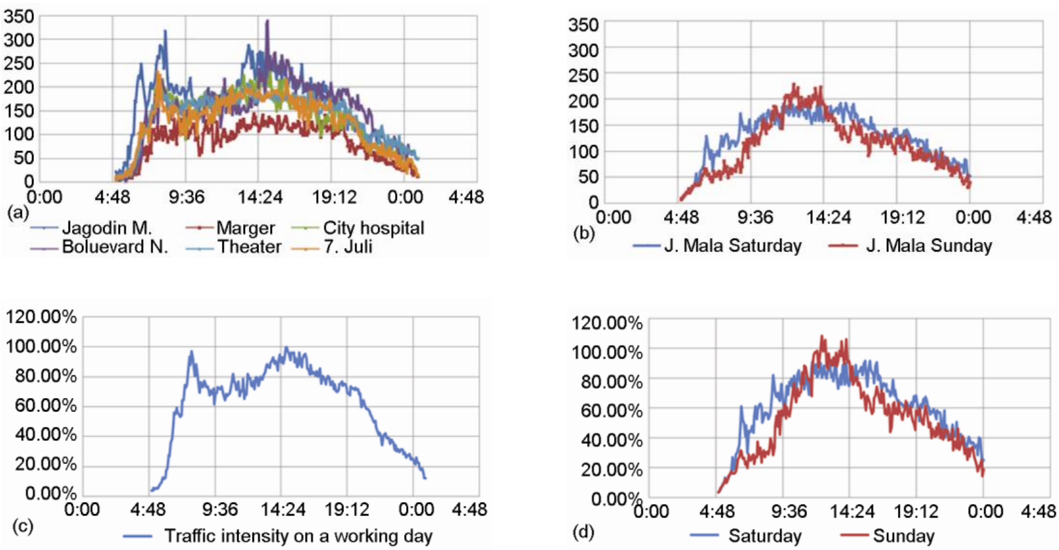


Figure 1. Traffic in the city of Niš: (a) Traffic frequency in vehicles per 5 minutes on monitored crossroads; (b) Traffic frequency in vehicles per 5 minutes in J. Mala on a weekend; (c) Traffic intensity on a working day; (d) Traffic intensity on a weekend

Wind measurement

From the data obtained from the Central Meteorological Station Niš, fig. 2, it is obvious that there are two main wind directions: North-West (~330°, from the Morava river valley), and East (~90°, from the Nišava river valley). Apart from the available data, measurements were continuously performed, and the measured wind data were used.

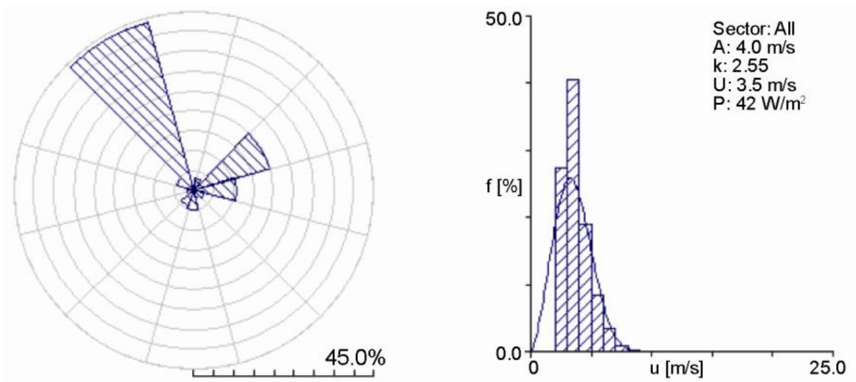


Figure 2. Wind direction in the city of Niš (left), and wind speed distribution (right)

The anemometer that was used was the second generation cup anemometer with a direction sensor mounted on the same shaft with the speed sensor. During the winter measurement period, there was no frosting of the sensor, considering the local climate.

The measuring range of the anemometer was 0.5-50 m/s, with the precision of 0.1 m/s. Wind speeds lower than 0.5 m/s were measurable, but with lower accuracy. Wind direction was measured with the precision of 22.50°, which should be improved in the following period, by applying a new sensor, mounted on another shaft.

The sampling rate was 1 second, while the measuring results were shown as average over a 5-minute period. This technique was used to reduce the influences of wind turbulence on the measurements. The characteristics of the anemometer are presented in tab. 2.

Table 2. Technical data of used sensors

Wind speed measurement		Wind direction measurement	
Measuring range	0.5-50 m/s	Measuring range	0-360˚
Accuracy	±0.1 m/s	Accuracy	±0.1˚
Temperature range	–40-80 ˚C	Temperature range	–40-80 ˚C
Relative humidity	0%-100% RH	Relative humidity	0-100% RH
Acquisition speed	1 sample/second	Acquisition speed	1 sample/second

Characterization of atmospheric turbulence

The amount of turbulence in the ambient atmosphere has a major effect on the dispersion of air pollution plumes, since turbulence increases the entrainment and mixing of unpolluted air into the plume, thereby acting to reduce the concentration of pollutants in the plume. It is, therefore, important to categorize the amount of atmospheric turbulence present at any given time. For the atmospheric stability analysis the Pasquill [19] method was used.

The stability of the atmosphere for the period of December 2008 was determined on the basis of the weather data when atmosphere was mostly neutral to stable, which was expected for the winter conditions. Additional weather data were obtained from the internet archives [20]. Weather conditions presented in fig. 3 were used as input data. In the graph, value 1 corresponds to unstable value A, neutral value D corresponds to value 4, and stable F corresponds to value 6.

Figure 3. Change of atmospheric stability during a day on December 23, 2008

Computational intelligence models for CO_2 emission estimation

Feed forward neural network models

Feed forward networks often have one or more hidden layers of non-linear neurons followed by an output layer of linear neurons. Multiple layers of neurons with non-linear transfer functions allow the network to learn non-linear relationships between input and output vectors. For the estimative model, two different networks were designed and tested (fig. 4). Both of these networks have six inputs (air temperature, wind speed, wind direction, traffic frequency, time of day and atmospheric stability) and one output (CO_2 concentration). The first network had one hidden layer with 10 neurons, while the other one had two hidden layers with 12 and 7 neurons.

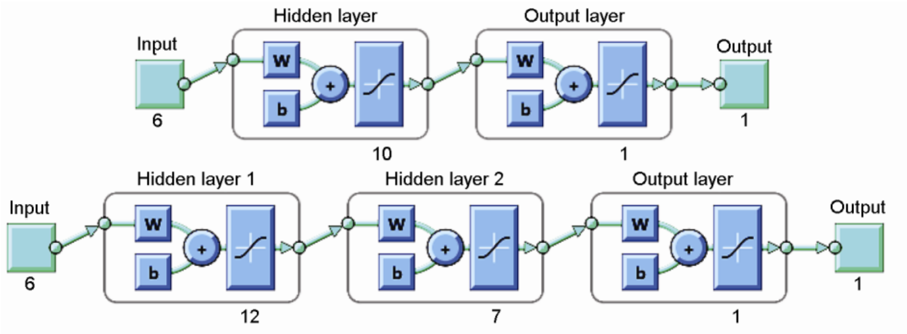


Figure 4. Neural networks with one and two hidden layers used for CO_2 emission estimation

These multilayer feed forward networks were trained for function approximation (non-linear regression). The training process required a set of examples of proper network behavior – network inputs *u* and target outputs *y*.

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance, as defined by the network performance function. There are generally four steps in the training process: assemble the training data, create the network object, train the network, and simulate the network response to new inputs. The common performance function for feed forward networks is the mean square error [21] between the network outputs $\hat{y}$ and the target outputs *y*, defined as follows:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}\ (y-\hat{y})^2 \tag{1}$$

For training both of these multilayer feed forward networks, 1245 data sets were used, with 267 sets used for validation and another 267 sets for testing. Optimization methods for performance function use the Jacobian of the network errors with respect to the weights. The gradient and the Jacobian are calculated using a back propagation algorithm, which involves performing computations backward through the network.

Back propagation [21-23] is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and non-linear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the user. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

Standard back propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back propagation refers to the manner in which the gradient is computed for non-linear multilayer networks. There are a number of variations on the basic algorithm that are based on other standard optimization techniques, such as conjugate gradient and Newton methods.

Properly trained back propagation networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs.

The performance of a trained network can be measured to some extent by the errors on the training, validation and test sets, but it is often useful to investigate network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The regression value of a neural network with one hidden layer was $R = 0.9328$, and the regression value of a neural network with two hidden layers was $R = 0.9523$.

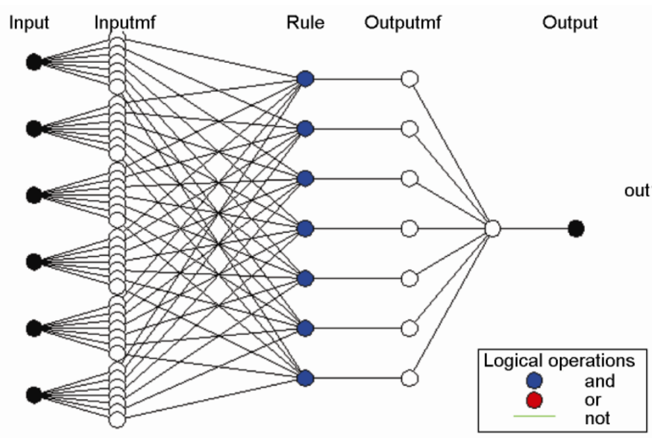
ANFIS model

To estimate the air pollution level, Takagi-Sugeno-Kang (TSK) fuzzy models [22], having rule structure with fuzzy antecedent and functional consequent parts, have been used, and this structure qualifies them 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 the application of powerful learning techniques for model identification from data.

To develop models, the structure identification and parameter adjustment [23] tasks needed to be solved. For the problem of structure identification, a clustering technique was used [21]. An exponential potential function was used to rank and select the most representative cluster centers from plant I/O data, and these cluster centers were then used to generate an initial TSK fuzzy model.

For training of ANFIS structure, 1245 data sets were used. The hybrid learning algorithm of ANFIS was used and it consisted of two alternating parts, back propagation/gradient descent (BP/GD) which calculated error signals recursively from the output layer backward to the input nodes, and the root least squared error (RLSE) method, which found a feasible set of consequent parameters. The regression value of trained ANFIS structure was $R = 0.9066$.

The structure of ANFIS estimator with six inputs and one output is shown in fig. 5(a). The inputs and outputs are the same for all the models.



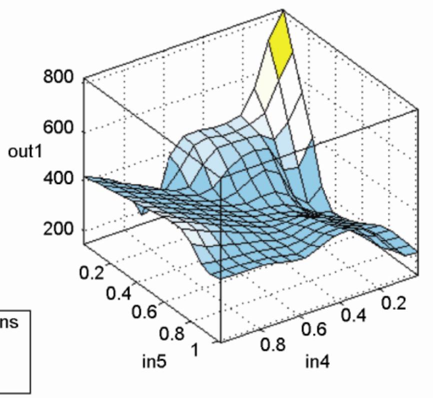


Figure 5. (a) ANFIS structure used for CO_2 emission estimation and (b) fuzzy model output surface

Interpretability of the obtained results was an issue of interest. Figure 5(b) presents the output surface for the fuzzy model with two inputs and a modest number of primary fuzzy sets with Gaussian membership functions after training. It is obvious that some theoretical knowledge can be confirmed from such results. Furthermore, rules with trained optimal parameters can be arranged in a readable form providing understandable conclusions that can be extracted from the data using the estimative model.

NARX network model

The non-linear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling. One can implement the NARX model by using a feed forward neural network to approximate the function *f*. The defining equation for the NARX model is [24]:

$$y(t) = f[y(t-1), y(t-2),\ldots,y(t-ny), u(t), u(t-1),\ldots,u(t-nu)] \tag{2}$$

where $u(t)$ and $y(t)$ represent the input and output of the network at time t, and the function f is some non-linear function, in this case a neural network. The next value of the dependent output signal y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. When the function can be approximated by a Multilayer Perceptron, the resulting system is called a NARX network (fig. 6) which is a recurrent neural network [24].

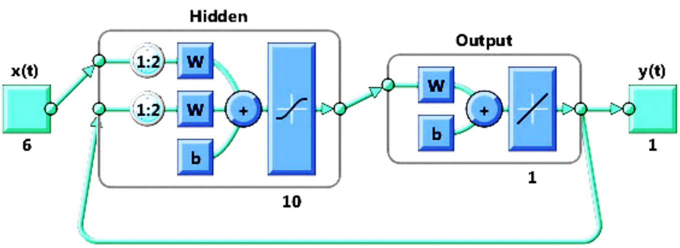


Figure 6. NARX neural network used for CO_2 emission estimation

There are many applications of the NARX network. It can be used as a predictor, to predict the next value of the input signal. It can also be used for non-linear filtering, in which the target output is a noise-free version of the input signal. The use of the NARX network is demonstrated in another important application, the modeling of non-linear dynamic systems.

The output of the NARX network can be an estimate of the output of some non-linear dynamic system that is modeled. The output is fed back to the input of the feed forward neural network as part of the standard NARX architecture. Because the true output is available during the training of the network, it is possible to create a series-parallel architecture, in which the true output is used instead of feeding back the estimated output. This has two advantages, the first is that the input to the feed forward network is more accurate and the second is that the resulting network has a purely feed forward architecture, and static back propagation can be used for training.

Since CO_2 concentration can be assumed as time series with some degree of randomness, NARX networks are a logical choice, since the current state is not independent of previous states, as is the case with feed forward neural networks. Every predicted state is estimated based on the current inputs in feed forward neural networks, and the estimation in NARX network is done based on the current inputs, previous inputs and previous states. In order for the parallel response to be accurate, it is important that the NARX network is properly trained so that the errors in the series-parallel configuration are very small. Otherwise, the accumulation of error might occur during estimation.

For the training of these recurrent neural networks, 1245 data sets were used, with 267 sets for validation and another 267 sets used for testing. The training was done by Levenberg-Marquardt backpropagation [24] and regression value was R = 0.9685. The training of NARX network needed more computational time, since more inputs were used overall. The network also had additional nodes, so more weighting factors needed to be adjusted.

Simulation results and model testing

Since all the models used comparable but slightly different sets of 1245 data sets, another set of data that was measured for two hours was used for real testing and comparison of the results. Figure 7 shows the diagram of measured CO_2 concentration and concentrations estimated by a neural network with one hidden layer, a neural network with two hidden layers, and an ANFIS structure.

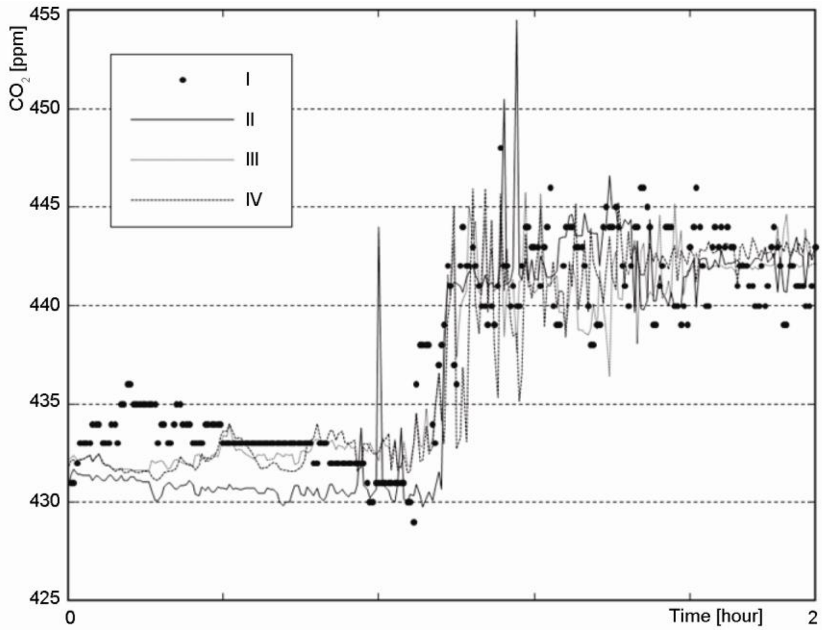


Figure 7. Experimental verification of accuracy of trained neural networks and ANFIS model: I – measured data, II – estimation of ANN with one hidden layer, III – estimation of ANN with two hidden layers, and IV – estimation of ANFIS

All three estimations are comparable and quite similar, although the two-layer ANN has the smallest mean absolute error (MAE). However, the neural networks used are a complete black box system, while the ANFIS structure has some sort of interpretability and transparency of the results, and some theoretical knowledge can be confirmed, or even used for system improvement.

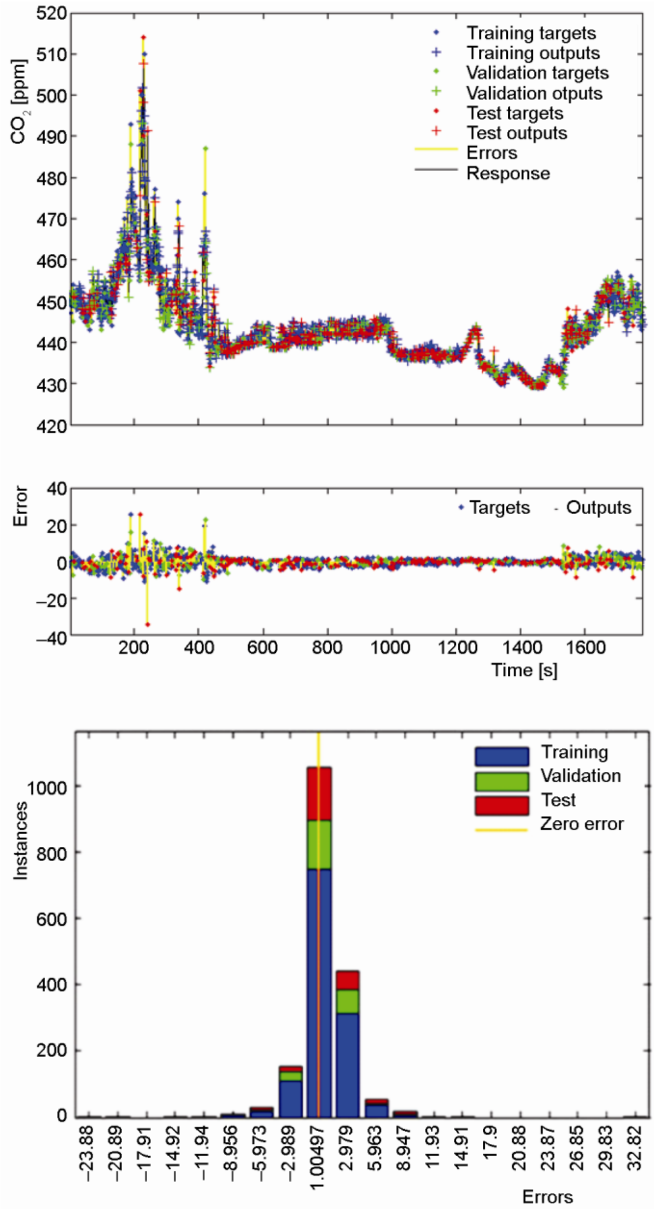


Figure 8. Experimental verification of accuracy of trained NARX neural network, error diagram, and error distribution

For higher CO_2 concentrations, especially for the rapid rise of CO_2 concentration, all the models give a satisfactory estimation but additional improvements can be done, due to the non-stationary stochastic nature of the process. This improvement can be done by choosing the different training data sets, considering another input (other sources of CO_2 emission), or by changing and improving the model structure.

The NARX network showed the best performance during training, so it was expected that it would show the best performance overall. That was expected on the basis of the non-linear autoregressive characteristics and exogenous inputs, and CO_2 concentration as time series, on the other hand. This is also proven in fig. 8 where performance over training, validation and test data is shown. The regression of the training data was $R = 0.9686$, $R = 0.9395$ for validation data, and $R = 0.9233$ for testing data. Figure 8 also shows the change of error during 1800 time samples and error distribution.

One can notice that the increase in traffic frequency led to an adequate CO_2 concentration level increase on the measuring location. The atmospheric conditions during this measurement were stable, with wind speed < 1 m/s.

Conclusions

The modeling problem studied in this paper originates from the CO_2 emission in urban environment, which is a highly non-linear and complex process, thus making conventional modeling difficult. The results of the estimated traffic induced CO_2 emission show good agreement with the measured CO_2 concentrations near the street. The estimative models for the CO_2 content were identified using computational intelligence. In short, the applied neural networks, ANFIS network and NARX network were all capable of capturing the non-linearities in process data, the training was efficient, and the prediction accuracy of the obtained models was good. The proposed hybrid fuzzy estimative model based on the TSK fuzzy reasoning also provided other features, such as interpretability of the models, use of all sources of information on the process, *etc*. The NARX network showed, as expected, the best performance evaluation, since it considered previous states and inputs as well. However, the NARX network required a more advanced training algorithm and the computational time was greater.

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

The results obtained show that it is possible to assess the influence of the District Heating Plant, traffic and households, which are the largest CO_2 sources in the city of Niš.

This methodology can improve our knowledge of the air quality in, primarily, highly populated areas. Hopefully, a better understanding of atmospheric phenomena, as well as the pollution dispersion, will lead to a better understanding of the necessity to maintain, and even improve, the quality of the entire environment.

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