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Prediction of carbon monoxide concentration near roads by means of artificial neural networks

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Abstract

The artificial neural networks (ANN) as a tool to predict air pollution were presented taking into account meteorological conditions and parameters which characterise the source of pollutants. A comparison was made between the two methods for calculation of carbon monoxide concentration in the region of a city road. The first method was based on a hybrid model which was a combination of ANN (a neural model based on radial basis functions – RBF) and the Pasquille model. In the other method the multilayer perceptron – MLP only, was applied to predict the level of carbon monoxide near the roadside edge. Topologies and the flow diagrams of signals in both networks were given and statistical estimation of the two methods was presented.

1 Introduction

Along narrow roads in built-up areas (cities), the state of atmosphere affected by pollutants emitted by vehicles is dramatic. This phenomenon is particularly intensive when in spring, autumn or winter cars with not heated enough engines drive on the roads. The cars may be equipped with autocatalysts system but it

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starts operating only after reaching a certain temperature. The actual level of air pollution depends on two opposing phenomena: the emission of pollutants depending mainly on traffic intensity and technical state of vehicles, and on pollutants dispersion. The conditions of dispersion are determined, in turn, by meteorological conditions which are beyond our reach and to a large extent on topographic features, buildings near the roads and conditions of ventilation. The situation is very unfavourable when a road in the built-up area is narrow, with a large number of vehicles moving along it at the same time at rather low velocities. An increased concentration of pollutants usually occurs within the region of vehicle motion, i.e. along the road itself. In the case of side winds, maximum pollutant concentrations move towards the roadside. The level of pollution within a particular hazard region, i.e. at the road edge can be predicted using artificial neural networks (ANN's). Complexity of the system considered causes that classical methods, which can be applied, give remarkable calculation errors reaching even 40-60% [1,2].

2 Artificial Neural Networks

Practical applications related to artificial neural networks caused that a number of specialised networks have been developed to solve particular problems. Several types of networks designed for different aims can be distinguished. In general, they can be divided into the following groups [3]:

- Single-layer networks, e.g. a single-layer perceptron, Kohenen network, vector quantization network,
- Multilayer feed forward networks, e.g. multilayer perceptron (MLP), networks with radial basis function (RBF), fuzzy logic (FLN),
- Recurrent networks, e.g. Hopfield, Elman and Jordan networks.

The artificial neural networks found broad application in solving environmental problems [4-8].

Multilayer networks MLP and RBF are the most usefull in those applications and are employed in the study. Schematic diagram of MLP and RBF networks are shown in Fig. 1.

In order to determine the MLP network topology for a given problem, the following should be specified

- the number of hidden layers,
- the number of neurones in particular layers,
- transfer functions and scaling coefficient,
- weights of connections.

The input-output transfer function in the MLP network has the form:

$$y = F(x) = f\left(\sum_j w_{oj} f\left(\sum_k w_{jk} f\left(\cdots f\left(\sum_m w_{nm} x_m\right)\cdots\right)\right)\right) \quad (1)$$

where f(·) corresponds to the neurone transfer function.

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A similar character of a feed forward flow of information from the input to the output has the network in which RBF is used.

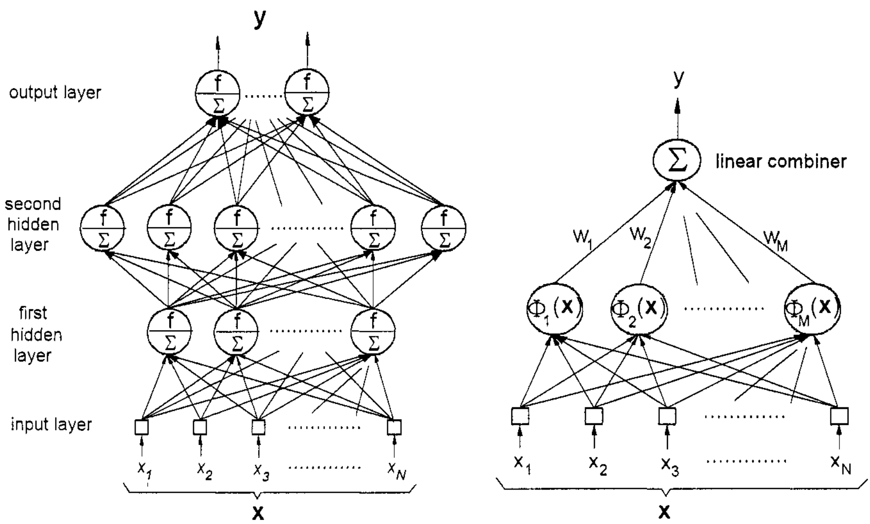

Figure 1: Structure of MLP (left panel) and RBF (right panel) network.

The artificial neural networks of radial basis function – RBF, are the networks in which neurones in the hidden layer realise the function changing around selected centres. Thus, the hidden neurones map radially the space around given points. The output neurone makes a superposition of hidden neurones signals. This enables mapping of data space.

The input-output transfer function in the RBF network has the form:

$$y(x) = \sum_{k=1}^{M} w_k \cdot \phi\left(\|x - c_k\| / \alpha_k\right) \qquad (2)$$

where: c_k, k=1,..., M – centres
α_k – scaling factors
$\phi\left(\|x - c_k\|\right)$, k=1,...,M – transfer function
w_k – weights

To define topology of the RBF networks, the following five elements should be determined:

- the number of basis functions M,
- the form of function ϕ (the form of Gauss function was assumed),
- location of centres c_k, k = 1,...,M (usually in a random way),
- scaling factor α_k, k = 1,...,M,
- weights w_k, k = 1,...,M.

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3 Hybrid Model – the Application of RBF Network

The level of CO near a road was predicted using a hybrid system.
Total emission coming from the traffic is decomposed into points of emission located at the road segments. The model contains two dispersion coefficients σ_y and σ_z dependent on meteorological conditions (the state of atmosphere) and the distance from emitter. In this approach the dispersion coefficients are calculated depending on the state of atmosphere expressed by coefficient "m".

According to Pasquille's formula [9], the concentration of pollutant emitted by the single emitter of height H in any point of surface of co-ordinates (x,y,z) in the range of the emitter operation, along the wind line, is determined by the formula [10]:

$$S^i_{xyz} = \frac{E}{2 \cdot \pi \cdot u_m \cdot \sigma_{yi} \cdot \sigma_{zi}} \cdot exp\left(-\frac{y_i^2}{2 \cdot \sigma_{yi}^2} \right) \cdot \left[exp\left[-\frac{(z_i - H)^2}{2 \cdot \sigma_{zi}^2} \right] + + exp\left[-\frac{(z_i + H)^2}{2 \cdot \sigma_{zi}^2} \right] \right] \quad (3)$$

where:

S^i_{xyz} – concentration of pollutant emitted by the single emitter, mg/m^3
E – pollutant emission, mg/s
U_m – mean wind velocity, m/s
H – the height of an apparent point of emission, m
z – height of the receptor over the ground level, m
σ_{yi}, σ_{zi} – atmospheric dispersion coefficients, m

The distance between emission source and the receptor, calculated along and perpendicular to wind direction is defined by the formula:

$$x = (X_r - X_e)sin\alpha + (Y_r - Y_e)cos\alpha \quad (4)$$
$$y = (X_r - X_e)cos\alpha + (Y_r - Y_e)sin\alpha \quad (5)$$

where:
X_r, Y_r – co-ordinates of the receptor,
X_e, Y_e – co-ordinates of the emission source,
α – angle between north and wind direction.
Mean wind velocity is determined by the formula

$$u_m = \frac{u_a}{m+1} \cdot \left(\frac{H}{h_a} \right)^m \quad (6)$$

where:
u_m – mean wind velocity in the range < 0, H >, m/s
u_a – measured wind velocity at the anemometer height h_a, m/s

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u_a – measured wind velocity at the anemometer height h_a, m/s
h_a – anemometer height, m
H – height of the apparent emission point, m
m – coefficient,
Dispersion is characterised by atmospheric (turbulent) dispersion coefficients. These coefficients can be calculated from the formulae:

$$\sigma_y = A \cdot x^a \tag{7}$$

$$\sigma_z = B \cdot x^b \tag{8}$$

where:
σ_y, σ_z – dispersion coefficient, m
x – distance from the point of emission, m
A, B, a, b – constants calculated from the relations:

$$A = 0.08 \cdot \left[6m^{-0.3} + 1 - ln\left(\frac{H}{z_0}\right)\right] \tag{9}$$

$$B = 0.38 \cdot m^{1.3} \cdot \left[8.7 - ln\left(\frac{H}{z_0}\right)\right] \tag{10}$$

$$a = 0.367 \cdot (2.5 - m) \tag{11}$$

$$b = 1.55 \cdot exp(-2.35 \cdot m) \tag{12}$$

where:
z_0 – aerodynamic ground roughness coefficient
m – coefficient corresponding to the stability class of atmosphere according to Table 1.

Table 1.The stability class of atmosphere and the coefficient m.

State	Stability class	Values of coefficient m
1	Strongly instable	0.080
2	Instable	0.143
3	Slightly instable	0.196
4	Neutral	0.270
5	Slightly stable	0.363
6	Stable	0.440

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The total emission of the whole source E (from selected road segment) determined by the equation:

$$E = \sum_{i=1}^{n} S^{i}_{xyz} \tag{13}$$

where:

S^{i}_{xyz} - emission from the single source, mg/m^3.

In our study coefficient "m" was calculated using the artificial neural networks with radial basis function (RBF). In this approach the network constitutes an integral part of the mathematical model (hybrid system). At the network input the following meteorological values are introduced: wind direction (0÷360°), wind velocity (0,4÷2m/s), temperature (10÷28°C), air humidity (20÷70%) and clouding (0÷1). RBF calculates the value of coefficient "m", which in turn is applied in the Pasquille model. A schematic diagram of the hybrid system - Pasquille model and neural network is shown in Fig. 2.

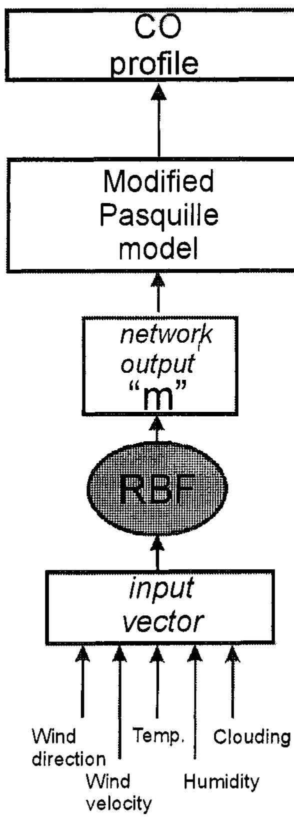

Figure 2: Scheme of hybrid prediction model.

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In training and testing the network experimental data obtained near a selected road segment (average of 30 min.) was used. The network was trained (weights w_k were determined in the network) using the method of genetic algorithm [11,12]. Another method of weights determination was not possible in the case analysed because the evaluation of model fitness to experimental data by the least squares method requires first the assumption of weight values in the network, then calculation of coefficient "m" and finally, calculation of values resulting from the Pasquille model. The network was configured for five neurones in the hidden layer, i.e. 5 weights had to be determined. Size of the training and testing sets was 40 and 10 measuring cycles, respectively. A comparison of experimental and calculated data for the network trained both for the training and testing sets is shown in Fig. 3. It follows from the statistical evaluation that fitting of the calculated to experimental data is not satisfactory. In the case of ideal fitting points would lay along diagonal of the diagram. The mean square error was 85.1% for the training network, and 50.2% for the testing network. This means that the application of the Pasquille model in the case discussed depends not only on proper evaluation of the state of atmosphere equilibrium. Propagation of pollutants depends on the effects which are not included in the Pasquille model, and which take place in reality, e.g. occurrence of air flow turbulence in a large scale in the region of vehicle movement.

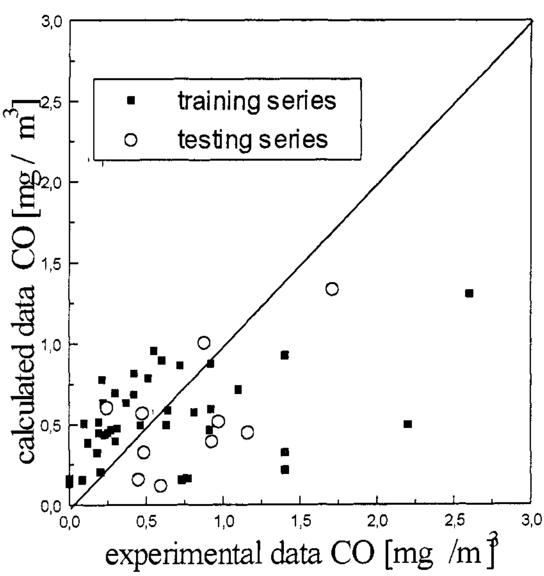

Figure 3: Comparison of experimental data and hybrid model data.

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4 Prediction of CO Concentration by Means of MLP

In the second method of prediction a multilayer perceptron was applied. Carbon monoxide concentration near the road edge was calculated. The following climatic parameters were introduced in the network input: wind direction, wind velocity, temperature, air humidity and clouding. Additionally, at the input the intensity of cars (0,6÷1,64 car/s) and trucks traffic (0,1÷0,6 truck/s) and location of a receptor (height above the roadway) were introduced. In calculations a logistic function was used as the transfer function and one hidden layer was applied. At the output which enabled a determination of CO level, a linear transfer function was used. The method of calculations is shown schematically in Fig. 4.

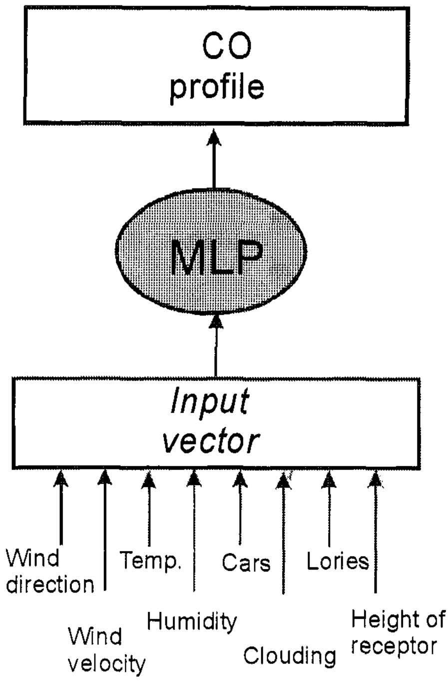

Figure 4: Scheme of MLP prediction model.

The training and testing sets were the same as in the case of presented earlier hybrid model. The input and output data were average values for a 30 min period. The training set was used to fit weights in the network. The network weights were determined during training by Lavenberg-Marquardt method [13]. The network topology was defined for 8 inputs, two neurones in the hidden layer and one output. Thus the values of 21 weights had to be determined.

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Results obtained using the neural model revealed good fitting of the network operation to the problem analysed. The mean square error of prediction did not exceed 5% both in the case of training and testing set. A comparison of experimental and calculated data both for the training and testing sets is given in Fig. 5.

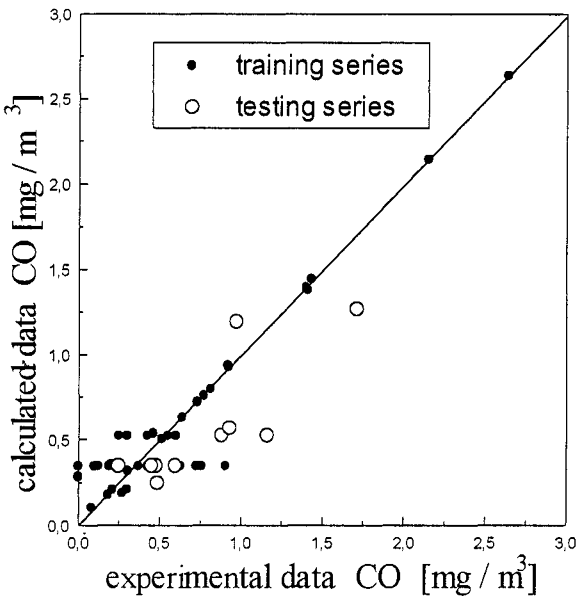

Figure 5: Comparison of experimental and MLP model data.

5 Conclusions

1. A new calculation technique based on artificial neural networks was proposed. Applicability of ANN was presented in two aspects: as assisting the calculations made using the Pasquille model (a hybrid system) and as an independent method for forecasting of a pollution level.
2. As an example of the prediction of air pollution, the forecasting of carbon monoxide concentration was selected.
3. Disadvantages of the applications of the modified Pasquille model in the calculation of gas pollutant propagation were listed. The better solution was obtained using MLP network.
4. After adjusting the network type and topology, ANN's may be used to predict of other air pollutant concentration.

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