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A neural network based model for the analysis of carbon monoxide contamination in the urban area of Rosario

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Abstract

A neural network based model for estimating (hourly mean concentrations) carbon monoxide in the urban area of Rosario City, in Santa Fe, Argentine is presented. The data series of carbon monoxide and emission inventory is also a result of this work (up to now no data were reported for Rosario). It is based on a typical neural network architecture, e.g. Lawrence [5]. Several inputs like mean hourly traffic flux -segregating different type of vehicles-, wind speed and direction, humidity, temperature, radiation intensity and geometrical parameters of the street are used. The difference between the Canyon Model and the model here proposed is the consideration of humidity, radiation intensity and temperature. Different Gaussian plume models (modular in nature) are linked to consider the contributions due to punctual, linear and area sources (different urban emission sources); e.g. Dabberdt *et al.* [3], Johnson *et al.* [4]. Gaussian plumes are used to calculate the background concentration which is added to the contribution of the specific vehicular flux in the street where the receptor point is placed. This last contribution was calculated by the Canyon Model. The contribution of the vehicular flux is the most important, and may be affected seriously by the mentioned variables. A performance comparison of the Canyon Model (a modified version, e.g. Benz *et al.* [1]) and the neural network based model applied to a receptor point in the city, will be done. This is the first work concerning this topic carried out in our city, and according to the consulted literature, in our country.

1 Introduction to the carbon monoxide contamination problem in our city

The city of Rosario lies in the *pampa húmeda*, that is, a flat land without topographic accidents. Thus, rigorous models are not mandatory for the concentration estimate in the commonest atmospheric pollutants. Consequently, a Gaussian model was developed for the evaluation of the carbon monoxide concentration estimate (background) coupled to the Canyon Model, e.g. Benz *et al.* [1]. Nevertheless, at this project stage, there are not sufficient emission data for the background calculation (estimate) yet.

Up to now, only a partial emission inventory for vehicular flux exists. The data bank describes, e.g. Benz *et al.* [1], hourly vehicular emissions and street characteristics at selected city points. Also, some projections to future emissions were performed, adopting a growth rate of 5% (data taken from the car industry reports) for vehicular flux. Thus, the tendency for the next ten years can be analyzed.

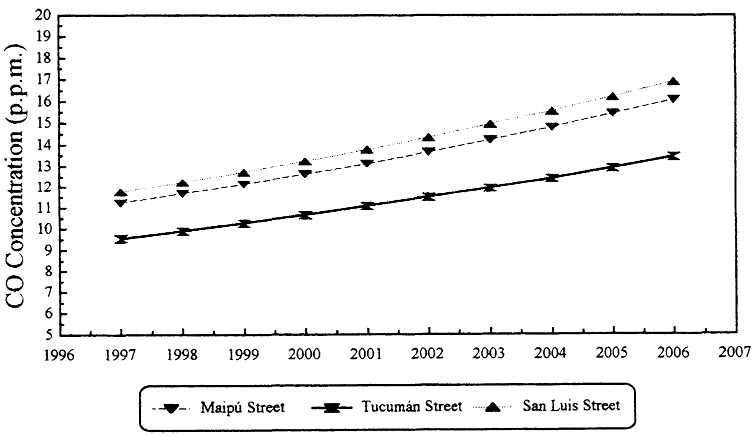

Figure 1: Tendency of CO concentration (eight - hours average) at different points in downtown.

Figure (1) shows the evolution of CO concentration at different points downtown. Providing the present conditions were not modified (e.g., engine quality, circulation policy downtown, etc.), by the year 2000 many streets would achieve the permitted limit value of CO concentration. Nevertheless, this hypothesis should be analyzed considering a realistic local situation in terms of engine aging and engine displacement distribution. This theme will be developed in future studies.

As was pointed out above, a new modelling strategy for the problem using neural networks is reported. The objective is to decide if this model strategy can be used for CO concentration estimation in our city and, on the other hand, to explore two interesting points:

1) Comparison of the behaviour of both, the neural network model and the previous developed one (the improved Canyon Model, e.g. Benz *et al.* [1])
2) Find out which variables are the most important to explain the CO diffusion from the set of primary variables here selected.

2 The neural network based model

The model calculates the mean hourly carbon monoxide concentration using as independent variables (inputs), meteorological data and relative composition of the vehicular flux. The network learns an input-output mapping that is static. Thus, the philosophy used is different from other works; e.g. Ruiz-Suárez *et al.* [7], Mlakar & Boznar [6], Boznar *et al.* [2] among others.

2.1 Neural network architecture: The training phase

A neural network structure known as perceptron multilayer is presented. For the network training, the backpropagation method was used. Both, the batch and the pattern method for the learning process were analyzed. After several trials it was concluded that the last strategy was the best for this problem.

Considering transfer function's characteristics, two kinds of structures were analyzed:

1) A homogeneous one with sigmoid transfer functions in all hidden layer neurons.
2) A hybrid one where the first hidden layer was split into two halves, the left half uses the sigmoid transfer function, and the right half uses a sine transfer function.

The second structure was analyzed looking for better results. Nevertheless the best result was obtained with the first structure. This behaviour is owing to the relatively great training errors obtained, because of the domain uncertainty and the incompleteness of the measurement process.

Also, several architectures (for example different number of internal layers and number of neurons) were analyzed. The basic adopted structure is a network with three layers of neurons, all of them with sigmoid functions. The final number of neurons and layers was constrained by the available number of data (up to this moment only 340 patterns).

Due to one of our targets is the analysis of the different variables affecting the CO diffusion, different input sets were proved. Thus, the corresponding neural network is built using the same basic structure in all the cases. Concretely, we have the following input set (variables suspected to influence the CO concentration):

i. Vehicular flux -vehicles/hr.- (for each type: cars, taxis, medium vehicles, trucks and buses)
ii. Wind speed (meters/sec.) and wind direction (radians)
iii. Solar radiation (Watts/m^2)
iv. Humidity (%)
v. Pressure (Hg mm.)
vi. Rain intensity (mm of water)
vii. Temperature (Celsius degree)

We have 11 variables in the input set. Three different input pattern dimensions were used: The first with the complete input set. The second with only seven variables (no considering items (iv), (v), (vi) and (vii) above mentioned). Finally, the last network was build using only six variables (eliminating item (iii) from the second pattern).

In this form it is possible to obtain the different effects on the CO concentration due to the action of the above mentioned variables. Of course, the final conclusion will be obtained analyzing more data and using a sensitivity analysis of each variable.

Training errors

In the best case the training error was less than 1%, while the worst error was obtained in the batch mode operation (6%). Most neural networks based on the full input set (11 variables) have presented errors lower than the reduced ones (during the training step). Indeed, pattern mode produced better results than batch learning mode. Finally, as was mentioned above, in all the cases homogeneous sigmoid functions produced better results.

2.2 Model validation

The model validation was carried out for each type of network, and using approximately a set of 100 patterns. For the case of the complete input set, a mean error about 21% have been obtained and 75% of the patterns were verified with an error less than 30% (the defined threshold value).

For the network using seven variables in the input set (and using the same threshold level) we found out that the mean error was approximately the same (around 21%) but with 88.5% of the patterns inside the threshold level.

Finally, with six variables in the input set, we obtain a mean error of 20% and 87% of the patterns produced an error less than the defined threshold level.

It must be concluded that the eliminated variables (from the input set) have not a major influence on the output variable (CO concentration); almost the same error was obtained but better estimate performance (lower dispersion). This can be seen from the threshold level behaviour of the reduced networks compared to the best performance of the full input set neural network.

Analyzing our results, it can be concluded (constrained to our data set used in this work) that humidity, pressure and temperature are not important to estimate CO concentrations.

Moreover, our results suggest that even if solar radiation is more important (related to the previous mentioned set), its elimination would also demonstrate that the resulting network could estimate CO concentrations with the same performance. Thus, we can conclude that the vehicular flux (and its distribution) and the wind speed and direction are the most important variables to estimate the CO concentration (assuming fixed the geometrical parameters of the street and the distance from the emission to the receptor point). This conclusion agrees with the basic formulation of the Canyon Model that use precisely these variables to model this phenomenon, e.g. Dabberdt *et al.* [3].

3 An application example

Model was used to estimate and to compare the concentration of carbon monoxide in a specific point placed downtown by using hourly emission data -vehicular fluxes- (measured during several days to achieve higher precision in the input parameters to the model), meteorological data and measured carbon monoxide concentration values -the six model inputs- to test the estimation capability.

Analyzing the mean values of the estimation errors and the threshold levels -number of estimation inside a confidence band- it can be concluded that the neural network can estimate CO concentrations. Indeed, the neural network based model is very similar in performance to the Canyon Model. It is important to remark here that a modified Canyon Model was used, e.g. Benz *et al.* [1]. This last work presented a better correlation than the Canyon Model, because it eliminated the under and overestimate introduced by the classical Canyon Model; e.g. Dabberdt *et al.* [3], Johnson *et al.* [4].

In the previous cited work was found out for the modified Canyon Model (using the same data and input variables -six variables- that the ones used for the corresponding neural network) the following performance: 75% of the trials are compressed in a band with an absolute error less than 30%, almost 10% more lies in a band with an absolute error less than 40%, while less than 1% percent presents an absolute error larger than 50% (see Figure (2)). After our results in this work, it can be concluded that both models have almost the same performance.

It was also found out that the neural network based model presents a uniform distribution of the error value along the space of CO concentrations. Nevertheless, the use of the model in other points (extrapolation) must be carefully studied, because up to here only a few single points (streets) was considered. Thus, geometrical parameters like the canyon dimensions and the receptor point in relation to the traffic line, among others, were not considered in the patterns used in the learning phase.

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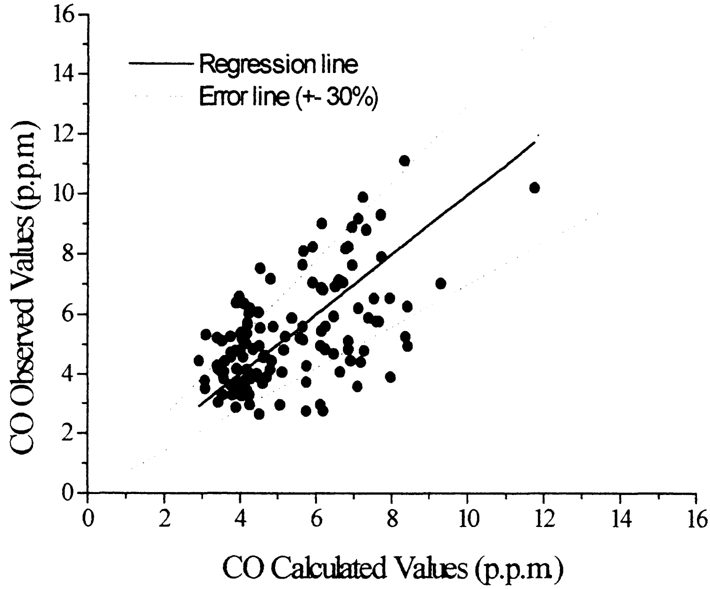

Figure 2: Calibration of the modified Canyon Model (Benz, *et al.* [1]).

4 Conclusions

The carbon monoxide contamination in the Rosario City, mainly downtown, is analyzed. A neural network based model was used for the concentration estimate of this pollutant using as input data a set of usual variables (meteorological data, emission inventory, geometrical parameters of the street) and others that are not considered in the commonly employed simplified models, like for example, the Canyon Model, or statistical based methods. In fact, the potential relationships among the following variables were explored: radiation intensity, humidity, temperature and the CO concentration.

It was found out that there is only a little relationship among radiation intensity, humidity, temperature and pressure and the CO concentration estimate. Both types of models, neural network based models and the Canyon Model, give similar results. Also, the same basic distribution of the estimate error (without bias in lower and high concentration values as the common Canyon Model) was obtained.

Standard backpropagation algorithm was used to perform non-linear prediction considering the measurements domain as stationary time serie. In such case the network produces in response to the input vector a one-step prediction.

Future works will deal with neural network considering dynamic properties that make it responsive to time-varying signals.

Finally, an emission inventory for urban area is under development, specially for carbon monoxide emissions (vehicular traffic). For punctual and area sources, the collection of the emission values is quite difficult. There are many problems (lack of adequate financial support, data collection for industry emissions, etc.) that must be solved in the future.

The final objective of this project is to obtain, based on an emission inventory and meteorological data, a carbon monoxide concentration map of downtown Rosario, finding the critical points and the tendency for the future.

Acknowledgments

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Key words

Carbon monoxide contamination, urban traffic, neural network based model

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