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Prediction of 8 hour average of carbon monoxide concentrations, in Santiago, Chile

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Abstract

Carbon Monoxide (CO) is considered a harmful pollutant emitted mainly by motor vehicles. In large cities like Santiago, CO concentrations may reach values that exceed the norm that health organizations have established as a safe limit to which the population may be exposed (10 mg/m^3 , 8 hour moving average). It is important to be able to predict with at least 30 hours in advance, when concentrations will exceed this limit, because restriction to vehicle circulation may imply a relevant decrease with respect to expected values when no actions are taken.

We show here a study on the possibility to predict maximum values of 8 hour moving average of CO concentrations using past values of CO concentrations and meteorological forecasts as input to multi linear regressions and neural network models. The neural network model seems to leave more room to adjust free parameters with one year data in order to predict the following year values. We have worked with data of three years measured in two of the monitoring stations located in the urban area of Santiago.

Introduction

Topographic and meteorological conditions and the activity of a large population in Santiago, Chile make this city is one of the most polluted in the world. At present, health authorities have defined air quality by the value of the

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24 hour average concentration of particulate matter with diameter less than 10 microns (PM10). When this quantity exceeds certain levels , an increasing amount of restrictions are imposed to industry emissions and to motor vehicles circulation. A high correlation has been found between ambient concentrations of PM10 and Carbon monoxide (CO). Carbon monoxide is a colorless, odorless, tasteless and toxic gas that is a product of incomplete combustion. When CO is inhaled, it combines with hemoglobin, inhibiting its ability to transport oxygen to body tissues. Inhibition of 50% of the hemoglobin in a person causes death [1]. Any fuel burning appliance has the potential to produce dangerous levels of this gas. In large cities, ambient concentrations of CO are due mainly to emissions by motor vehicles (90% in Santiago, Chile). In Santiago, a safety limit of 10 mg/m^3 (9 parts per billion (ppb)) for the 8 hour average concentration of CO has been established. Daily maximum of this quantity, as measured in a centric monitoring station, was exceeded 14 times during 1998. It will be very useful to have a forecasting method that could send a warning when high concentrations of CO are expected for the following day. If on these occasions authorities impose restrictions to motor vehicles circulation, actual measured concentrations can be well below the expected values. In addition, this will imply an improvement of air quality conditions in terms of PM10 concentrations.
Among methods for pollutant concentrations forecasting, linear regressions and neural network techniques are the most used. Models for prediction of particulate matter [2-4] and gaseous pollutant [5-9] concentrations several hours in advance have been reported in recent years. Neural networks have been used as a tool for carbon monoxide concentrations forecasting in a zone highly dependent on traffic [10]. In this paper we report a study aimed to predict if during the next day the safety limit for the eight hour average of carbon monoxide concentration is exceeded. We have used values of hourly average concentrations of CO and meteorological information measured during 1998, 1999 and 2000 in two of the official monitoring stations located in the city of Santiago.

The data

The surveillance of air quality in Santiago is performed by a network of eight monitoring stations distributed in a convenient form throughout the urban area and which provide continuous information on concentrations of CO, SO_2, NO_x, O_3 and PM10. At these stations there are also instruments to measure temperature, relative humidity, wind speed and wind direction. We based our study on hourly averages of CO concentrations reported at two of these stations: "Pudahuel" and "Parque", during years 1998, 1999 and 2000, data obtained from measurements of infrared radiation absorption. We do not consider the whole year of data, but the period between May 1st and August 31, when usually the worst conditions occur. For each year, we considered then a total of 123 days. During this time the number of days when the maximum of the 8 hour moving average of CO concentrations exceeded the level 9 ppb were 8, 11 and 5 in Pudahuel and 14, 10 and 8 in Parque for 1998, 1999 and 2000 respectively. In developing a forecasting method for the maximum of the 8 hour moving average of CO concentration (CO8) we have considered past values of one hour and eight

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hour averages of CO concentrations plus the meteorological data available at the stations as inputs to different models.

The forecasting method

Our aim is to predict the maximum value of of CO8 one day in advance using information on CO concentrations until 6 PM of the previous day. Our approach is based on a neural network scheme which can be explained in short referring to Figure 1.

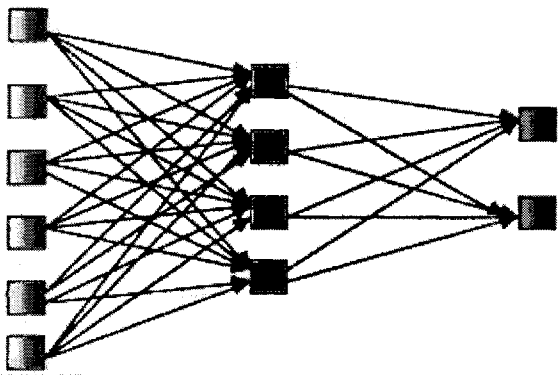

Figure 1: Feed forward neural network.

Inputs are the values of the variables considered relevant to generate the outputs. Each input is connected to all the nodes in the hidden layer. Every node in the hidden layer generates a signal which is a function of a linear combination of the incoming inputs. This function, called "activation function", in most cases is chosen to be a sigmoid:

$$f(X) = \frac{1}{1 + e^{-X}} \tag{1}$$

The signal thus generated is sent to every node in the next layer, which can be another hidden layer or the output layer. In cases when inputs are successive values of a time series and the outputs are future values of the same series, at each of the outputs we will have a nonlinear regression. The values of the weights in all of the linear combinations involved are calculated using an optimization algorithm that looks for the reproduction of a set of sample cases. The optimization algorithm used in our calculations is the generalized Delta rule [11]. In the special case when there are no hidden layers and the activation function is the identity, we will be in the presence of a linear regression.

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In order to determine what variables are relevant for the prediction of daily maximum of CO8, we trained our model initially with variables that appeared significant on previous studies on forecasting of other pollutants and then proceeded to discard those that in preliminary calculations did not imply a decrease in prediction error. The adjusting of the weights for a given station at a given year was performed with all the cases of that year (from May to August). We were careful in order to not to increase arbitrarily the number of nodes in the hidden layers because the total number of weights to determine should not be greater than the amount of sample cases. This practical rule would be consistent with the assumption that the system under study is deterministic and the set of data has a smooth distribution. Once the connection weights were optimized in order to reproduce the input-output relations for a given year we analyzed if with these same weights we could generate correct forecasts for the following year in the same station. One of our goals is to predict if the maximum of CO8 is greater than 9 ppb. Since the number of days when this happens is a small fraction of the total of 123 days considered per year , the optimization procedure to adjust the weights will produce a model that is biased to reproduce better the cases that do not exceed the safety level. This situation may be corrected in part if we repeat a number of times the cases when the level is exceeded, increasing artificially the size of the set of sample cases.

Results

We have investigated the ability of feed forward neural networks to forecast the maximum of CO8 for the next day based on information of CO concentrations in the present day up to 6 PM and meteorological information from the present day and the next day. This assumes that we have independent reliable meteorological forecasts available. However, working with historical data we have used the actual values of meteorological variables when information from the next day was found relevant for the CO8 forecast. Table 1 shows which variables from a pre established set resulted necessary to generate the best forecasting model for every year in each of the two stations. Cases exceeding the 9 ppb limit were repeated 10 times in Pudahuel station and 5 times in Parque. The criterion to select the best model was the minimum percent error, calculated as:

$$PE = \frac{\langle |y_{tp} - y_{ta}| \rangle}{\langle y_{ta} \rangle} \times 100 \qquad (2)$$

where y_{tp} is the predicted value, y_{ta} is the actual value, and < > means average over the sample cases.

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	PUDAHUEL			PARQUE		
	1998	1999	2000	1998	1999	2000
CO1 0 hr					X	
CO1 8 hr				X	X	
CO1 12 hr		X				
CO1 18 hr	X	X	X	X	X	
CO8 max				X	X	X
CO8 min						X
T max	X	X	X			X
ΔT	X	X	X	X	X	
Ave RH	X	X	X	X	X	X
Ave WS	X	X	X	X	X	X
Dummy week end			X	X		X
Dummy rain						X
T min forecast				X	X	X

TABLE 1: Variables used as input to feed forward neural network to forecast maximum CO8 for next day.

In this table, the variables are 1 hour average of CO concentrations measured at 0, 8, 12 and 18 hr on the present day, maximum and minimum of CO8 found in the last 24 hours until 6 PM on the present day, maximum temperature on the present day, difference between maximum and minimum temperature on the present day, average relative humidity and average wind speed on the present day, a dummy variable that is 1 if the next day is saturday or sunday and zero otherwise, a variable that is 1 if the total precipitation on the present day exceeded 0.3 mm and the minimum temperature forecasted for the next day.
According to this, in Pudahuel, the best fitting for 1998 was obtained with a feed forward neural network with 5 units in the input layer, 4 nodes in a single hidden layer and one output unit (5-4-1). This produced a 40% prediction error, where 6 of the 8 days exceeding the 9 ppb limit were predicted correctly to exceed it. As a matter of comparison, the linear network (without hidden layer and identity activation function), with the same inputs, produced a 50% prediction error, again with 6 of the 8 days exceeding the limit predicted correctly to exceed it. Keeping fixed the weights of the 5-4-1 network and applying them to predict the 1999 cases we obtained a 46% prediction error and 6 of the 11 days exceeding the limit. Keeping the 1998 weights of the linear network and applying them to the 1999 data we got a 62% prediction error and hitting 5 of the 11 days that should appear exceeding the 9 ppb limit. With similar explanations for other years, results are summarized in Table 2 for Pudahuel station and in Table 3 for Parque station. It is worth to mention that the neural network model produces a few false positives, that means days predicted to exceed the 9 ppb limit that did not actually happened. However, most of these days corresponded to cases when the authorities imposed restrictions to vehicle circulation when high

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concentrations of PM10 were expected, measure that distorted the natural course of the events.
We must notice that when maximum of CO8 for a given year is predicted based on weight adjustment using data from the same year, we have kept the total number of weights smaller than the amount of cases in sample set (which is greater than the number of days in the period, because of repetition of the cases exceeding the 9 ppb limit) implying that an optimization procedure was necessary.

1998			98 - 99		1999			99-2000		2000		
net	%	8	%	11	net	%	11	%	5	net	%	5
5-4-1	40	6	46	6	6-4-3-1	50	7	67	4	6-4-1	36	3
5-1 lin	50	6	62	5	6-1 lin	62	5	72	3	6-1 lin	38	0

TABLE 2: Performance of the best networks for prediction of maximum of CO8 on the next day in Pudahuel station.

1998			98 - 99		1999			99-2000		2000		
net	%	14	%	10	net	%	10	%	8	net	%	8
8-8-1	35	11	87	2	8-5-3-1	35	8	71	2	8-4-3-1	38	4
8-1 lin	41	11	93	0	8-1 lin	36	5	58	1	8-1 lin	37	2

TABLE 3: Performance of the best networks for prediction of maximum of CO8 on the next day in Parque station.

We observe that in both stations, the neural network with hidden layers performs better than the linear model in all cases. The generalization from one year to the next seems poor, specially in Parque. This result may be attributed to the fact that CO concentrations in this station depend strongly on vehicle traffic since it is located at a few meters of a congested road, and it is very likely that the pattern of emissions changes significantly from one year to another. Even errors in the auto-tests using the same year data appear considerably greater than those obtained for particulate matter (PM10) in a similar calculation [4]. A possible explanation for this is that memory effects from previous pollutant concentrations are less important for gases like CO than for PM10, and then measured CO concentrations depend more strongly on actual emissions and meteorology.
According to the results shown, a possible application of a neural network as a tool to generate warnings due to CO8 concentrations, should be restricted to the use of early data of a given year to adjust weights in order to make predictions on days around the end of June, when enough time has past in order to have

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reliable values for them. From then on, the weights may be recalculated daily, using information of the past.

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