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Forecasting hourly PM2.5 in Santiago de Chile with emphasis on night episodes

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HIGHLIGHTS

- The performance of statistical hourly PM2.5 forecasting model is shown.
- Accuracy achieved with a neural network model is better than persistence.
- High concentrations episodes are correctly forecasted.
- Daily averages from hourly forecasted values are captured.

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ABSTRACT

We present the results of an hourly PM2.5 concentrations forecasting model in Santiago, Chile. The study concentrates on the comparison between model and observed values at the monitoring station with the highest concentrations (Cerro Navia station) for the time period between April and August, which is the season when high concentration episodes are frequent. The forecasting model is a feed forward neural network, The input variables are past values of hourly PM10 and PM2.5 concentrations measured at the city station with the highest values during episodes, concentrations from a neighboring station and some observed and forecasted meteorological variables. Training is performed with 2010 and 2011 data and the model is tested with 2012 values. Information is collected until 7 PM of the present day and percent error forecasting up to 15 h in advance, starting at 8 PM of the present day, is of the order of 30%. Accuracy of forecasting is significantly better than different forms of persistence and may be considered as a useful tool for anticipating episodes.

1. Introduction

Fine particulate matter atmospheric concentrations are being measured since 1989 in a network of monitoring stations located in the metropolitan area of Santiago, the capital of Chile. PM2.5 concentrations show average values that are far above the limits recommended by international health organizations.

The city is located in a valley which is approximately 50 km wide, having an average altitude of 750 m over sea level, with a smooth slope, higher to the east and lower to the west. To the east we find the Andes Mountains with altitudes up to 5000 m and to the west there is a coastal mountain range with altitudes up to 2000 m. Climate may be classified as semi-arid cool, with monthly average temperatures ranging from 7 °C in July to 20 °C in January. Thermal amplitudes on some sunny days in June and July may be as high as 25 °C, with minimum temperatures around 0 °C. Annual average precipitation is 260 mm. In winter, between April and August, dispersion of atmospheric pollutants in the valley is very poor, which is related to strong surface thermal inversions and weak winds, associated to anticyclone conditions at a regional scale. During this period of the year, the Ministry of the Environment applies several restrictions to emission sources in order to protect the population from toxic air pollution levels. Nevertheless, during 2012, on 25 days the PM2.5 24 h moving average surpassed 80 $\mu g/m^3$ at some time of the day. Although at present air quality policies are based on PM10 concentrations, starting 2016 PM2.5 will be the focus pollutant. PM2.5 standards are in action since 2012, with a 24 h average standard of 50 $\mu g/m^3$ and an annual limit of 25 $\mu g/m^3$. Focusing on PM2.5 instead of PM10 has become a tendency in several countries, because of the ability of the finer particles to penetrate deeper in the respiratory tract. An increase of

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the fine fraction of the particulate matter present in the breathable air, implies a higher probability for producing diseases in the population (Kim et al., 2015).

The main sources of PM2.5 in Santiago are wood stoves and public and private transportation according to the latest Emissions Inventory (MMA, 2014). Source apportionment studies reach similar conclusions (Jorquera and Barraza, 2012). Wood burning is a major source of PM2.5 in Santiago because space heating with low technology stoves is extensively used (Gramsch et al., 2014). Although, wood stoves in the urban area are not the main heating system, falling behind gas and kerosene, they contribute heavily to Santiago's pollution. In addition, transport of wood stove emissions from surrounding rural areas is another source of pollution in the city.

In recent years, several atmospheric particulate matter forecasting models have been developed as an aid for air quality management in different parts of the world. Two families of models may be distinguished: statistical and deterministic models. Although a preference towards deterministic chemical models for PM10 and PM2.5 forecasting is perceived, the accuracy for next day forecasting at the city level with these does not seem greater than what can be obtained with statistical models. Several studies suggest that a combination of both approaches seems the best option (Stern et al., 2008; Konovalov et al., 2009; Neal et al., 2014). Besides, computation resources needed to run next-day forecast deterministic models are so high, that in most instances these models are not implemented. On the other hand, statistical models are much easier, quicker and economical, computationally speaking (Fernando et al., 2012).

Thus, it seems very convenient for environmental authorities to have an operational air quality forecasting model available in order to anticipate situations that may put in danger the population. In general, it is easier to implement models to forecast daily averages or 24 h moving averages rather than hourly averages. Three types of neural models, a linear model and a persistence model have been developed in order to forecast daily averages of PM2.5 in El Paso (USA) and Ciudad Juarez (Mexico) (Ordieres et al., 2005). Perez and Salini (2008) have implemented three types of PM2.5 forecasting models in Santiago de Chile: linear, neural network and a clustering algorithm. The output of the model were the maxima of the 24-h moving average of PM2.5 concentrations for the following day and this value can be compared with the measured values in four monitoring stations. The inputs are current values of $PM_{2.5}$ concentrations and measured and forecasted values of some meteorological variables. Their results show that a combination of a neural network and a clustering algorithm is a convenient option. Cobourn (2010) proposed a model based on nonlinear regression for the forecasting of daily average of PM2.5 in Louisville, Kentucky. He reports a detection rate of 83% of the exceedences of the 35 μg/m^3 daily average standard. Sun et al. (2013) use a hidden Markov model (which can be considered as a statistical model) in order to forecast daily average concentrations 24 h ahead. They are able to predict most of the exceedance days in Concord and Sacramento, California.

In spite of the high detection rate of the previous models, forecasting hourly averages is more convenient for the efficacy of actions of pollution control taken by the authorities, because in general restrictions based on 24 h averages come with a delay. Perez et al. (2000) developed a very simple multilayer neural network (MLP) that predicts 1-h average concentrations of $PM_{2.5}$ from 1 to 24 h in advance, where errors run from 30% for early hours to 60% for late hours. Initially, only lagged values of the pollutant were considered as input, and it was shown that improvement was possible by including the values of meteorological variables like relative humidity and wind speed. A model for forecasting expressway fine particulate matter was proposed some time ago (Thomas and Jacko, 2007), where 1-h average concentrations 1-h in advance were obtained with a linear model and a feed forward neural network. A wavelet-based neural network model was used to forecast 1-h average concentrations 1-h in advance in Delhi (Prakash et al., 2011). Pai et al. (2013) reported the results of an hourly roadside PM2.5 forecasting model in Taipei. They use a statistical grey model, and claim to generate concentrations up to 72 h in advance with an average correlation of 0.9 with observed values. Borrego et al. (2011) have applied three deterministic models in order to forecast hourly PM2.5 concentrations over mainland Portugal, obtaining correlations between 0.5 and 0.64 with observed values. In this paper we report the results of the implementation of a statistical model intended to forecast hourly values of PM2.5 concentrations from one to twenty hours in advance in the city of Santiago. Given that several high concentrations episodes are usually observed in the city, it is important for us to accurately forecast these cases.

2. Data

PM10 and PM2.5 concentrations were obtained from two monitoring stations belonging to the official monitoring network, (Macam network). It consists of eleven stations distributed through the city, which report one hour averages of these pollutants with a delay of one half hour (see Fig. 1). Chilean standard for the 24 h average is 50 μg/m^3, and when this average exceeds 80 μg/m^3, restrictions to emissions apply (MMA, 2011). Our goal is to forecast hourly concentrations of PM2.5 in Cerro Navia station, which shows the highest values during most of the high pollution season in Santiago. From these forecasted values we are able to generate the 24 h averages in order to establish if the limit of 80 μg/m^3 is exceeded. Fig. 2 shows the hourly average PM2.5 concentrations in Cerro Navia station for years 2010, 2011 and 2012. The peak around 9 AM is due to the rush hour traffic. High concentrations during the evening and night are related to: rush hour traffic, the onset of residential heating and poor ventilation at this time of the day. For the period between April and august, average concentrations and number of exceedences to the 80 μg/m^3 for 2010 were 45.02 μg/m^3 and 29, for 2011, 45.9 μg/m^3 and 28 and for 2012, 44.1 μg/m^3 and 24. We can verify then, that is no great difference from one year to the

Fig. 1. Map of Santiago and location of PM2.5 monitoring stations. Cerro Navia and Pudahuel, on the left side, register the highest concentrations.

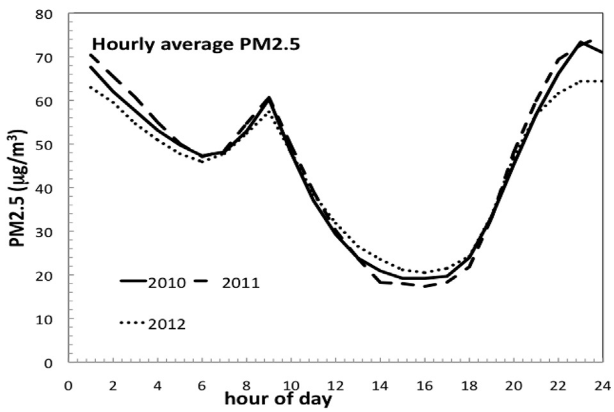

Fig. 2. Average hourly PM2.5 concentrations over the period April–August 2010, 2011 and 2012 for different hours of the day.

next. Fig. 3 shows the typical onset of an episode. On June 6, 2012, after low hourly PM2.5 concentrations during the early afternoon, around 6 PM a very rapid increase of particle concentration is observed. It has to be noted that the increase during episodes is so rapid that it is very difficult for any model to predict it (Stern et al., 2008). Accordingly, the 24 h moving average increases, and around midnight the limit of 80 µg/m^3 is exceeded. Weather forecast for the region indicated poor ventilation for June 7. Being able to forecast this exceedance is crucial, given that restrictions to emissions are enforced under these conditions of air quality.

In a previous work, it has been found that knowledge of actual and forecasted values of daily thermal amplitudes (difference between maximum and minimum temperature. Typically, minimum temperature occurs at sunrise and maximum in the early afternoon) is useful for the forecasting of the maximum of the 24-h moving average of PM10 concentration during the following day (Perez and Reyes, 2006). The authors have also used as an input to the model the estimated value of an index called "meteorological potential of atmospheric pollution" (PMCA, Ruttlant and Garreaud, 1995). This is a discrete variable that ranges from 1 to 5 and it is a marker of the ventilation conditions in the region. It is forecasted daily by meteorologists as a result of a synoptic analysis. A value 1 is associated with the absence of thermal inversion and the presence of active frontal systems. A maximum value 5 is related to clear days with high pressure over the city, under the onset of a coastal-low in central Chile (80 km to the west of Santiago). The later conditions have large thermal amplitudes, with very low morning temperatures (of the order of 0 °C) and high maximum afternoon values (greater than 20 °C). Under these conditions, the thermal inversion of subsidence frequently occurring in a subtropical valley, couples with the marked radiative thermal inversion during winter cold nights. High values of PMCA are also verified before frontal passages, on cloudy days with very stable atmospheric conditions. These cases are less frequent and under these conditions the onset of the episode does not follow the pattern shown in Fig. 2. A PMCA value 4 was forecasted for June 7, 2012. The atmospheric conditions associated to particulate matter episodes such as those presented in Fig. 2 are not exclusive of Santiago, Chile, but they can be observed in other places, eg. in the region of San Joaquin Valley, California, which is a subtropical valley with strong similarities with the central valley of Chile where Santiago is located (Chen et al., 2014; Livingstone et al., 2009).

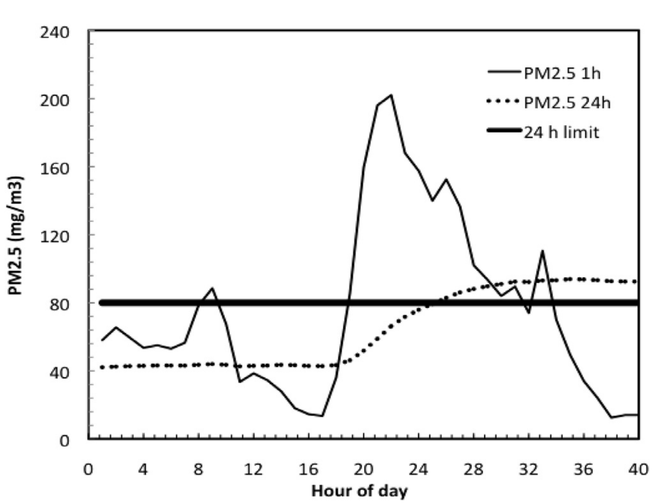

Fig. 3. Typical onset of a PM2.5 episode in Cerro Navia station. Restriction to emissions apply when the 24 h average is greater than 80 µg/m^3.

3. Forecasting with a multilayer neural network

Based on previous experience with Santiago forecasting models of pollution and given the positive results obtained in many other cities around the world (Perez et al., 2000, 2006, 2008; Ordieres et al., 2005; Voukantsis et al., 2011; Zhou et al., 2014), this work uses a neural network model in order to forecast hourly concentrations at different times at Cerro Navia station. After exploring different options, it was found that best results are obtained with a feed forward neural network with 13 input variables, 8 hidden nodes and one output, which corresponds to the forecasted hourly PM2.5 concentration with a given amount of hours in advance.

Input variables are:

- Hourly PM2.5 concentration at 6 PM in Cerro Navia station
- Hourly PM2.5 concentration at 7 PM in Cerro Navia station
- Hourly PM10 concentration at 6 PM in Cerro Navia station
- Hourly PM10 concentration at 7 PM in Cerro Navia station
- Hourly PM2.5 concentration at 6 PM in Pudahuel station
- Hourly PM2.5 concentration at 7 PM in Pudahuel station
- Hourly PM10 concentration at 6 PM in Pudahuel station
- Hourly PM10 concentration at 7 PM in Pudahuel station
- Wind speed at 7 PM in Cerro Navia station
- Relative humidity at 7 PM in Cerro Navia station
- Thermal amplitude of present day in Cerro Navia station
- Forecasted thermal amplitude for the following day in Cerro Navia station
- Forecasted ventilation factor for the following day.

Selected input variables are the result of a pruning procedure. We started with a larger amount of candidate input variables (meteorological and one hour average PM2.5 concentrations previous to 8 PM). Only those that improved forecasted PM2.5 values were kept. The observation that values of relative humidity and wind speed are good predictors for future values of PM2.5 concentrations agrees with studies in different parts of the world (Chu et al., 2010; Zhou et al., 2014; Voukantsis et al., 2011). The reason to include the one hour averages of PM10 and PM2.5 concentrations at 6 PM and 7 PM as an input is to capture the rapid increase in concentrations at this time (see Fig. 3). The slope of the increase is a good predictor for the tendency for the next hours. Later concentrations cannot be included, because environmental authorities need to generate a public forecasting report for the following day between 8 PM and 9 PM.

The goal of the present work was to forecast hourly PM2.5 concentrations at Cerro Navia station from one to twenty one hours in advance, from 8 PM of the present day to up to 4 PM of the following day for the period between April 1st and August 31, 2012. Training was performed with data from the same period for years 2010 and 2011. For each time delay, a different network was trained and different weight connections were generated. Three parameters were evaluated in order to estimate the accuracy of forecasting:

$$\text{Pearson correlation } CORR_t = \frac{\left\langle \left(y_{tp} - \left\langle y_{tp} \right\rangle\right)\left(y_{ta} - \left\langle y_{ta} \right\rangle\right) \right\rangle}{\sqrt{\left\langle y_{tp} - \left\langle y_{tp} \right\rangle \right\rangle \left\langle y_{ta} - \left\langle y_{ta} \right\rangle \right\rangle}}, \quad t = 1, \ldots, 21 \tag{1}$$

$$\text{Normalized percent error, } NPE_t = \frac{\left\langle \left| y_{tp} - y_{ta} \right| \right\rangle}{\left\langle y_{ta} \right\rangle} \tag{2}$$

$$\text{Percent error, } PE_t = \left\langle \left| \frac{y_{tp} - y_{ta}}{y_{ta}} \right| \right\rangle \tag{3}$$

where triangular bracket means average over the sample, y_{ta} is actual value and y_{tp} is the forecasted value. Normalized percent error is used in order to eliminate distortion in the case of low concentrations.

In Fig. 4, the correlation between the observed values and the neural network forecasting results is shown, as well as the persistence model. The figure shows the results from one to 21 h in advance for all days in the period mentioned. Persistence in this case means that the delayed value is the same than the 7 PM value (this means that concentrations for hours later than 7 PM are all the same). Comparison with a multilinear regression with the same input variables as the neural network is included. We observe that correlation for the neural network model is reasonably good up to 15 h in advance. These correlations are of the same order of magnitude than those obtained with deterministic PM2.5 forecasting models (Borrego et al., 2011) and neural network PM10 forecasting models (Grivas and Chaloulakou, 2006; Russo et al., 2013). Although in average, errors with the neural network model are less than with the linear model, the small difference between them indicates that the selection of input variables is more important than the details of a suitable algorithm.

Fig. 5 displays the NPE obtained with the neural network model. NPE is compared with the error produced by assuming that the actual value is the average over the period for that hour (Persistence Average) and with the performance of the multilinear regression introduced in Fig. 4. By comparing the neural network and linear model results, a conclusion similar to the correlation calculation may be established. In this figure, the PE obtained with the neural network model for days with high values of PM2.5 (hourly concentrations greater than 80 μg/m^3) is shown. Errors for this range, being relatively low, are very promising, given that forecasting high concentrations is one of the most important goals of an air quality forecasting model. This may be verified by analyzing Fig. 6, in which a comparison between observed and forecasted values at 11 PM during June, 2012 is displayed. It corresponds to a 4 h in advance forecasting for the month when most of the episodes occur. The highest concentrations are observed around 11 PM, the time at which these episodes start. In this figure, five nightly episodes may be identified. From these, four are very well captured by the neural network model. Fig. 7 shows the results of the forecasting model at 7 AM of the following day for the same period than the previous figure, which represents a 12 h in advance prediction. Paying attention to the range of concentrations, the most important peaks in this case correspond to the decay of hourly concentrations from the night episodes. Although forecasting errors are greater than those for the 11 PM case, still tendency of concentrations is well reproduced. Fig. 8 shows the comparison between observed and forecasted values, for a sample episode case, using the neural network model, for June 6–7, 2012. Predictions from one to 21 h in advance are shown. We can verify that hourly values and 24 h moving average are closely approximated. The 80 μg/m^3 limit exceedence is correctly predicted. During 2012, 17 days with limit exceedance occurred. From these, 70% were correctly forecasted and we had several cases with quality similar as this of Fig. 8, where the curve of hourly values is reproduced and the behavior of the 24 h average is also captured.

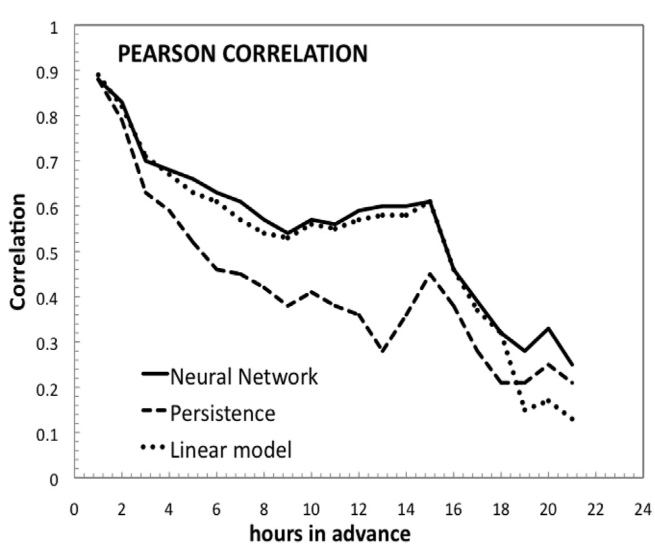

Fig. 4. Pearson correlation of PM2.5 forecasting using a neural network. Comparison with multilinear regression forecasting model and persistence of the 7 PM concentration.

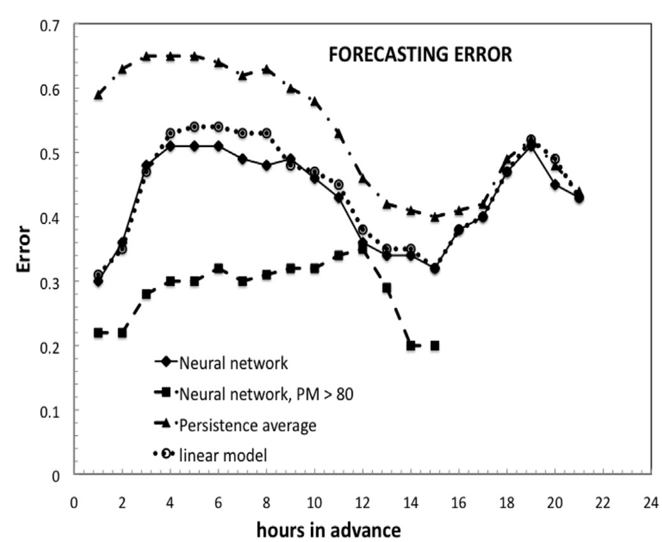

Fig. 5. Comparison of forecasting errors (NPE) obtained with a neural network model, a multilinear regression forecasting model and persistence of the average. Percent errors (PE) of high concentrations forecasting with the neural network is also displayed.

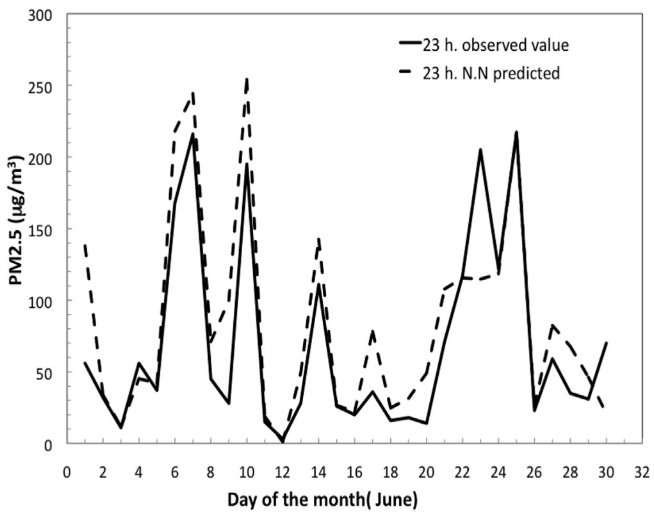

Fig. 6. Observed and forecasted values at 11 PM (4 h in advance from the time of data collection, June, 2012). Concentrations are in μg/m^3.

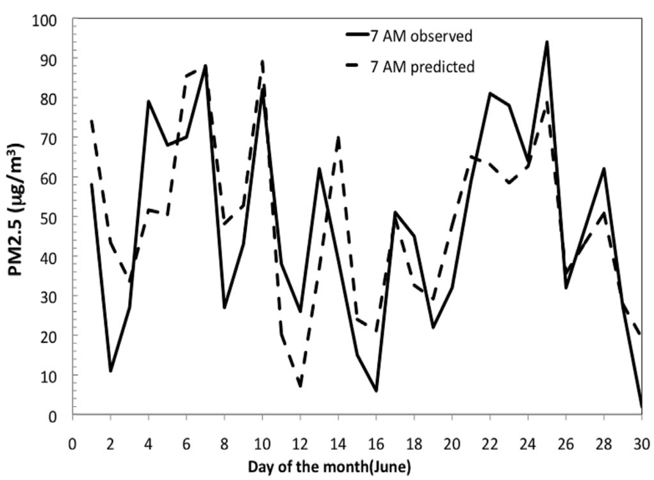

Fig. 7. Observed and forecasted values at 7 AM (12 h in advance from the time of data collection) during June, 2012. Concentrations are in μg/m^3.

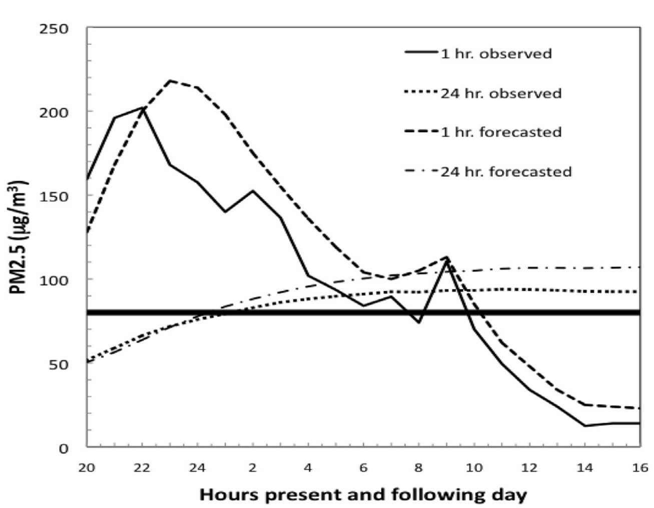

Fig. 8. Comparison between observed and forecasted values on June 6–7, 2012. Data is collected until 7 PM of June 6.

4. Discussion

Our results show that hourly values of PM2.5 concentrations at a relevant monitoring station in Santiago, Chile, may be forecasted with a reasonable accuracy with an anticipation of several hours using a statistical model (a neural network), provided that we have reliable historic data including pollutant concentrations and meteorological information. There are no many statistical forecasting models that estimate PM2.5 concentrations with more than 1 h in advance. Our predictions are more accurate than those of Perez et al. (2000), which may be attributed to the inclusion of a ventilation factor as input. After identification of predictor variables, namely, evening concentrations and values of parameters associated to ventilation we are able to estimate particle concentrations for the following night and day. We have shown that accuracy of hourly forecasted values is relatively better for nightly episodes of high concentrations. This is an indication that episodes obey a deterministic pattern of tendency of PM2.5 concentrations and meteorological condition. Our modeling is not directly comparable to that of Pai et al. (2013), because their time series shows a pseudo periodicity, typical of a roadside site (which is not our case) and the grey model they use does not seem suitable for episode forecasting. Being able to anticipate hourly concentrations may be useful for environmental authorities in order to take efficient actions for pollution control. The described model may be used operationally and accuracy is higher than that obtained with previous models. Although with deterministic models a similar accuracy may be obtained (Borrego et al., 2011), a neural network model requires significantly less computer resources. It must be mentioned that the analyzed monitoring station is located in the zone of lowest altitude in the city, and it registers the highest values among the network of 11 stations in continuous operation. Our findings may apply to other cities with similar geographical and meteorological conditions, where thermal inversions and atmospheric stagnation in winter nights are observed.

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