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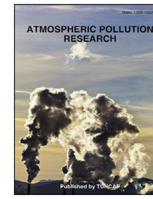

Recursive neural network model for analysis and forecast of PM10 and PM2.5

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A B S T R A C T

Atmospheric particulate matter (PM) is one of the pollutant that may have a significant impact on human health. Data collected during three years in an urban area of the Adriatic coast are analysed using three models: a multiple linear regression model, a neural network model with and without recursive architecture. Measured meteorological parameters and PM10 concentration are used as input to forecast the daily averaged concentration of PM10 from one to three days ahead. All simulations show that the neural network with recursive architecture has better performances compared to both the multiple linear regression model and the neural network model without the recursive architecture. Results of PM forecasts are compared with the air quality limits for health protection to test the performance as operational tool. The inclusion of carbon monoxide (CO) concentration as further input parameter in the model, has been evaluated in terms of forecast improvements. Finally, all models are used to forecast the PM2.5 concentration, using as input the meteorological data, the PM10 and CO concentration, to simulate the situation when PM2.5 is not observed. The comparison between observed and forecasted PM2.5 shows that the neural network is able to forecast the PM2.5 concentrations even if PM2.5 is not included among the input parameters.

1. Introduction

Over the past years, the effects of atmospheric Particulate Matter (PM) on human health, on ecosystems and on buildings and monuments soiling have become a relevant subject of research. The PM penetrates into sensitive regions of the respiratory system, therefore its inhalation increases respiratory illness and can harm lung tissues and throat (Turner et al., 2011). The PM10 (particulate matter having an effective aerodynamic diameter smaller than 10 μm) is one of the most dangerous pollutants; indeed, high PM10 levels have been correlated to the increase in hospital admissions for lung and heart disease (Ostro et al., 1999). Several epidemiological studies (Dockery and Pope, 1994, Katsouyanni et al., 1997) highlighted that PM can severely affect human health, even in relatively small concentrations in ambient air. PM2.5 (PM with an aerodynamic diameter below 2.5 μm) impacts more negatively the human health than PM10, since it penetrates more deeply in the respiratory system (Dockery et al., 1993; Pope et al., 1995, 2002; Monn, 2001). For these reasons, there is a growing interest on studying the formation, evolution and possible control strategy of PM10 and PM2.5.

Meteorological conditions have an influence on the PM10 accumulation, they can govern the variability of atmospheric PM10 (Amodio et al., 2012; Rodriguez et al., 2001). Usually elevated PM10 concentrations are the result of unfavourable meteorological

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conditions (Grivas and Chaloulakou, 2006, Carnevale et al., 2010). In order to reduce the health effects of PM10, the European Commission has established health-based standards for PM10 and PM2.5 reported in the EU directive (2008/50/CE) in which the threshold for the daily average has been fixed at 50 μg/m3 not to be exceeded for more than 35 days in one year and with an annual upper limit of 40 μg/m3 for the PM10; moreover, an annual upper limit of 25 μg/m3 for the PM2.5.

Prediction of the atmospheric composition helps significantly in the management of the air quality; predicting air quality is still a challenge because of the complexity of the processes involved and the strong coupling across many parameters, which affect the modelling performances (Leksmono et al., 2006; Mallet and Sportisse, 2008). A classical forecasting method is based on multivariate statistical analysis, but in recent years the use of artificial neural networks (ANN) has been extended to model the particulate matter pollutants (especially PM10 and PM2.5) and ANN is becoming an effective and popular technique alternatively to conventional methods. Neural networks appear to be a useful approach to deal with nonlinear systems like environmental pollution. The ANN has been used to predict daily average of PM concentrations in accordance with the legislation and the existing air quality standards in association to the meteorological variables (Perez and Reyes, 2006; Voukantsis et al., 2011; Abderrahim et al., 2016) in order to control short-term population exposure to airborne particles. Even if in the last 15 years several studies have reported the use of the ANN techniques to forecast airborne PM concentrations, the specific literature about PM10 forecasting is quite recent and less common (Hea et al., 2014; He et al., 2015). For example, Kukkonen et al. (2003) employed five neural network models, a linear statistical model and a deterministic modelling system to evaluate the nitrogen dioxide (NO_2) and the PM10 concentrations and comparing their results showed a better forecast accuracy for neural networks than for other approaches, such as multiple linear regression. Hooyberghs et al. (2005) used an ANN model in order to forecast the daily average PM10 concentrations one day ahead. An attempt to predict hourly values of PM2.5 for the following day (Perez et al., 2000) and to forecast the 24 h moving average of PM10 (Perez and Reyes, 2002) in Santiago (Chile), showed better performances of the neural networks model respect to the multiple linear regression model. Corani (2005) compared the results obtained by several neural networks and a linear model locally trained to forecast the daily average of PM10. Grivas and Chaloulakou (2006) estimate the performances of various neural network models to provide reliable predictions of PM10 hourly concentrations, comparing them with a multiple linear regression model developed in parallel. Ordieres et al. (2005) compared the results among the neural-network models for the prediction of daily averages of PM2.5 concentrations and two classical models (a persistence model and a multiple linear regression). The results clearly demonstrated that the neural approach outperformed the classical models and that the use of meteorological predictors benefit their performance. These results suggest that ANN can be a useful tool to predict PM.

In this paper we analysed three years of continuous measurements of PM, CO concentration and meteorological parameters, in the seaside town of Pescara in central Italy. A neural approach has been used to predict PM10 and PM2.5 concentrations from one to three days ahead, using meteorological and chemical variables as input parameters. Respect to previous works we adopted a more sophisticated recurrent neural architecture, usually referred to as Elman Recurrent Network (Elman, 1990). Another aim of this study was to set up and compare two systems (a recursive neural network and a multiple linear regression model (MLR)), both using meteorological data to simulate air quality and predict critical pollution events. The prediction capabilities of the PM concentrations from one to three days ahead of the recursive neural network, the non-recursive neural network model and of the multiple linear regression model, were compared. A further application was to compare the ability of the three models to predict the PM concentrations one to three days ahead adding the CO concentration as an inputs parameter, since it is a short-term proxy of anthropogenic emissions. Finally, the ability of all models to forecast the PM2.5 concentrations, using PM10 concentrations as input parameter, has been tested.

2. Site and observations

The study area is a flat strip along the Adriatic coast; in particular, the observation site is in a small park in the south part of the urban area of Pescara, beside the sea at about 20 m from the coast (Fig. 1). Pescara (42.27° N, 14.15° E; at sea level, located at the estuary of the Aterno-Pescara river) is the major city of the Abruzzo region with about 120,000 residents, and 400,000 within the surrounding metropolitan area. Pescara has an international airport (the Abruzzo airport) within the urban area and one of the busiest ports of the Adriatic Sea. The Pescara valley is the most important industrial area of the region. The Abruzzo region is characterized by mountains (the Gran Sasso chain and the Maiella Mountain with peaks up to 2900 m a.s.l.) which range parallel to the coast line, hence, it is subject to local and regional meteorological processes such as mountain and sea breezes, and convective processes (Cristofanelli et al., 2013).

Continuous measurements, carried out by the Regional Agency for the Ambient Protection (ARTA), from 2011 to 2013 include temperature, relative humidity, wind speed/direction pressure, PM10, CO, ozone (O_3), nitrogen oxide (NO), NO_2, sulfur dioxide (SO_2), benzene, toluene, mxylene, 1,3butadiene, whereas continuous measurements of PM2.5 started on 1st February 2013. In Fig. 2 the time series of the observed atmospheric parameters are reported. The site is characterized by high humidity all the year, warm summer with temperature up to 30 °C, and mild winter, typical of the Mediterranean area. PM10 shows the usual annual cycle with high concentrations during winter due to lower planetary boundary layer height, and lower concentration during summer. Similar behaviour are evident in the CO and PM2.5 concentrations (Fig. 2). Another peculiarity of the site is the strong correlation between the concentrations of PM10 and CO suggesting a common sources for these compounds (see middle panel of Fig. 2). A detailed description of the measurement site and the analysis of meteorological observations can be found in Biancofiore et al. (2015).

3. Models

Multiple linear regression (MLR) is one of the statistical techniques used in several research applications, it can be applied to analyse the relationship among various variables and predict the outcome of a response variable. Multiple linear regression is used when the number of independent variables is greater than one. The model for MLR, given *i* observations, is:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik} + \varepsilon_i \tag{R1}$$

where, for a set of *i* observations, Yi is the predictand variable calculated by a linear combination of a coefficient β_0, a set of independent variables X (the predictors), coupled with the relative coefficient β_k, and a residual error ε. The objective of the MLR model is to use a group of variables to find a mathematical relationship between them. To exclude redundant variable, those that have a strong co-linearity relationship, we use a stepwise technique, see

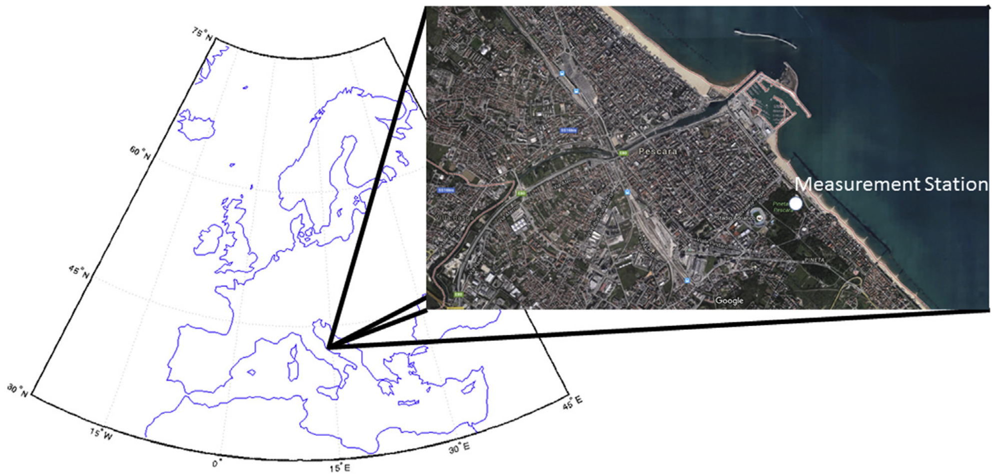

Fig. 1. Map of downtown Pescara (42.27° N, 14.15° E; at sea level) in central Italy. The measurement site is a station of the ARTA (Regional agency for the environmental protection), located in an urban park in front of the Adriatic Sea.

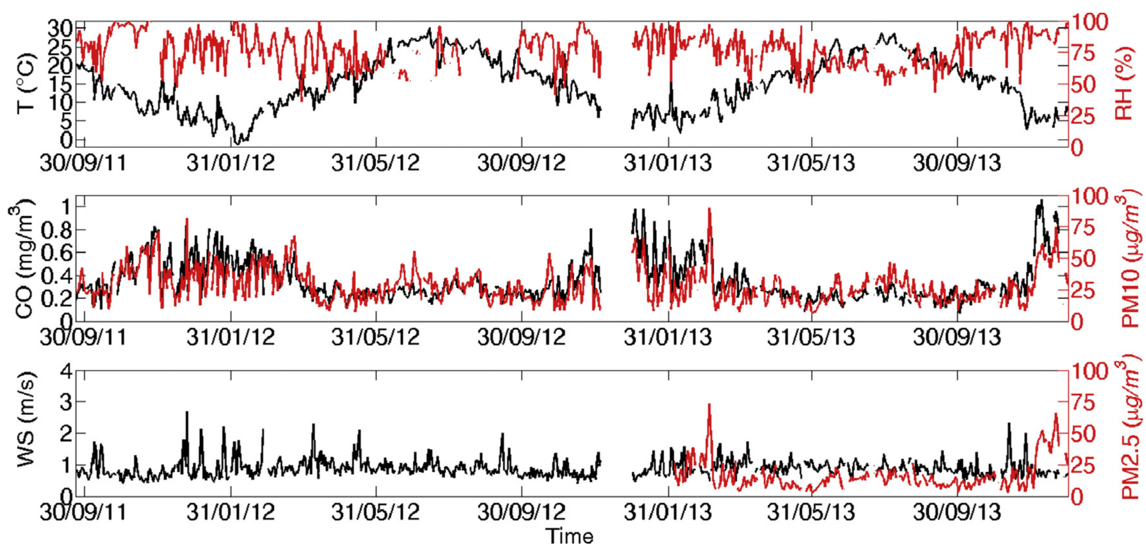

Fig. 2. Time series of temperature, relative humidity, CO, PM10, PM2.5 and wind velocity measured in Pescara (Italy).

Di Carlo et al. (2007) for details on this method.

ANN are mathematical models based on neurons connected or functionally-related to each other, imitating the behaviour of the human biological neurons (Vemuri, 1998, Braspenning et al., 1995). For practical purposes the neural architecture is usually built arranging the neurons within several layers, all neurons in a layer are connected to all neurons in the adjacent layers through synaptic weights which act as signal multipliers on the corresponding interconnections (Comrie, 1997; Gardner and Dorling, 1998). This kind of architecture is usually called feed-forward network (FF-NN) because the input signal is processed in several steps (layers) in one direction: the first layer is activated by the input variables and the signal is then transmitted to the second layer where this signal is elaborated; the status of activation of the second layer is then transmitted to the third layer and so on. In a recurrent neural architecture (RC-NN) few neurons of the input layer are set with the status of activation of the nodes in the intermediate layers. In other words, the processed signal is back-propagated to the input level. A schematic view of the recurrent neural device used in this work is shown in Fig. 3; the neurons are arranged in three layers: the first

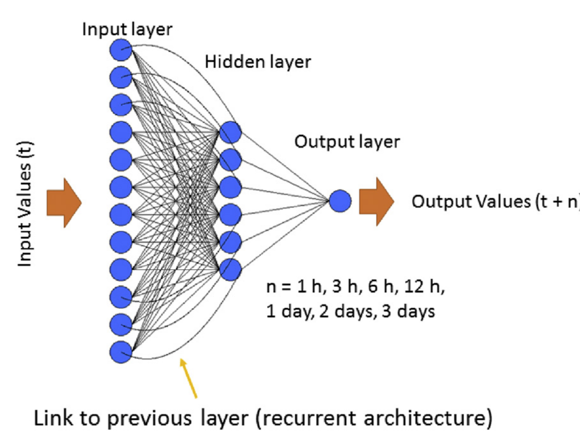

Fig. 3. Artificial neural network scheme with the recurrent architecture.

one is called input layer and is set with the predictors, while the neuron in the last layer provides the predicted quantity. In addition, the status of the neurons in the intermediate layer is backpropagated toward the input layer. In fact, the neurons in the second layer contain compressed information of the meteorological and chemical parameters at the previous time step, therefore the architecture shown in Fig. 3 implements a sort of dynamic memory of the events provided as inputs of the network (Elman, 1990).

The synaptic weights that connect the neurons, are quantified through the calibration, usually referred as the 'training' of the ANN, using the observed input/output patterns. This phase of calibration is carried out by minimizing the error function E using the steepest descent gradient backpropagation algorithm (Hecht-Nielsen, 1991; Haykin, 1998) and, at each training step, the error function E is calculated as the mean squared differences between the observed and predicted PM concentrations. In our implementation, the number of neurons in the first layer is established according to the number of input variables and the number of neurons in the second layer. The last layer contains a single neuron representing the output of the network, namely the predicted PM concentration. The number of nodes in the second layer has been chosen in order to limit the total number of weights to, at least, a few fold lower than the total number of training examples, thereby avoiding a critical problem known as overtraining of the network (Hecht-Nielsen, 1991). The limitation of the number of synaptic weights alone, may not be sufficient to avoid overfitting; in order to verify the actual generalization ability of the neural device, the training patterns are divided in two different subsets: the first subset is actually used to calibrate the network (data observed during 2011 and 2012), whereas the second one is used only to validate the results (data observed during 2013). At each training epoch, statistical errors are calculated with both subsets and the calibration process is stopped if the error evaluated with the validation subset becomes significantly different (greater of more than 1%) respect to the same parameter calculated with calibration set. For the practical implementation of our model, a modified version of the JETNET package developed by Lonbladd et al. (1992) has been used. The modification of the software was needed to include Elman's not implemented network architecture in the original package (Biancofiore et al., 2015).

4. Forecasting the PM10

Forecasting the PM10 levels is an important goal which may not only mean knowing in advance the potential areas and time that will be impacted by high concentrations of PM10, but also implementing action-plans to reduce the risk for the human health. Therefore, we used multiple linear regression and neural network models to forecast the PM10 concentration and compare results with the EU air quality limits (2008/50 EC).

4.1. Evaluation procedures

We evaluated the performance of the models using four indices: the correlation coefficient (R), the normalized mean squared error (NMSE), the fractional bias (FB) and the factor of 2 (FA2). R is calculated by dividing the covariance of the observed and simulated data by the product of their standard deviation. This parameter quantifies the overall correlation between the simulated and measured data and can vary from −1 to 1, where −1 represents the total anticorrelation, 1 is the total correlation and 0 is the absence of correlation. NMSE is found calculating the mean of the square of the difference between the pairs of modelled and measured values, finally this value is normalized by dividing by their product. This parameter gives emphasis to the whole error of the data set. The best NMSE value that can be achieved is 0. FB is calculated subtracting from the mean of the measured data, the mean of simulated data, then dividing by their mean. This parameter varies between −2 and 2. A positive value indicates that the model underestimates the measured data, while a negative value indicates an overestimation. FA2 is the percentage of ratio between measured and simulated data that lies in the range 0.5 and 2. FA2 ranges from 0, which indicates that no ratio is in that range, to 1, which indicates that all ratio lies in this range. More details can be found in Biancofiore et al. (2015).

4.2. Results of the simulations and models performance

To study the ability of the models to forecast PM10 levels, the data collected from 2011 to 2012 are used for the training of the model, whereas data measured during 2013 to test the performance of the following models: a) an artificial neural network that uses the Elman recurrent architecture; b) a neural network without the recurrent architecture and c) a multiple linear regression model. All models were used to forecast the PM10 concentration 1, 2 and 3 days ahead. In these simulations were used, as inputs, daily values of measured temperature, pressure, humidity, wind speed and direction and PM10 concentration at time t and, as output, the PM10 concentration at time $t + \Delta t$, where Δt were 1, 2 or 3 days. The variables used for the forecast were chosen taking into account the following factors: 1) the nature of the problem to be studied, 2) data availability, 3) results of previous work and 4) the output of the multiple linear regression model to exclude redundant variables. Afterwards the daily values of CO concentration at time t were added to the inputs parameters and the simulations were repeated using all models, to verify the role of this compound as PM proxy. Even if other compounds were measured, such as O_3, NO, NO_2, SO_2, benzene, toluene, mxylene, 1,3butadiene, we report here only the results including CO because in preliminary tests were funded that only the inclusion of CO as further input in the model, improves the forecast skill of the model. Table 1 shows the results of the simulations. In all simulations, the indices suggest that the ANNE performances overcome both those of the ANNF and of the MLR model. Using only meteorological inputs the neural network shows better performances respect to the MLR model, in all the three forecasts, 1, 2 and 3 days ahead. As expected, it is also shown that the performances of both model decrease moving away from the day when the data are taken. Fig. 4 compare the results of MLR, ANNF and ANNE, to forecast PM10 one day ahead, using as inputs parameters daily values of measured temperature, pressure, humidity, wind

Table 1
Summary of the performance of the three models (ANNE, ANNF and MLR) in forecasting PM10 concentration using different parameterization. R is the correlation coefficients, FB is the fractional bias, NMSE is the normalized mean squared errors and FA2 is the factor of two.

Δt	Parameters	R	FB	NMSE	FA2
1	ANNE; Meteo	0.84 (0.84–0.86)	0.0002	0.0652	0.9723
1	ANNF; Meteo	0.82 (0.78–0.84)	0.0001	0.0723	0.9614
1	MLR, meteo	0.57 (0.51–0.62)	0.0100	0.1619	0.8968
2	ANNE; Meteo	0.78 (0.75–0.80)	0.0025	0.0881	0.9577
2	ANNF; Meteo	0.73 (0.73–0.69)	−0.0007	0.1044	0.9420
2	MLR, meteo	0.56 (0.51–0.61)	0.0067	0.1638	0.8955
3	ANNE; Meteo	0.70 (0.67–0.74)	0.0015	0.1123	0.9395
3	ANNF; Meteo	0.68 (0.64–0.71)	0.0013	0.1200	0.9299
3	MLR, meteo	0.52 (0.46–0.57)	0.0077	0.1725	0.8805
1	ANNE; Meteo, CO	0.85 (0.83–0.87)	0.0023	0.0624	0.9735
1	ANNF; Meteo, CO	0.83 (0.80–0.85)	0.0008	0.0700	0.9638
1	MLR, meteo, CO	0.72 (0.68–0.75)	0.0103	0.1153	0.9374
2	ANNE; Meteo, CO	0.76 (0.72–0.78)	0.0017	0.0953	0.9529
2	ANNF; Meteo, CO	0.74 (0.70–0.77)	0.0016	0.1020	0.9444
2	MLR, meteo, CO	0.62 (0.57–0.67)	0.0085	0.1464	0.9082
3	ANNE; Meteo, CO	0.73 (0.70–0.76)	0.0015	0.1039	0.9407
3	ANNF; Meteo, CO	0.70 (0.66–0.73)	0.0010	0.1145	0.9347
3	MLR, meteo, CO	0.56 (0.50–0.61)	0.0092	0.1624	0.8965

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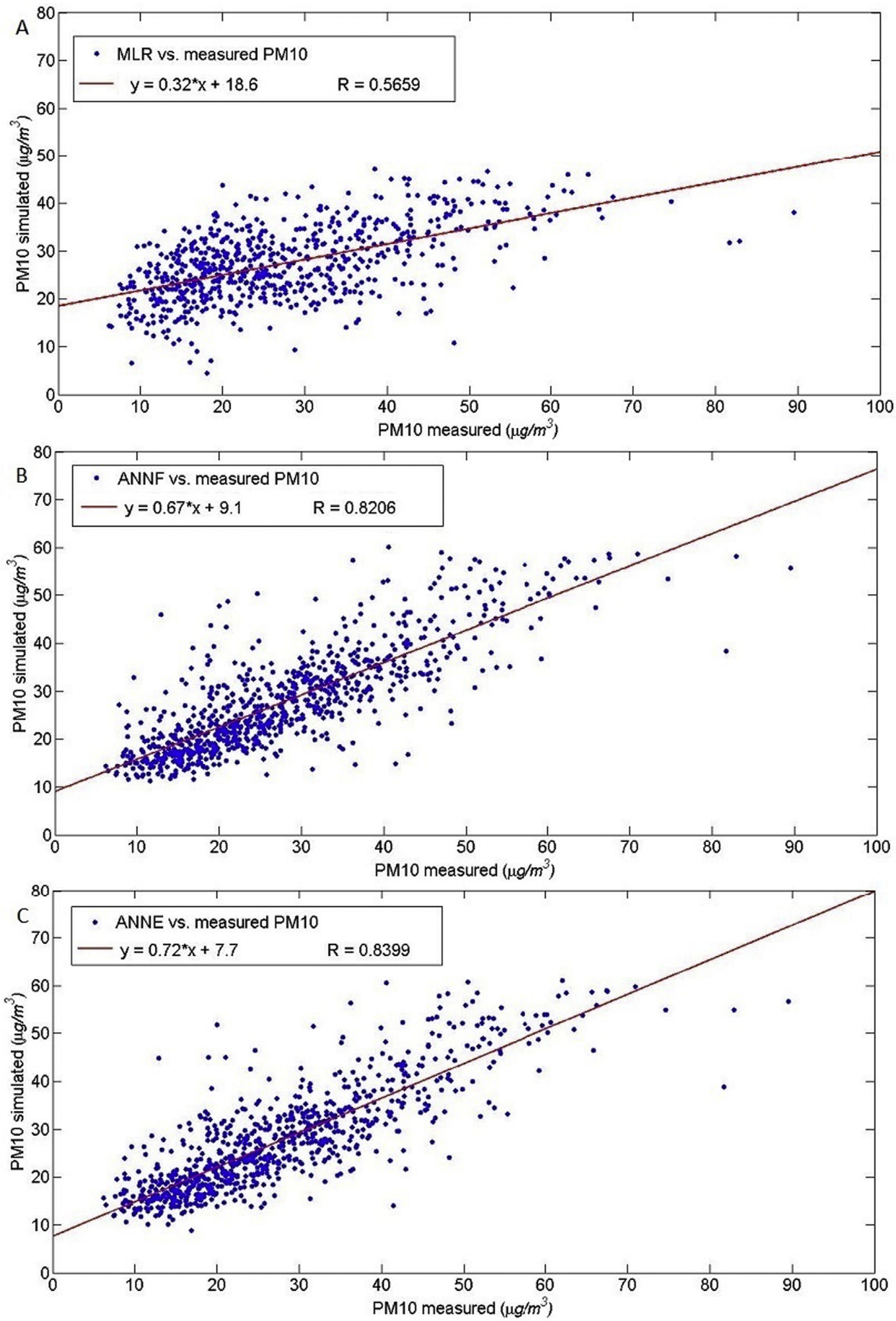

Fig. 4. Forecasted PM10, one day ahead, using the MLR (panel A), ANNF (panel B) and ANNE (panel C) versus measured PM10.

speed and direction and PM10 concentration at time *t*. From Fig. 4 it is clear that the neural network has better performance compared to the MLR, and that the Elman architecture improve the performance of the neural network.

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The strong correlation between PM10 and CO (Fig. 2) suggests to adding the CO concentration as a further input parameter. As expected, the performances of both numerical approaches significantly improve if we include the CO concentration in the input patterns. Comparing the results of neural network and multiple linear regression with and without the CO concentration, it is evident that the multiple linear regression model has a major benefit respect to the neural network, in terms of the model performances in forecasting PM10. The improvement of the models with the inclusion of CO as another input data, should be explained with the fact that it is a good short-term indicator of anthropogenic emissions, and the sources may be common for PM10 and CO. The result that the major improvement including CO as additional input, is observed for the MLR model is a further evidence that ANNE model is more robust of MLR, not only in terms of performance, but also because it is less dependent on the input parameters.

4.3. Comparison of the results with EU legislation

The results of the forecast 1 day ahead, obtained using the ANNE with the CO concentration among the input parameters, have been compared with the air quality limits for health protection. In the European Union, the threshold for the daily average of the PM10 is fixed at 50 μg/m^3. The tests are carried out in order to study the ability of the model to forecast the exceedance of the threshold fixed by the 2008/50/EC directive, since that point action is mandatory. Results of these tests are summarized in a contingency table (Table 2), where the three years of observations are reported dividing the daily average of PM10 in two classes: 1) observations and forecast below the EU threshold (<50 μg/m^3) and 2) those above this EU limit (>=50 μg/m3). The column (<50 μg/m^3) of Table 2 reports the number of days forecasted with PM10 < 50 μg/m^3, when also observations were below this limit (first row) and when the observations were above this limit (second row). The column (>=50 μg/m^3) of Table 2 shows number of days forecasted with PM10 concentration >=50 μg/m^3, when also the observations were >=50 μg/m^3 (second row), whereas the first row reports the number of days when the measurements were observed to be <50 μg/m^3. The column %O shows the percentage of observed days by classes that were forecasted to be in that class. In our case we have that 98% of the days with PM10 concentration below 50 μg/m^3 are forecasted correctly, by the model, whereas 57% of the day with PM10 concentration higher than 50 μg/m^3 are forecasted correctly. The %P row of Table 2, reports the percentage of forecast days by classes that were verified to occur. This row gives another important information about the model performance because 100−%P for the second column corresponds to percentage of false positives, therefore we have 30% of false positive. These results shows that the neural network has a good ability to foresee if the next day the PM10 will be above or below the limit: in 95% of the days considered in this study the prediction is correct (third raw of the %O column of Table 2). The cases of the days exceeding the EU limits are foreseen by the neural network in 70% of days since the false positive are, explained above, are only 30%. These results can be summarized with the fact that the neural network has excellent performances in predicting events that do not deviate too much from the mean. The performances of the neural network will

Table 2
Contingency table for the ANNE in forecasting 1 day ahead, dividing the days in two classes: PM10 less or above the EU threshold for the daily average. The column %O is the percentage of observed days by classes that were forecast to be in that class, whereas %P is the percentage of forecast days by classes that were verified to occur, see text for more details.

		Forecast			
		<50 μg/m^3	>=50 μg/m^3	Tot.	%O
Obs	<50 μg/m^3	759	14	773	98
	>=50 μg/m^3	24	32	56	57
	Tot.	783	46	829	95
	%P	97	70		

Table 3
Summary of model performance in forecasting PM2.5 concentration using different parameterizations. R is the correlation coefficients, FB is the fractional bias, NMSE is the normalized mean squared errors and FA2 is the factor of two.

Δt	Parameters	R	FB	NMSE	FA2
1	ANNE; Meteo, CO	0.89 (0.86–0.91)	0.0019	0.0559	0.9863
1	MLR, meteo, CO	0.87 (0.84–0.90)	0.0532	0.1291	0.9222
2	ANNE; Meteo, CO	0.84 (0.81–0.87)	0.0029	0.0740	0.9780
2	MLR, meteo, CO	0.79 (0.74–0.83)	−0.0464	0.2034	0.8604
3	ANNE; Meteo, CO	0.83 (0.80–0.86)	0.0007	0.0782	0.9669
3	MLR, meteo, CO	0.72 (0.66–0.77)	−0.0430	0.2505	0.8473

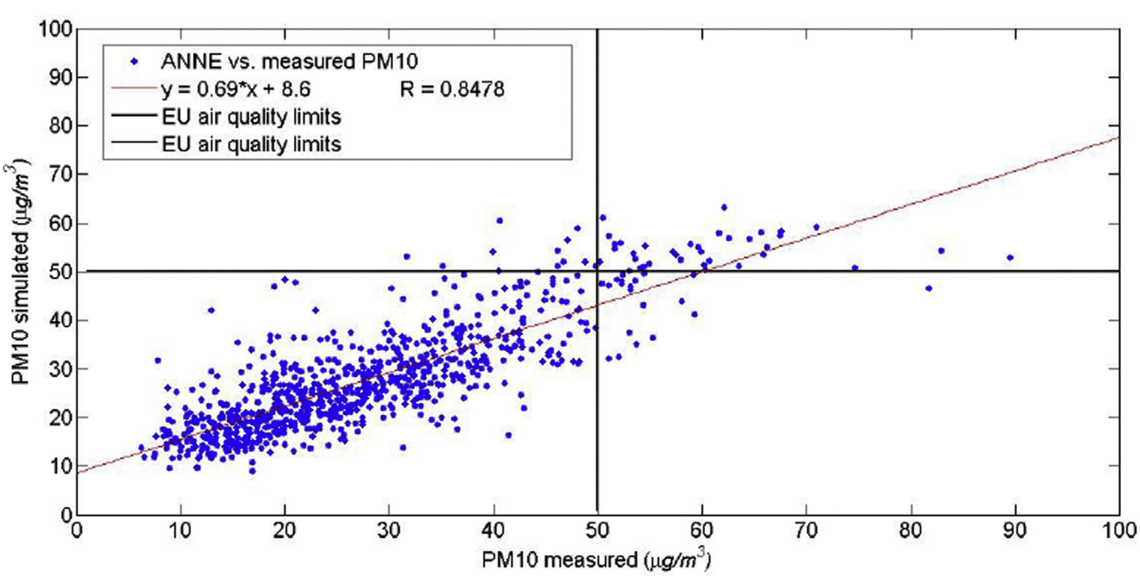

Fig. 5. Forecasted PM10 using the ANNE versus measured PM10. The black lines represents the EU air quality limits.

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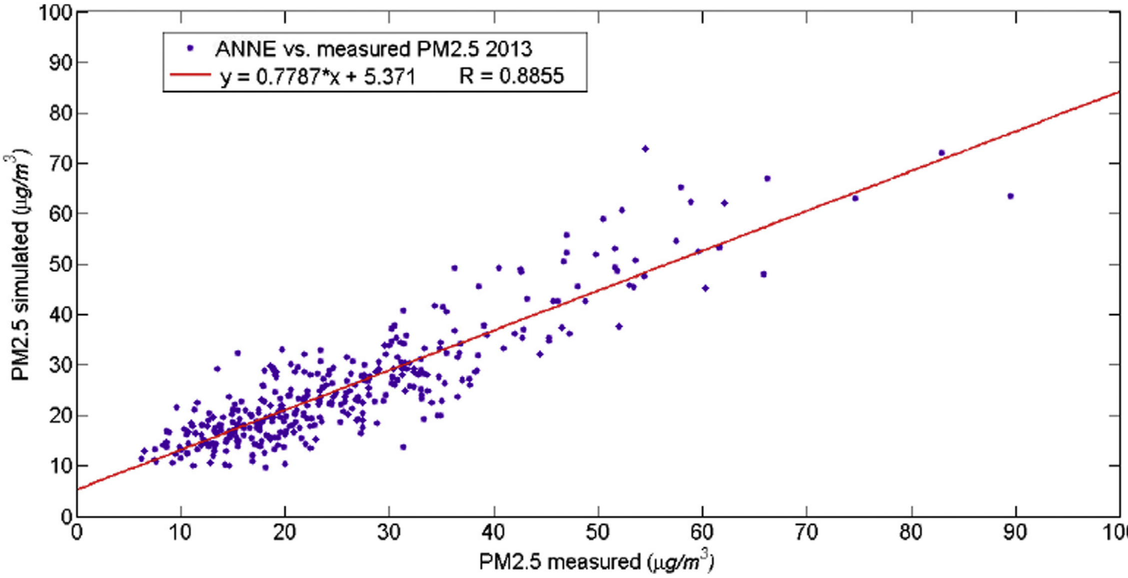

Fig. 6. Forecasted PM2.5 using the neural network model versus Measured PM2.5.

probably be better training the ANN to use a larger statistics including a larger number of high concentration events. Fig. 5 graphically shows these results. The top right quadrant represents the days when the neural network and the measurements are over the limits: in other words, the days that exceed the limits are simulated correctly by the model. The lower left quadrant represents the days in which the neural network and the measurements are under the limits: in other words, the non-exceeding days are simulated correctly by the model. The lower right quadrant represents the days in which the neural network simulations are under the limits, whereas the measurements are over the limits: this indicates the days exceeding the limits that the model fails to predict. Finally, the top left quadrant represents the days in which the neural network simulations are over the limits, whereas the measured data are under the limits, which is the false positive of the model.

5. Forecasting the PM2.5

Since the negative impact of the PM2.5 on the human health is now well documented, in this work the fine particles concentration has been forecasted starting from the PM10 concentration, which is more frequently measured. In these simulations meteorological condition, CO concentration and PM10 concentration were used as input parameters of the ANNE to forecast 1, 2 and 3 days ahead, the PM2.5 concentration. Table 3 summarizes the results of the PM2.5 forecasting.

The table shows that, in the forecast of PM2.5 1 day ahead, the neural network with recursive structure is better than the multiple linear regression model. In detail, each index considered shows best values in case of neural network compared to the multiple linear regression model: R, NMSE, FB and FA2 are 0.8855, 0.0559, 0.0019 and 0.9863 respectively in case of neural network, and 0.8696, 0.1291, 0.0532 and 0.9222 respectively in case of MLR. Comparing these values with those obtained simulating the PM10 concentration with the neural network only in 2013, it is possible to argue that the results of the simulations are very similar: R, NMSE, FB and FA2 are 0.8904, 0.0537, 0.0025 and 0.9835, respectively. These results are summarized in Fig. 6, which shows the good correlation between measured and forecasted data. The forecast 2 or 3 days ahead shows also that the neural network has better performances respect to the MLR.

6. Conclusions

In this paper daily averaged PM10 concentration is forecasted 1, 2 and 3 days ahead using three different models: a recursive artificial neural network, a feed-forward neural network and a multiple linear regression. The comparison of the three methods shows that the recursive neural network model has better performances in all the simulations. The addition of CO concentration as further input parameter improves the performance of the MLR model, and improves slightly also the performances of the neural network models. Since CO is a proxy of short-lived anthropogenic emissions, this result suggests that in areas, like that studied here, impacted by emissions due to fossil fuel combustion, the concentration of CO is a good proxy to be used in the models to forecast PM. The results of the simulation of the recursive neural network model are compared with the EU air quality limits of PM10. The recursive neural network model forecasts correctly 95% of the days studied in this work, but this percentage decreases to 57% if we take into account only the days when the limits are exceeded. Furthermore, the percentage of false positives is 30%. These results highlight the limits of the neural network model in simulating the concentrations peaks. Finally, recursive neural network and multiple linear regression models are used to simulate PM2.5 concentration using as inputs the meteorological conditions, the CO concentration and the PM10 concentration. The results show that it is possible to predict PM2.5, in case where it is not measured at all, using PM10 concentrations, as input parameter in the model. In conclusion the recursive artificial neural network model could be a powerful operational tool to obtain real time information on PM10 and PM2.5 and support stakeholders for the development of cost-effective control strategies to alert and protect the population.

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