Urban pollution modeling
using synoptic and local scale meteorological data

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Objectives

A*ir pollution* (AP) is a complex mixture of toxic components that might have serious impacts on human health and quality of life, especially for sensitive groups [1]. Short term forecasting models emerge as an effective approach in order to identify and predict episodes of high pollution levels.

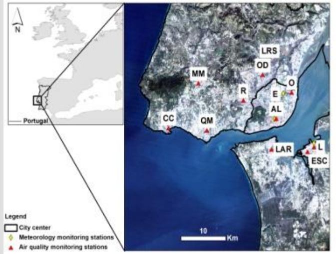

Fig. 1 Case study area and stations

This work main goal is to test the **potential predictive capability of linear and non-linear neural network models** when applied to the **concentration of PM10** measured at the urban area of **Lisbon** (Figs. 1,2), Portugal. The interaction between meteorological variables and PM10 was studied locally between 2002 and 2006.

Data

- *Daily mean NO2, NO, CO, PM10*
- *Daily maximum PM10*
- *PM10 at 00:00 UTC*
- *Daily circulation weather type (CWT)*
- *Boundary layers heights (03:00, 09:00, 21:00 UTC)*
- *Daily maximum temperature*
- *Daily mean wind direction and intensity*
- *Daily mean humidity and radiance*

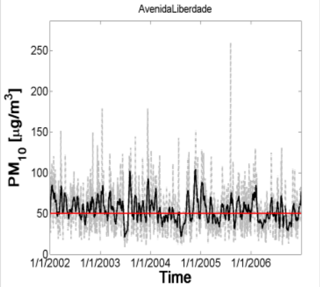

Fig. 2 Daily PM10 at Av. Liberdade

Method

1. The selection of variables was made independently for each monitoring station through a forward stepwise regression.
2. Linear (MLR) and non-linear (NN) neural networks (Fig. 3), which are mathematical models inspired by the biological nervous system [2], were applied in order to produce PM10 daily forecasts.
3. MLR models were trained with the Widrow-Hoff rule and the NN models with the Levenberg-Marquardt method. A cross-validation was applied with the available period being divided and the calibration-validation procedure was completed four times independently.
4. Two modeling approaches were tested: a) model the original PM10 concentrations (TOT); b) model the residual component after the removal of a periodic component from the original data, namely the weekly cycle (RES-7).

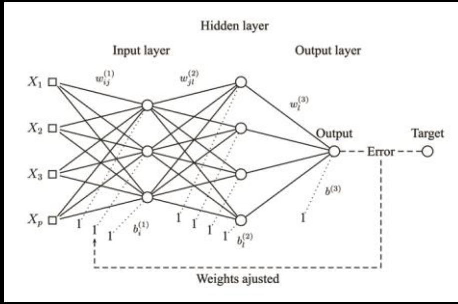

Fig. 3 Illustration of a feed-forward artificial neural network model with three layers. Input variables Xi=1,...,p can be perceived as "neurons", ω Represent the weights associated to each neuron and b are the bias vectors which combined will produce an output within certain error limits.

Results

- The most significant variables in predicting PM10 are pollutants related to road traffic emissions and meteorological variables related to atmospheric stability.
- The RES-7 approach presented the best results (Tables 1,2 and Fig. 4). Moreover, MLR and NN showed similar performances when evaluated by several performance criteria (Pearson Correlation (PC), skill against persistence (SSp), root mean square error (RMSE), false alarm rates (F and F50) and percent of correctness (PC and PC50).

	Model	PC	SSp	RMSE	F	PCS	F50	PCS50
PM_{10}	**TOT**-MLR	0.75	45.00	12.85	6	88	50	80
	RES-7-MLR	0.81	54.41	11.69	12	86	62	89
	RES-7-NN2	0.81	54.30	11.69	11	85	64	90
	RES-7-NN3	0.81	54.20	11.69	11	85	63	90

Table 1: Average performance indicators obtained for the PM10 calibration/validation process

Station	2002-2005	2006	%Δ
E	0.83	**(0.78)**	-5
O	0.79	**(0.86)**	7
AL	0.81	**(0.82)**	1
L	0.83	**(0.86)**	3
ESC	0.80	**(0.83)**	3
R	0.79	**(0.87)**	8
LAR	0.85	**(0.87)**	2
LRS	0.83	**(0.87)**	4
CC	0.75	**(0.78)**	3
QM	0.83	**(0.86)**	3
MM	0.82	**(0.86)**	4
OD	0.85	**(0.82)**	-3

Table 2: PC between observed and modelled PM10 for each station for 2002-2005 and for the independent forecast year (2006).

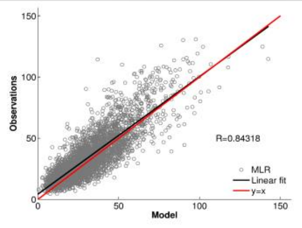

Fig. 4 Scatter plots of MLR results versus actual observed PM10 values for all monitoring stations and for the year 2006.

Conclusions

Results show that **good predictions of PM10** are possible, if the **local meteorological situation** described through the CWTs and complementary meteorological data **is taken into account**. Models achieved good predictive performance with high values of PC, SSp, PC, and a low F.

Similarly to previous studies for other pollutants, our **validation results show that linear models on average perform as well or better as non-linear models** for PM10.

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Acknowledgments

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