EVALUATION OF NEURAL NETWORK, STATISTICAL AND DETERMINISTIC MODELS AGAINST THE MEASURED CONCENTRATIONS OF NO_2, PM_{10} AND $PM_{2.5}$ IN AN URBAN AREA

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INTRODUCTION

This work is part of the EU funded project "Air Pollution Episodes: Modelling Tools for Improved Smog Management - APPETISE" that extended from 2000 to March 2002 (http://www.uea.ac.uk/env/appetise/). To our knowledge the APPETISE project has represented the first concerted attempt to undertake a model-intercomparison exercise between advanced statistical and present day deterministic air quality modelling approaches. Furthermore this intercomparison has been undertaken in a rigourous fashion and has considered a wide range of statistical performance measures (e.g., Dorling et al., 2002).

The model evaluations also include investigation of the advantages and disadvantages of models for various applications, i.e., the fitness-of-purpose of the models. Neural network, deterministic and other kinds of models commonly produce complementary results, and can therefore also be used in combination. The final aim is therefore to produce recommendations on the suitability of various models, or various classes of models, for specific applications.

This paper addresses model evaluation work that considered the hourly concentration data of NO_X, NO_2 and PM_{10}, measured at three stations in the Helsinki Metropolitan Area, from 1996 to 1999. The comparison addressed the nowcasting of air quality; the concentrations are predicted using measured or pre-processed meteorological data. We have selected the Helsinki Metropolitan Area to be the study area, mainly due to the easy availability of all necessary information.

INPUT DATA AVAILABLE FOR MODEL COMPUTATIONS

The input data includes traffic flow, air quality, meteorological and meta-data. All traffic flow, air quality and pre-processed meteorological data are presented as hourly averaged values. Directly measured synoptic meteorological data are presented as three-hourly values. The air quality stations of Vallila and Töölö are located in busy traffic environments, and the station on Runeberg Street is located in a street canyon (e.g., Karppinen et al., 2000a,b). The location of these stations in the Helsinki Metropolitan Area in 1999 is presented in Figure 1.

We used a combination of meteorological data from the stations at Helsinki-Vantaa airport (about 15 km north of Helsinki downtown) and Helsinki-Isosaari (an island about 20 km south of Helsinki). The mixing height of the atmospheric boundary layer was evaluated using the meteorological pre-processor, based on the sounding observations at Jokioinen (90 km northwest) and the routine meteorological observations.

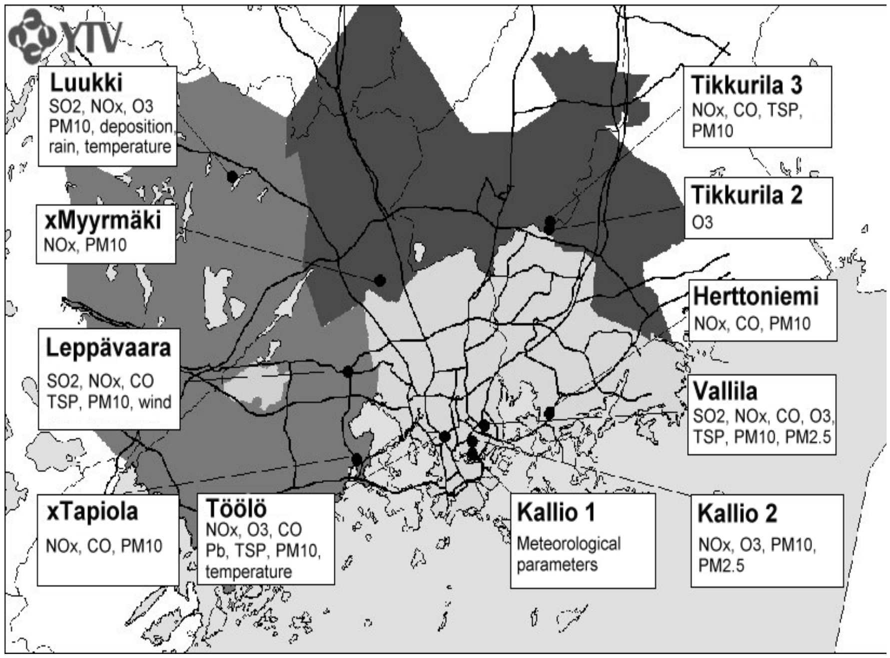

Figure 1. Location of the air quality monitoring stations in the Helsinki Metropolitan Area in 1999. The legends show the name of the station and the pollutants that are measured continuously. The figure also shows the location of an urban meteorological station (Kallio 1). The four cities in this area have been illustrated with different shades of grey. Reference: Helsinki Metropolitan Area Council.

THE MODELS

Deterministic models

The urban dispersion modelling system (UDM-FMI; Karppinen et al., 2000a,b) includes a multiple source Gaussian plume model and the meteorological pre-processor. The dispersion model is an integrated urban-scale model, taking into account all source categories. The dispersion from a road network is evaluated with the Gaussian finite-line source model CAR-FMI (Contaminants in the Air from a Road) (e.g., Kukkonen et al., 2001). The deterministic atmospheric dispersion models of FMI apply pre-processed meteorological data.

Statistical models

The feed-forward back-propagation multi-layer perceptron (MLP) is selected as the neural network architecture for the air quality modelling. The Multi-Layer Perceptron (MLP) is the most commonly used type of feed-forward neural network. Its structure consists of processing elements and connections. The processing elements, called neurones, are arranged in layers, input layer, hidden layers and output layer. An input layer serves as a buffer that distributes input signals to the next layer, which is a hidden layer.

There are six models in all, five Artificial Neural Network (NN) models and one linear model. The NN models applied are the following: NNG-L model is assuming heteroscedastic Gaussian noise, NNS-L is assuming homoscedastic Gaussian noise, NNL-L is assuming Laplacian noise, NN2-L is assuming two component mixture heteroscedastic Gaussian noise, NN3-L is assuming three component mixture heteroscedastic Gaussian noise. The LIN model is linear.

For a more detailed description of the statistical models, the reader is referred to, e.g., Gardner and Dorling (1998 and 1999) and Kolehmainen et al. (2000 and 2001).

RESULTS

Selected results have been presented in Tables 1-3. The missing data have been replaced using the so-called hybrid method, i.e., a combination of linear interpolation and SOM (Self-Organizing Map). The computations with deterministic models have utilised only the so-called raw data (i.e., the original non-imputed data), and the those with neural network models have utilised both the raw and imputed data.

CONCLUSIONS

A number of conclusions can be drawn based on the computations. The use of pre-processed meteorological data during the forecasting period substantially improves the performance of the neural network models, compared with the predictions obtained using no meteorological data (i.e., utilising a simple time series prediction based on previous concentrations). Clearly, this result is to be expected physically.

The results discussed in the following correspond to neural network applications using the pre-processed meteorological data.

The results show an improved performance for nonlinear neural network models, compared with the corresponding linear models. This result is also to be expected physically, allowing for the strongly non-linear dependencies of urban NO_2 and PM_{10} concentrations on various factors, such as the corresponding emissions and the relevant meteorological parameters. The so-called heteroscedastic neural network models perform better than both those with constant variance.

The results obtained with various non-linear neural network models by UEA and UKU show a good agreement with the measured concentration data for NO_2 at the two stations considered. For instance, the corresponding IA values range from 0.72 to 0.91 for the neural network. In the case of PM_{10}, the corresponding IA values are somewhat lower. Physically, it is to be expected that it is more difficult to predict the concentrations of PM_{10}, due to a wider variety of sources such as non-combustion traffic sources, resuspended particulate matter and urban background concentrations.

The statistical model performance parameters for NO_2 for the best of the neural models of UEA and UKU, and the deterministic modelling system of FMI are of the same order. The deterministic modelling system is expected to perform better for the prediction of the spatial concentration distributions within urban areas, compared with the neural network models. The main physical reason for this is that the location of the road and street network can be incorporated into deterministic modelling systems in a more natural manner.

In future work, predictions with deterministic models will be performed using forecasted meteorological data, i.e., air quality forecasting. The deterministic models cannot benefit in any way from previous concentration data (clearly, statistical and neural network models utilise these); these models rely only on the meteorological forecasts from NWP models.

Table 1. The statistical analysis of the predicted and measured hourly time series of NO_2 and PM_{10} concentrations at the stations of Töölö and Vallila in Helsinki, using the statistical models of University of East Anglia. Pre-processed meteorological data was applied. The models are defined in the text. Notation: "Raw" and "Imputed" refer to the original measured data and the data in which the missing values have been filled in. FB = Fractional Bias, IA = Index of Agreement, R^2 = correlation coefficient squared.

	Pollu-tant	1996			1997			1998			1999		
Model NNG-L													
Station **Töölö**		FB	IA	R2	FB	IA	R2	FB	IA	R2	FB	IA	R2
Raw	NO2	-5.6%	0.89	0.66	3.0%	0.90	0.67	-3.7%	0.91	0.69	-5.8%	0.91	0.72
	PM10	-16%	0.71	0.36	-1.5%	0.50	0.14	-11%	0.79	0.45	-2.2%	0.80	0.43
Imputed	NO2	-5.8%	0.89	0.66	4.3%	0.90	0.67	-3.4%	0.90	0.66	-6.3%	0.91	0.72
	PM10	-16%	0.73	0.39	-2.6%	0.80	0.44	-12%	0.79	0.46	-2.2%	0.76	0.38
Vallila													
Imputed	NO2	-9.1	0.87	0.61	2.8%	0.86	0.56	-1.2%	0.88	0.61	-8.3%	0.87	0.59
	PM10	-18%	0.70	0.34	-11%	0.71	0.32	6.5%	0.75	0.33	-2.8%	0.77	0.26
Model LIN													
Töölö													
Raw	NO2	-4.4%	0.78	0.41	-3.2%	0.84	0.50	-9.1%	0.84	0.53	-11%	0.81	0.47
	PM10	-14%	0.60	0.22	-14%	0.71	0.40	-13%	0.37	0.06	-11%	0.75	0.38
Imputed	NO2	-5.2%	0.78	0.41	-3.1%	0.83	0.47	-8.2%	0.84	0.52	-10%	0.82	0.48
	PM10	-15%	0.65	0.25	-14%	0.72	0.42	-15%	0.71	0.35	-9.3%	0.26	0.03
Vallila													
Imputed	NO2	-10%	0.83	0.50	-1.7%	0.80	0.43	-6.1%	0.81	0.45	2.4%	0.04	0.01
	PM10	-24%	0.64	0.28	-13%	0.66	0.27	-0.4%	0.47	0.09	-19%	0.75	0.20
Model NNL-L													
Töölö													
Raw	NO2	-3.9%	0.88	0.63	3.6%	0.89	0.64	-1.8%	0.90	0.67	-4.5%	0.90	0.68
	PM10												
Imputed	NO2	-6.6%	0.87	0.61	3.8%	0.90	0.66	-1.4%	0.90	0.66	-3.9%	0.91	0.70
	PM10												
Model NNS-L													
Töölö													
Raw	NO2	-2.4%	0.85	0.54	3.5%	0.86	0.56	-3.3%	0.87	0.59	-5.1%	0.89	0.63
	PM10												
Imputed	NO2	-5.4%	0.87	0.59	4.6%	0.85	0.52	-0.4%	0.86	0.57	-2.7%	0.87	0.59
	PM10	-18%	0.64	0.26	-1.7%	0.76	0.36	-8.7%	0.77	0.39	-1.0%	0.73	0.31
Model NN2-L													
Töölö													
Raw	NO2	-6.6%	0.89	0.66	1.7%	0.91	0.69	-3.9%	0.91	0.71	-6.6%	0.91	0.71
Model NN3-L													
Töölö													
Raw	NO2	-5.9%	0.89	0.66	2.2%	0.91	0.68	-3.2%	0.92	0.72	-7.2%	0.92	0.73

Table 2. The statistical analysis of the predicted and measured hourly time series of NO_2 concentrations at the stations of Töölö and Vallila, using the multi-layer perceptron neural network model of University of Kuopio, with pre-processed meteorological data, and imputed concentration data.

Station	1996			1997			1998			1999		
Töölö	FB	IA	R2	FB	IA	R2	FB	IA	R2	FB	IA	R2
	-12%	0.82	0.49	9.7%	0.75	0.34	1.3%	0.85	0.54	5.9%	0.80	0.43
Vallila	-8.4%	0.83	0.51	11%	0.81	0.47	-3.7%	0.82	0.46	-2.9%	0.73	0.30

Table 3. The statistical analysis of the predicted and measured hourly time series of NO_2 concentrations at the stations of Töölö and Vallila, using the deterministic modelling system of the Finnish Meteorological Institute.

	1998			1999		
Station	FB	IA	R2	FB	IA	R2
Töölö	0.6%	0.77	0.36	-4.6%	0.75	0.32
Vallila	21%	0.70	0.27	19%	0.68	0.24

ACKNOWLEDGEMENTS

This project has been funded by the European Community under the Framework V "Information Society Technology" Programme (1998-2002). We also wish to thank Helsinki Metropolitan Area Council for their help in utilisation of the air quality monitoring data.

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