COUPLING OF NEURAL NETWORK AND DISPERSION MODELS: A NOVEL METHODOLOGY FOR AIR POLLUTION MODELS

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INTRODUCTION

Air pollution models have not so far been able to reproduce the ground level concentrations because, for example, it is recognised that deterministic models many times cannot provide an adequate correlation between hourly predictions and observed data paired in time and space. A supervised Neural Net (NN) model in forecasting concentrations levels, have to take in to account the influence of the system variables, such as source emission factors, turbulence conditions, local topolography, reactions rate, by using an appropriate training on the available experimental data. The proposed approach deals with the development of an integrated model that optimises the performances of each methodology (NN and dispersion models). We have applied a Neural filter to an operative model (VHDM: Virtual Height Dispersion Model). VHDM (Tirabassi and Rizza, 1994) is used for evaluating ground level concentrations from elevated sources that applies a new Gaussian formulation, where the source height is expressed by simple functions of the vertical profiles of wind and turbulent diffusivity. The dispersion model can be applied routinely using as input simple ground level meteorological data acquired by an automatic network.

The real novelty of the methodology lies in the inclusion of the Concentration Levels Predicted by Dispersion Model (CLPDM) as input variables of the neural network (Pelliccioni and Tirabassi, 2001). In practice, the dispersion models results are filtered by the neural nets to take into account the local conditions of the pollutant dispersion, typical of the investigated site.

THE DISPERSION MODEL AND THE NEURAL NETWORK

Gaussian models, which are the best known and most widely used, are based on a solution of the two-dimensional advection equation where both the wind and exchange coefficients are assumed constant. The Gaussian model solution is forced to represent an inhomogeneous atmosphere through empirical parameters of dispersion, the so-called "sigmas". We utilized a practical model (VHDM) for evaluating ground level concentrations from elevated sources that applies a new Gaussian formulation for transport and vertical diffusion (Tirabassi and Rizza, 1994). The source height is expressed by simple functions of the vertical profiles of wind and turbulent diffusivity following the idea of Lupini and Tirabassi (1981). They shown that the ground level concentrations admit a lower and upper bound that represent solutions at the ground level of two diffusion equations of Fickian-type with the two virtual sources μ_s and ς_s respectively. In VHDM the cross-wind integrated ground level concentration is approximated by means of a Gaussian formula with a source placed at the geometric average of the two virtual source heights ς_s and μ_s.

The model accepts experimental profiles of the wind and eddy diffusivities, as well as the theoretical profiles proposed in the scientific literature, such as the vertical profiles of the wind and eddy diffusion coefficients predicted by the similarity theory.

As Neural Network architecture we used a 3-layer perceptron model (MLP) (Faussett, 1994). The first layer contains the input variables of the net, the second (the hidden layer) it is composed from a number of neurons to be determined according to the underlying model the data and the third one contains the variables to reproduce. This architecture can simulate both a dynamic evolution (temporal dependence of the data) and a spatial distribution of the variables. In our simulation the net will be used for reproducing the spatial distribution of the ground concentration levels beginning from the information on the atmospheric turbulence included in the dispersion models.

EXPERIMENTAL SETUP

We evaluated the performances of the VHDM model in the cases of a tall emission source, using the Kincaid data set experiment. The Kincaid field campaign (Bowne and Londergan, 1981) concerns an eleveted buoyant release in a flat farmland (Illinois, USA) with some lakes. During the experiment, SF_6 was released from 187 tall stacks and recorded on a network consisting of roughly 200 samplers positioned in arcs from 0.5 to 50 km downwind of the source. The data set includes the meteorological parameters as friction velocity, Obukhov-Monin length and height of boundary layer. The measured concentration patter is frequently irregular, with high and low concentrations occurring intermittently along same arc, moreover there are frequent gaps in the monitoring arcs. For the above reasons a variable has been assigned as a quality factor in order to indicate the degree of readability for the arcwise maximum (Olesen, 1995). The quality indicator (from 0 to 3) has been assigned. Here, only the data with quality factor 3 were considered.

The perceptron model used for the two simulations is made up of a 3-layer architecture with 7 neurons in the input layer, 8,10 and 12 in the hidden layer and one output neuron (containing the concentration levels to be reproduced). Different values of hidden layers neurons were chosen to optimize the NN performances. The first input layer contains the input variables of the net, in our case atmospheric turbulence through the friction velocity, the Monin-Obukhov length, temperature and wind speed near the ground, the mixing height, the distance of the monitors from the source and the concentration levels predicted by the VHDM model related to the CLPDM. In fact the above parameters identify various turbulent regimes and different transport-diffusion scenarios where the air pollution model could present different behaviour and so results matching the measured data with different realist ways.

We have used 300 selected patterns as input to MLP, representative of more reliable measurements (quality indicator equal to 3).

RESULTS AND DISCUSSION

To determine the best choice of the parameters, during the phase of training, we have calculated the sensibility of the Neural Network varying both the number of the neurons of the hidden layer and the rates (in percentage) of the input patterns. The results are outlined in the Table 1 and in the Figure 1 where the correlation between observed and predicted concentration levels are given. It is evident as the correlation coefficient increase as soon as it grows the percentage of the data used during the phase of training and that a plateau is observed around R=0.7 considering since 40% to the 80% of the data.

It is worth to notice that, for the considered dataset, the correlation coefficient is of R=0.286 using only the model VHDM, always however smaller of the results using the coupling of NNs and the dispersion model. To appreciate the capabilities of the proposed methodology, some simulations are performed using the NN alone without the value of concentration coming from the dispersion model (Table 2) employing 12 neurons in the hidden layer.

The results show that the best performance in absolute it is verified applying the neuronal filter to the dispersion model, using 12 neurons hidden to the 100% of the dataset (R=0.915).

In Figure 2 are presented the predicted and measured concentrations using the VHDM model alone, while in Figure 3 results applying the neural net to the model results are shown. It is evident from analysing the two figures the great improvement in the results due to the neural net (R_{VHDM}=0.286 – $R_{VHDM+NN}$=0.915). Moreover, NN is able to reduce the systematic overestimate of concentration values by VHDM.

Table 1. Correlation coefficient for different choice of hidden neurons and percent of input pattern.

Hidden Neurons	Percent of data training (%)	Correlation Coefficient (R)
8nn	20	0.603
8nn	40	0.648
8nn	60	0.747
8nn	80	0.710
8nn	100	0.886
10nn	20	0.592
10nn	40	0.721
10nn	60	0.739
10nn	80	0.728
10nn	100	0.880
12nn	20	0.605
12nn	40	0.674
12nn	60	0.699
12nn	80	0.725
12nn	**100**	**0.915**

Table 2. Correlation coefficient concerning a direct simulation (without CLPDM) of the concentration data.

Hidden Neurons	Percent of data training (%)	Correlation Coefficient (R)
12nn	100	**0.868**
12nn	80	0.666
12nn	60	0.710
12nn	40	0.680
12nn	20	0.619

CONCLUSIONS

We have applied the neural filter to an operative dispersion model (VHDM: Virtual Height Dispersion Model). The proposed approach relies on the development of an integrated model that optimises the performances of each methodology. In particular, we filter the concentrations evaluated by an air pollution model with a neural net so as to account for the systematic influence of important variables.

A comparison between the performances of the dispersion model alone and with its results filtered by the neural nets (the new proposed methodology) was executed. As can be seen from the correlation coefficient values, the evaluation of the concentration levels shows a marked improvement when the neural network is added downstream to the dispersion model.

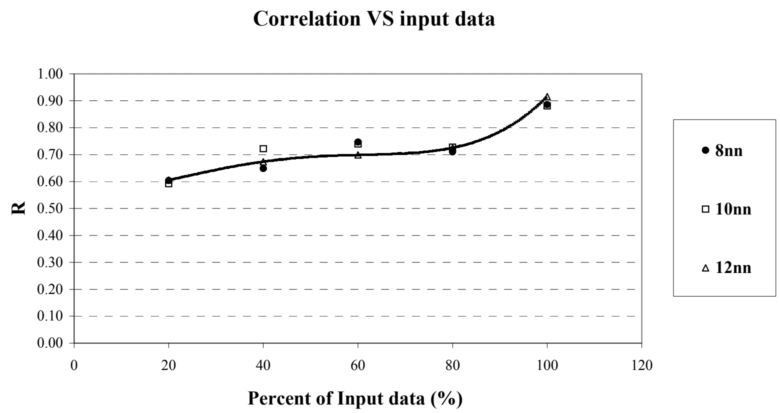

Figure 1. Correlation coefficient of VHDM+NN versus different percentage of input data.

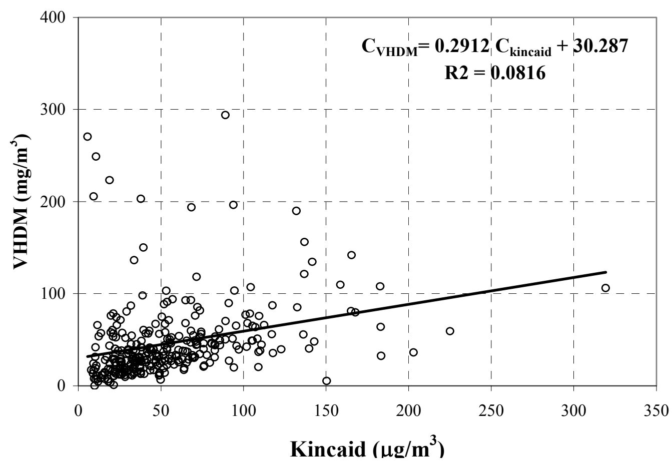

Figure 2. Predicted and measured concentrations using the VHDM.

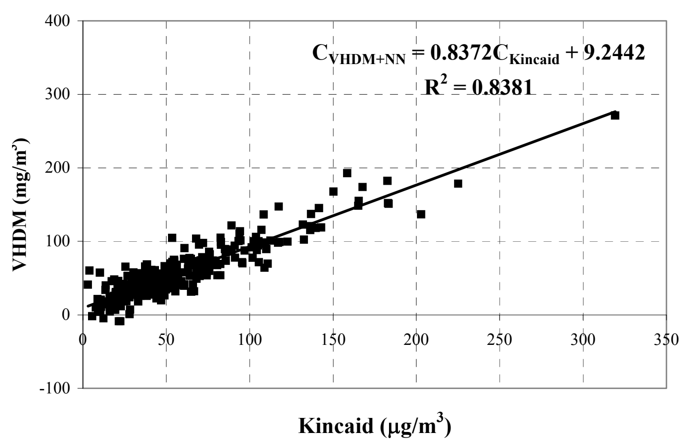

Figure 3. Predicted and measured concentrations using the VHDM+NN.

The Kincaid data set was used to evaluate the performances of the coupled models. This data set is widely used (so it is possible in a easy way to compare our results with results of other models) and it represents actual dispersion scenarios showing all the difficulties of models in representing the dispersion of material in the atmosphere in a realistic way. The presented methodology obtains better results than that obtained by other air pollution models with the Kincaid data set (see Olesen, 1995).

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