APPLICATION OF A NEURAL NET- AIR DISPERSION MODELLING ON THE INDIANAPOLIS URBAN DATA SET

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ABSTRACT
In this work is presented the development of an integrated model composed by a Neural Net and a dispersion model. Using the concentrations predicted by an air dispersion model (ADMD) as input to a Neural net, we evaluated the performances of this new methodology in the cases of a releases from an elevated emission source using the urban data set of the Indianapolis field study as test case.

INTRODUCTION
The air pollution models constitute a sophisticated tools that reflects the knowledge on turbulent transport in the atmosphere. However, this models have not so far been able to reproduce satisfactorily ground level concentrations because the influence of important variables is not perfectly described. The results they provide are affected by a considerable margin of error, the most important of which is the uncertainty linked to the intrinsic variability of the atmosphere and to local topography.
Most operative models for estimating the dispersion of gases and particles in the atmospheric boundary layer are based on the Gaussian approach. Such models cannot properly simulate complex non homogeneous conditions in a three-dimensional and K-models are widely used in the field of air pollution studies.
In reference to the prediction of complex systems it is well known that neural networks can work as universal approximators of non-linear functions and, consequently, can be used in assessing the dynamics of such systems (to take account of the available experimental data). Usually, they have become a useful tool either where no precise phenomenological model is available or when uncertainty in input and output signals complicates the application of deterministic modelling as, for example, in environmental systems.
The NN applications in atmospheric systems have been used for short term forecasting since the early nineties (*Boznar* et al., 1993), when a model was constructed to predict atmospheric sulphur dioxide in a polluted industrialized area of Slovenia. Other works have reported the use of NN for forecasting daily maximum ozone levels as *Comrie* (1997) in various urban areas, using average daily meteorological data as input parameters. A critical review of the NN applications in atmospheric science has been attempted by *Gardner et al.* (1998) whose comparison among models turns out to be rather unbalanced, since each model was trained with different kinds of data.
The proposed approach relies on the development of an integrated model that optimises the performances of each methodology (air dispersion models and NN).
The concentrations evaluated by an air pollution model are coupled with a Neural Net (NN), so as to adjust the influence of important variables on dispersion models (which may produce systematic under- or over-prediction of measured concentrations) and, contemporaneously, to minimize the input neural net parameters. In particular, an optimised 3-Layer Perception with error-backpropagation learning rules is used to filter the air pollution concentrations evaluated using an operative analytical non-Gaussian model (ADMD) that takes account of the vertical profiles of wind, of the turbulent diffusivity. We evaluated the performances of this methodologies in the cases of a releases form an elevated emission source using the urban data set of the Indianapolis field study.

METHODOLOGY

General characteristics of the ADMD model

ADMD is an operational model that allows to study the transport and the turbulent diffusion of pollutants in atmosphere on it local scale and under steady conditions. The modelling approach is based on k-theory and using advanced operative boundary layer parameterization and is based on a non-Gaussian analytical solution of advection diffusion equation (*Lin and Hildemann;* 1997). This solution is an extension of the solution obtained by *Yeh and Huang* (1975) and *Berlyand* (1975) for the transport and the vertical diffusion and for the Gaussian solution for the horizontal diffusion. Particularly, the adopted solutions accept wind and turbulent diffusion coefficients profiles that vary with power laws of height, so it is necessary to introduce a parameterization by approximating actual profiles by least square method with power laws. The model can simulate different scheme of multiple sources with meteorological conditions that vary in the time at every step each of them is treated as steady.

Brief discussion on Artificial Neural (ANN) net model

An ANN is a set of interconnected neurons that is fully described by the number of neurons, the interconnection architecture, the interconnection weights, and the activation and the transfer functions. One particular ANN architecture, especially adapted for forecasting tasks, is known as the multilayer perceptron (MLP) with an error-backpropagation supervised learning rule (*Rojas,* 1996). This net architecture is able to reproduce non linear models, by means of an accurate choice of the variables of the system and of the meaningful patterns.
The ANN learning, basically consists of adjusting weights in order to accomplish a given task.
Typical types of learning is supervised learning, that deals with the adaptation of weights in order to minimise some energy or error function, usually related to a distance between the ANN output and some target examples.
A learning algorithm is a method by which a network of computing units self-organizes to reproduce the desired model. This is done in learning algorithms by providing some examples of the desired input-output mapping to the network. The main correction step is performed iteratively until the network learns to produce the desired response.
In order to assure that the ANN has learned the underlying information that relates input to output data well, it is necessary to split the available data into a learning set (Train) and a test set (Test). The learning set comprises the samples for training the ANN. The test set picks up the error function as the optimisation algorithm proceeds. As architecture we used a 3-layer perceptron model. The first input layer contains the input variables of the net linked with all relevant parameters. The second layer consists of the neurons of the hidden layer. The third layer is the output layer, which consists of the target of the forecasting model.
The novelty of the proposed methodology lies in the choice of the input variables: in fact, the inclusion of the predicted model concentrations as input values of the network means that it must perform a twofold task. The first of these is to start from a situation close to like that predicted by a dispersion model which already include emission and turbulence factors. The second is linked to the fact that models perform well under certain hypotheses, while tending systematically to differentiate in performance when reality falls short of the ideal situations. In this case, the NN functions as a filter of the model, correcting it so that it can give the best reproduction of the real situation.
In the simulation using ADMD we have adopted 4 variables as input to the MLP: the mixing height, the Monin-Obukhov Length, the downwind distance Source-Receptor and the, most important, the Concentration Levels Predicted by ADMD dispersion model (C_{ADMD}). In the simulation, the perceptron model is made up of a 3-layer architecture with 4 neurons in the

input layer, 8 in the hidden layer and one output neuron (containing the concentration levels to be reproduced).
The NN input parameters identify various turbulent regimes and different transport-diffusion scenarios where the air pollution model could present different behaviors. We used 371 selected patterns, each determined by the four input variables at some downwind distance and turbulence condition, as input to MLP, representative of more reliable measurements.

Validation of ADMD with the Indianapolis data set

The model ADMD has been validate through the results of the experiments conducted in urban area to Indianapolis (Indiana, USA) in the months of September and October 1985. During these experiments a SF6 tracer has been released at the height of 83.8 meters from a source, situated inside the urban area of Indianapolis. The concentrations have been monitoring by ground stations, from a system of 160 receptors situated on arcs to 12 different distances from the source: 0.25, 0.5, 0.75, 1, 1.5, 2, 3, 4, 6, 8, 10 and 12 Km.
The roughness has been valued 1 m. The concentration measurements have been integrated in the cross wind direction.
The table 1 shows the results coming from comparison of the concentrations observed and those calculated by ADMD respectively considering all the stability cases and using the statistical indices described by *Hanna* (1989).

Table.1. Statistical indices related to application of ADMD

	NMSE	**FA2**	**R**	**FB**
ADMD	1.26	0.52	0.33	0.52

By the examination of the statistic indexes, it is evident that the model ADMD presents poor performances in simulating releases of pollutant in an urban area to Indianapolis.

RESULTS AND DISCUSSION

To perform the net training we have been drawn out in random way the 50% of the data during the training phase and the other 50% has been used for the generalization.
Results indicates a improving of all the main statistical indices (Table 2).

Table.2. Statistical indices related to application integrated model (ADMD+NN) for train and test phase.

	NMSE	**FA2**	**R**	**FB**
ADMD+NN(Train)	0.47	0.61	0.88	-0.52
ADMD+NN(Test)	0.38	0.68	0.77	-0.41

During the training a good correlation coefficient was obtained (R=0.88), while the data for the generalization (that are independent and different from those used for the training) give R=0.77. The FB indicates a low overestimate (FB=-0.41) of pollutant when we used the NN upstream to the dispersion model.
So the neural net adequately reproduces the pollutant levels, despite the system can be considered as complex scheme. Besides, to appraise if the input variable C_{ADMD} was discriminating, we have run the same net without the concentration derived by the dispersion model (C_{ADMD}) and we get as correlation during the generalization R=0.68 (to compare with R=0.77), therefore the choice of C_{ADMD} is discriminating for the quality of the net.
As it regards the features related to the atmospheric dispersion, it is recognized that: the concentration have to decrease with the distance; have to reproduce for the pollution levels the same tendency with the atmospheric stability classes (the pollution decreases from

unstable to stable); the distance of the maximum concentrations increases with the stability classes (From A to F) when we applied the Gaussian models.
In order to verify the above features we run again a new simulation with the selected ADMD+NN model. We have considered as NN input, the Monin-Obukhov length, linked to the Pasquill stability classes and three values of the mixing height (Zi=400m-1000m-2000m). As Gaussian models, we use a models different from ADMD (ISCST).
For both, we have calculated the maximum pollutant levels (C_{MAX}) and the related maximum distance from the emission (D_{MAX}). The results for the Gaussian models are the following**:**

Table 3. Value of the maximum pollutant levels (C_{MAX}) and the maximum distance (D_{MAX}) as calculated by a short term Gaussian models (ISCST).

1/L m^{-1}	Pasquill	D_{MAX}(ISCST) (m)	R_D(ISCST)	C_{MAX}(ISCST) ($\mu g/m^3$)	R_C(ISCST)
-0.0875	A	700	1.00	2.64	1.00
-0.0389	B	1500	2.14	1.64	0.62
-0.0081	C	2900	4.14	1.29	0.49
0.0000	D	11300	16.14	0.58	0.22
0.0081	E	33000	47.14	0.21	0.08
0.0389	F	183000	261.43	0.06	0.02

The ratio distance (R_D) and concentration (R_C) are adimensional fraction between the maximum distance (D) or concentration (C) corresponding to A stability classes and all the others. As is evident for the Gaussian model, the pollution C_{MAX} decreases with the stability classes (from A to F) and the impact distance D_{MAX} quickly grows. Once fixed the neural network parameters, a simulation has been made for evaluating the calculation of the impact of the maximum concentration D_{MAX} taking as reference three levels for the mixing height (400m-1000m and 2000m). The results for the ADMD+NN model concerning the calculation of the impact of the maximum concentration D_{MAX} are shown in the table 4.
In comparison to the Gaussian dispersion model, the model ADMD+NN produces the same decrement of the pollutant relationship with the stability classes (compare R_C(ISCST) and R_C(ADMD+NN)). Further, when the mixing layer is low (400m), the concentration levels are taller, while the calculated levels when the mixing layer is taller (1000m-200m) are close to those derived from the Gaussian dispersion model.

Table 4. Value of the maximum pollutant levels (C_{MAX}) and the maximum distance (D_{MAX}) as calculated by ADMD+NN model.

Pasquill	Zi (m)	D_{MAX}(ADMD+NN) (Km)	R_D(ADMD+NN)	C_{MAX}(ADMD+NN) ($\mu g/m^3$)	R_C(ADMD+NN)
A	400	7.031	1.00	7038.1	1.00
B	400	6.24	0.89	7323.7	1.04
C	400	6.635	0.94	4244	0.60
D	400	7.031	1.00	3876.6	0.55
E	400	7.031	1.00	3601.5	0.51
F	400	5.052	0.72	3360.5	0.48
A	1000	12.302	1.00	6637.4	1.00
B	1000	6.635	0.54	5999.1	0.90
C	1000	7.427	0.60	1839.3	0.28
D	1000	3.073	0.25	1587.9	0.24
E	1000	3.073	0.25	1639.2	0.25
F	1000	3.073	0.25	2062	0.31

Pasquill	Zi (m)	D_{MAX}(ADMD+NN) (Km)	R_D(ADMD+NN)	C_{MAX}(ADMD+NN) ($\mu g/m^3$)	R_C(ADMD+NN)
A	2000	4.656	1.00	5713.4	1.00
B	2000	5.052	1.09	5166.1	0.90
C	2000	2.281	0.49	1098.9	0.19
D	2000	1.517	0.33	1009.4	0.18
E	2000	1.517	0.33	1058.4	0.19
F	2000	2.001	0.43	1468	0.26

The results obtained for the D_{MAX} with ADMD+NN model is very interesting (see R_D(ADMD+NN)). We find that the maximum distance simulated by the NN decreasing with the atmospheric stability (from A to F), in contrast with the behaviour of Gaussian model (see R_C(ISCST)). Could be this the main reason of bath performances of Gaussian models in this urban case.

CONCLUSIONS

The results show good performances of this methodology when applied to the urban Indianapolis dataset. Further, results indicates a net improving of all the main statistical index, decreasing the error between the calculated values and the measured ones and we reproduce the same decrement, predicted by Gaussian models, of the pollutant ratio R_C with the stability classes. By the ADMD+NN model, we obtained the ratio R_D a trend in contrast with the Gaussian model.

The urban situation would involve an decrease of the plume impact during stable condition in comparison to the simple Gaussian model. This could be explained with the effects due to increase of surface drag, to wake turbulence and decreases the mean wind speed.

After all, the ADMD model represents a theoretical reality (virtual) while the neural network, being trained from the reality of the data, repairs the model toward the true reality (the particular urban reality).

REFERENCES

Berlyand M.Y. (1975) Contemporary problems of atmospheric diffusion and pollution of the atmosphere. *Translated version by NERC, USEPA, Raleigh,NC, U.S.A., 1975.*

Boznar M, Lesjak M, Mlakar P., (1993). A Neural Network based method for the short-term predictions of ambient SO2 concentrations in highly polluted industrial areas of complex terrain. *Atmos. Environ.*, ***27B*** *(2), 221-230.*

Comrie R.S, (1997). Comparing neural network and regression models for ozone forecasting. *Journal of the Air and Waste Management Association* ***47***, *653-663.*

Gardner M.W, Dorling S.R., (1998). Artificial Neural Networks (the Multilayer Perceptron)-E Review of applications in the atmospheric sciences, *Atmos. Environ.*, ***32(14/15),*** *2627-2636*

Hanna, S.R., 1989. Confidence limits for air quality models, as estimated by bootstrap and jackknife resampling methods. *Atmospheric Environment* ***23***, *1385-1395.*

Lin J.S. and Hildemann L.M. (1997), A generalised mathematical scheme to analytically solve the atmospheric diffusion equation with dry deposition, *Atmos. Environ.* ***31***, *59-71.*

Rojas R., (1996): Neural Networks: a systematic introduction, *Springer-Verlag, Berlin Heidelberg.*

Yeh G.T. and Huang C.H (19759. Three-dimensional air pollutant modeling in the lower atmosphere. *Bound. Layer Meteor.*, ***9***, *pp. 381-390.*