NEURAL NETWORKS USED AS A CONTROL TECHNIQUE FOR DISPERSION MODELLING OVER A URBAN AREA

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ABSTRACT

The Air Quality Strategy and part IV of *The Environment Act,* within the United Kingdom, highlights the need for local authorities to undertake air quality assessments. However, many of the dispersion modelled studies undertaken for this purpose do not accurately predict short term average concentrations (i.e. one day or less) and have limited validation data for short-term averages. The inability of dispersion models to predict short term averages is generic of the typically used Gaussian dispersion model. The work presented in this paper has concentrated on investigating, developing, designing and testing an innovative method of linking dispersion modelled and monitored results using artificial neural networks. The objectives of the study were to establish the relationships between short term (1 hour) air pollution monitored data, air pollution data produced through dispersion modelling and meteorological data and to use the findings to create and validate a new intelligent 'control' model to correct errors in dispersion modelling results, such as those that occur during low wind speeds, when many Gaussian models are known to under predict. The study shows that artificial neural networks can be used to simulate the complex relationships between dispersion modelled and monitored data. The adopted method is amenable for use with many dispersion models and geographical areas. It is most suited to occasions when in-depth air pollution analysis is necessary, for short term averages, as now statutorily required in the UK and many other countries.

BACKGROUND

The European Union's (EU) Daughter Directives set limits for a variety of air pollutants, including some short term limits for 1 hour averages. Similarly, the World Health Organisation (WHO) has set limit values with averaging periods as low as 15 minutes. The United Kingdom (UK) as part of their obligation to achieve the EU air pollution limits have set similar objectives for air pollution, however, the UK has also incorporated some of the tighter WHO guidelines, including 15 minute averages. As part of the UK government's aim of achieving the UK objectives local authorities have had to undertake, under *The Air Quality Strategy* [1] and part IV of *The Environment Act* [2], air quality review and assessments. About 124 out of around 450 [3] local authorities in the UK have recently completed a review and assessment of local air quality which has culminated in the declaration of Air Quality Management Areas (AQMAs) in many areas, where air pollution objectives are likely to be exceeded. Some of these objective exceedance are related to short term objectives. Before an AQMA is declared the area of exceedance needs to be identified. With current modelling limitations for short term objectives this task, especially for short term objectives, is difficult and prone to errors.

In some cases sophisticated monitoring can be carried out to accurately measure short term air pollution concentrations, however, due to the expense of collecting short-term monitored data modelling of air pollution, typically involving gaussian dispersion models, has had to be undertaken to fill in the 'gaps'. Any modelling will always have a degree of error associated with it as it is a limited simulation of the real world and it is impossible to include all relevant variables that can affect the end results; it is an approximation that uses the most significant variables to provide an estimate. Typical ways of estimating air pollution involve the use of dispersion models, monitored data and emission inventories, as well as standard statistical techniques. However, the use of dispersion models for predicting air pollution is prone to uncertainties: emission inventory data is normally based on estimates for a source of pollution and rarely based on monitored data; dispersion models are based on a Gaussian probability function of pollution dispersion from a source to a 'receptor', using emission inventory data and meteorological data as an input; dispersion models estimate pollution at a point by summing the contribution from each source; there is no calculation made for accumulation over time e.g. from the last calculated period); and dispersion model inputs are not exact. The performance of the current methods could be substantially improved, if the conditions under which these methods did not reasonably estimate were known, and steps were taken to 'control' this under performance. However, to achieve this 'control' would require substantial, time-consuming, analysis of large amounts of data.

The basic relationships between monitored and modelled air pollution is inter-variable dependant and non-linear. Neural networks are useful in areas where there are many variables, which are inter-dependent and have non-linear relationships, they are a quick and efficient means of creating prediction models, and time can be spent analysing results rather than creating or designing the initial models. Therefore, it was considered appropriate to utilise neural networks for the prediction of air pollution. Previous studies [4] found that the variables most applicable to the relationship between dispersion modelled data and monitored data were wind speed, temperature, the past hour's monitored pollution level and the current hour's modelled pollution level. These variables have been used with the neural networks to increase the accuracy of the results from dispersion modelling.

Artificial neural networks are based on biological neural behaviour [5] and are typically used in pattern recognition and can be used for equation estimation [5, 6], where other techniques may prove unreliable or too time consuming. Neurons are used as connection points between the input and outputs. The greater the number of neurons the greater the accuracy and power of the network [5]. Each neuron is based on an equation which tends to be linear, logarithmic (natural) or tangential, though in reality anything could be used providing there is a solution. These equations have weights and bias (i.e. a multiple and an addition element) that can be changed depending on the training or learning of each neuron (memory). A general approach to neural networks, and brief review of their use in atmospheric/pollution modelling, is presented by Peace [4] and additionally by Gardner and Dorling [7], both these publications discuss how to implement a neural network and a have detailed discussion on the multiperceptron, which is typically used for air pollution.

Neural networks have previously been used in relation to air pollution modelling by typically replacing the dispersion model, while utilising monitored data for a specific pollutant only [7, 8, 9, 10, 11]. However, this requires the provision of many sites where the required monitored data is available, which is not the case for most local authorities. Many urban local authorities, within the UK, possess one site with short-term monitoring equipment, which could be used with the suggested methodology. In this study neural networks have been used in a unique way to estimate the relationships between monitored air pollution, modelled air pollution and monitored meteorological data, to produce more accurate results.

METHODOLOGY

The ISC3 dispersion model [12] has been used to produce the dispersion modelled output in conjunction with the local emissions inventory [13] and local meteorological data. Data was also collected from the local continuous air quality monitoring station data (AURN), a high accuracy chemiluminescent automatic monitoring station belonging to NETCEN's calibration club. These monitoring stations are vigorously validated and calibrated on a regular basis [14] and provide typically hourly averaged concentrations.

The dispersion modelled data and other monitored data, both air pollution and meteorological, were used in the training and simulation of the neural networks. Training and simulation were only carried out for one receptor point due to limited short term monitored data. However, from the concept point of view and the fact that many urban local authorities do not have numerous monitoring stations, the use of one monitoring station for background training data was deemed adequate. A feed-forward neural network, using three layers, is typically used for air pollution, as other work has shown this to be the optimum compromise between the time to train and the ability of the neural network to simulate data [7, 10, 15, 16, 17]. Hence, in this study the neural networks' structure were based on feed-forward networks with three layers (excluding the input layer). Trial runs found that the optimum neural network consisted of a tangential, logarithmic and linear layers (activation functions in each layer), with 12, 6 and 1 neurons respectively. Different combinations of activation functions and different numbers of neurons, for each layer, were tested. The last layer has one neuron as there is only one output from the neural network (pollutant concentration). Training was carried out by creating various sets of input and output data, with different variables and varying amounts of data (i.e. number of hours), summaries are presented in Table 1 for the two artificial neural networks (ANN) reported here. Data ranges were normalised so that the values of each variable would be within similar ranges, this allows the neural network to calculate the weights and biases without favouring one particular variable. The largest data set (in terms of number of hours) was found to train the neural networks the best, presumably because there was a significant number of different data 'scenarios' represented within this data. As the results for the training site are not necessarily representative of the whole area, the trained neural networks were then validated at other sites where they had not been trained.

TABLE 1: INPUT DATA INCLUDED

INPUT	**ANNa**	**ANNb**
$\mathrm{HOUR}_{(k)}$	Yes	Yes
$\mathrm{WIND\ SPEED}_{(k-1)}$ (*10)	Yes	Yes
$\mathrm{TEMPERATURE}_{(k-1)}$ (-273)	Yes	Yes
$\mathrm{DISPERSION\ MODEL}_{(k)}$	Yes	Yes
INCREASE IN WIND SPEED (+15)	Yes	No
4am CONCENTRATION	Yes	Yes

As carbon monoxide is cheaper to measure, due to its relative concentration (ppm rather than ppb) and associated complexity of the equipment, the validation was carried out on carbon monoxide.

Three additional sites, to the AURN station site (Site 4), were chosen at background locations. Each site was monitored for at least 5 working days (i.e. not a weekend or holiday) and the collected data used to validate the chosen neural networks. As part of aim of this study was to predict short term concentrations to a higher level of accuracy, rather than long term average values, a small sample (i.e. 5 working days) was chosen to indicate if the neural networks produce better short term averages, at sites other than the training site. The AURN site (Site 4) and Site 3 are both classed as background sites, however, both are heavily influenced by local traffic due to their locations. Sites 1 and 2 are also background sites but are further away from the main arterial routes within the study area. All sites are also influenced by localised industrial activity. Site 2 is close to the edge of the study area. The data sets for the neural networks were created as described previously, except that the neural networks were not trained further and additional receptor points were added to the dispersion model in order to generate the relevant input data to the neural networks.

RESULTS

Results are presented in Table 2. The iteration value refers to the number of iterations (training cycles) that were used to initially train the neural network.

Table 7.2 depicts the correlation between the monitored data and the neural network and dispersion modelled results. In general the neural networks have higher correlation than the dispersion modelled results. However, the neural networks at Site 2, with the exception of ANNa at 25 iterations, have a lower correlation than the dispersion modelled data. This lower correlation could possibly be due to Site 2 being close to the local authority border, where outside emission sources (that where not modelled) may have impacted. The better performing neural networks, in terms of correlation, generally have a higher correlation for a lower number of iterations, indicating that the neural networks are becoming too well trained at higher iterations and loosing their ability to generalise.

The percentage error decrease has been calculated using the following equation:

$$\text{Error decrease} = \frac{((\text{Model prediction} - \text{Monitored}) - (\text{ANN prediction} - \text{Monitored})) \times 100}{\text{Monitored}}$$

Where:

Error decrease = Percentage error decrease;
Model prediction = Dispersion modelled result (mean);
Monitored = Monitored data (mean); and
ANN prediction = Artificial neural network prediction (mean).

The percentage error decrease is in general higher, for the same number of iterations, for ANNa than for ANNb. However, for ANNb the percentage error decrease is higher for a lower number of iterations and for ANNa higher for a higher number of iterations. The percentage error decrease is highest at all sites, except Site 4, for ANNb. Therefore, it appears that ANNb is over generalising at higher iterations, but in general is better at predicting.

TABLE 7.2: RESULTS

Site	Iteration	Correlation for ANNa	Correlation for ANNb	Correlation for dispersion model	Percentage error decrease for ANNa	Percentage error decrease for ANNb
1	25	0.56	0.3	0.33	13	26
1	50	0.52	0.39	0.33	18	22
1	75	0.54	0.46	0.33	19	17
1	100	0.54	0.46	0.33	19	17
1	125	0.54	0.47	0.33	19	17
1	150	0.54	0.48	0.33	19	16
1	175	0.54	0.49	0.33	19	15
1	200	0.54	0.49	0.33	19	15

2	25	0.09	0.01	0.08	19	36
2	50	0.02	-0.06	0.08	28	28
2	75	-0.05	-0.07	0.08	34	21
2	100	-0.05	-0.07	0.08	35	2
2	125	-0.05	-0.07	0.08	35	19
2	150	-0.05	-0.07	0.08	34	18
2	175	-0.06	-0.08	0.08	35	16
2	200	-0.06	-0.08	0.08	35	16
3	25	0.1	0.12	0.06	28	54
3	50	0.04	0.11	0.06	48	45
3	75	0.01	0.09	0.06	63	35
3	100	0.01	0.08	0.06	64	35
3	125	0.01	0.08	0.06	64	33
3	150	0.01	0.08	0.06	64	3
3	175	0.01	0.08	0.06	65	28
3	200	0.01	0.08	0.06	66	27
4	25	0.42	0.59	0.01	28	56
4	50	0.4	0.52	0.01	44	42
4	75	0.33	0.43	0.01	51	33
4	100	0.33	0.43	0.01	52	33
4	125	0.33	0.41	0.01	52	31
4	150	0.33	0.4	0.01	51	28
4	175	0.33	0.38	0.01	52	26
4	200	0.32	0.37	0.01	52	25

CONCLUSION

To summarise, the neural networks appear to have higher correlations and the lowest percentage error. These two neural networks deliver an improvement in correlation and a decrease in percentage error, in relation to the error associated with dispersion model results, as demonstrated in Table 2. In Table 2 neural network b (ANNb) has an average error decrease of 27.9% and neural network a (ANNa) an average error decrease of 38.9% compared to the dispersion modelled results. However, ANNb is better at predicting if the neural networks are only trained for a few iterations.

This study demonstrates that the application of the neural networks trained on as much data as possible, out perform the dispersion model in terms of their ability to reflect hourly fluctuations and reduced error, even at sites that the neural networks have not been trained at. However, the neural networks have been trained and tested only at background locations. Further research on the utilisation of a more advanced dispersion model would possibly increase the accuracy of the neural network results and consideration of other non-background sites.

The results are promising and the methodology of combining dispersion modelled and monitored data, could be utilised in the future within local authorities to enhance dispersion model results, or even extended to link directly with emission inventories, removing the dispersion modelling process altogether. The discussed methodology could also be utilised within current dispersion models to increase the accuracy.

The methodology could also be used in conjunction with less sophisticated dispersion models, such as PAL (US EPA Point Line and Areas source dispersion model), to increase their accuracy to that approaching a more advanced and expensive dispersion model and thus decrease the cost. Once the neural network has been set-up it is fairly easy to re-train and could be trained on local data on a regular basis to provide a more up to date picture of pollution and the resulting increased accuracy. The resulting artificial neural networks could also be used within Air Quality Management Areas, linking to real-time data (the 4am value) to provide a forecast for the days pollution and hence feed into 'Action Plans' to avoid pollution scenarios.

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