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NEURAL NETWORK PREDICTION MODELS AS A TOOL FOR AIR QUALITY MANAGEMENT IN CITIES

The aim of the study was to examine the possibilities of developing a prognostic methods for the air quality management in cities. The study was focused on the development of the neural network models for predicting the classes of air quality in terms of the daily dust PM_{10} concentration. The air quality class was predicted for the following day based on average and maximal daily concentrations. The MLP and RBF models were tested and the results obtained proved to be satisfactory. In the optimal models, false prognoses (in testing series) constituted only 1.9% in the case of predicting average daily concentration and 7.4% in the case of predicting maximum daily concentration. A small prediction error confirmed that neural network models can be an effective tool for the air quality management in cities.

1. INTRODUCTION

A lower and lower air quality in large and industrial cities contributes to the exacerbation of the life quality of their inhabitants. Polluted air is one of the crucial factors increasing health risk. High concentrations of pollutants in cities may incidentally (smog) generate the situations hazardous to the health and life of their inhabitants. Industry, communication and transport (car transport in particular) as well as municipal management (heat and electricity delivery, air conditioning) are responsible for a serious deterioration in air quality [1]. A serious air pollution may be caused by certain meteorological conditions and atmospheric circulation types as well as by the features which can be attributed to cities [2], [3].

In the management of health risk, the forecasts of air quality play a vital role. Those forecasts enable us to announce the warnings and emergency states as well as to impose the necessary limits on air pollutant emissions. In the air quality forecasting, an exact value of the pollutant concentration is not always needed. In order to warn people against hazardous concentrations of air pollutants, it is sufficient to determine the ranges (classes) of the concentrations forecasted. The prediction of the air quality in cities is difficult due to

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a complex cause – various effects of pollutants and poor parametrisation of many factors and conditions. The processes of creating the fields of air pollutant concentration are influenced by the numerous and various factors and conditions. Usually, the factors necessary for creating such fields in cities are not sufficiently recognised, both for the previous and the following day. First of all, there has been unsufficient recognition of the pollutant emissions, especially in the regions with a number of stationary and movable sources of pollutant. Each source may be characterised by its individual size and changeability of air pollutant emission levels. Each source is located in different surroundings and characterised by different technical parameters of waste gas emission.

Additional difficulty in predicting the air quality in cities is deformation of meteorological fields due to the process of shaping the urban heat island and due to breeze. Moreover, it must be stressed that the processes responsible for the changes in meteorological conditions and air pollution concentration fields are dynamic, and the mutual interactions of some selected factors are complex and non-linear. Numerical and deterministic models of forecasting can be applied, provided that they are complete with various simplifications and coefficients. In spite of this, the effects obtained using those models are frequently not satisfactory.

Artificial Neural Networks (ANN) are a useful tool for description and prediction of air pollutant concentration fields in cities [4]–[9]. Because they allow the dependencies to be generalized and the impact of secondary factors to be reduced, ANN make is possible to use incomplete erroneous measurements. ANN have been applied especially in forecasting air pollution level in cities.

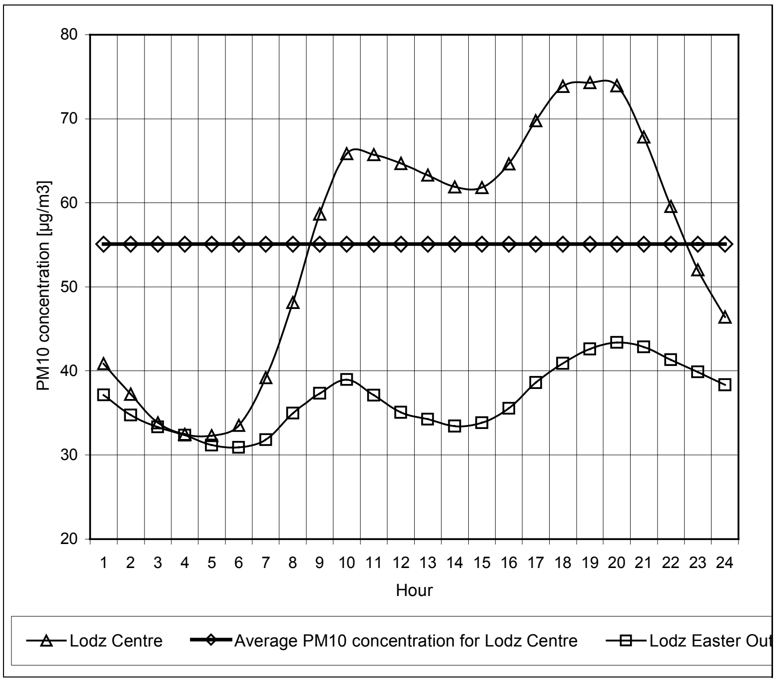
This study presents the results of the investigations aimed at improving the effectiveness of the ecological safety management in industrial cities by the development of the neural network models for predicting the air quality.

2. TERRITORY AND SCOPE OF RESEARCH

The neural prognostic models were tested in the city of Łódź (population: 800 000), the centre of Poland. Łódź agglomeration has quickly developed after 1860 and at present its population is 1 000 000. The centre of Łódź is densely covered with an interchangeable mosaic of tenement houses and factories. Because of long-lasting negligence in the development of urban infrastructure and spatial management, in the centre of Łódź (and in the centres of other agglomerations) coal heating of houses is predominant. The history of the city influences, to a large extent, the air quality, especially the pollutant emissions (localisation, parameters and the number of emission sources, the types of pollutants), and the creation of air pollutant concentration fields.

In the study, we made use of the results of the examinations performed by the Regional Inspectorate of Environmental Protection in Łódź in 2004–2007. The monitoring stations work in the system of the quality assurance. The measurements are carried out in the system of a continuous automatic monitoring. The results are averaged in one hour ranges. Such monitoring allows us to recognise the daily cycle of the air quality changes and to appoint the sub-period characterized by relatively highest air pollution. All the measurement results were verified.

In the present study, the monitoring data of air pollutant concentration represent cool season (November–March) when those concentrations and, thus, health risk are the highest. The forecasting models were tested on the dust PM_{10}. Such a choice can be explained by the fact that standard values of air quality were frequently exceeded. Generally, this phenomenon was typical of the centre of Łódź. In a highly developed centre, there are many low-energy sources of pollution and communication emission. Surpassing the quality standards is mainly due to the emission of dusts. In the city centre, a secondary dustiness, a result of a constant vehicular traffic, may be simultaneously observed. Dust emitters work under conditions of highly limited dynamics of vertical and horizontal air flow. Therefore, the data from the monitoring station located in the very centre of Łódź (Zachodnia St.) were examined. The process of air pollution and the special diversity of air pollutant concentration are determined by weather conditions. Hence, the data from the automatic monitoring of meteorological conditions in the centre of Łódź were used for the construction of an input vector.



Daily changes of average values of PM_{10} dust concentration in cool seasons in 2004–2007 (I, II, III, XI, XII) at monitoring stations in Łódź

A characteristic feature of the daily PM_{10} dust concentration in the centre of Łódź (in cool season) is the occurrence of two visible maxima: from 9.00 a.m. to 11.00 a.m. and from 5 p.m. to 8 p.m. The period with relatively high (sub-maximal) PM_{10} concentrations is long in the cool season: above 12 hours (figure).

Minimum daily concentrations, both in the centre and in the suburbs, occur from 4.00 a.m. to 6.00 a.m. The main daily amplitude of concentration values in the city centre exceeds 50 μg/m^3. In the monitoring station, located in a residential area in the eastern suburbs of the city, the daily concentration amplitude equals only 18 μg/m^3, which is determined by small values of daily maxima. The average daily amplitude of PM_{10} concentrations in the city centre is almost four times as high as that characteristic of the suburban areas of Łódź. This means that the dust of high concentration (and other air contaminants) in the centre during the day is emitted, first of all, from the low sources (energetic and communication emissions). The secondary effect is an increase in the air pollutant emission from the local sources (furnaces in houses, traffic).

3. PREDICTING MODELS

The possibility of using ANN Multi Layer Perceptron (MLP) type and Radial Basic Function (RBF) type modes was tested in order to predict the air quality. The modelling was carried out in the two separate phases. In the first one, the models of prediction were tested based on average daily values. In the second phase, the models were tested based on maximum one-hour daily concentration. Distinguishing between those phases is essential, since maximum one-hour daily concentrations are considerably higher than the average concentration from the whole period of 24 hours.

Table 1

Characteristics of input data used in air quality classification in terms of maximum PM_{10} concentration during day. The results obtained on the basis of data from winter season (I II, III, XI and XII, 2004–2007)

Parameter	Classes of PM_{10} concentration (μg/m^3)				
	I	II	III	IV	V
Range of classes (μg/m^3)	1–49	50–99	100–149	150–199	>200
Number of cases	107	232	123	46	36
Average maximum concentration during day (μg/m^3)	36.7	73.7	121.7	169.7	285.9
Average daily rainfall (mm)	2.02	0.84	0.53	0.4	0.44
Average daily radiation (W/m^2)	669	1209	1182	1092	1465
Average daily wind velocity (m/s)	4.7	3.5	2.9	2.6	2.3
Average daily vertical velocity (m/s)	0.0	–0.09	–0.11	–0.08	–0.11
Average maximum daily temperature(°C)	4.1	3.0	1.9	0.2	–0.2
Average daily minimum temperature (°C)	–0.1	–1.5	–2.6	–4.8	–7.0
Average daily atmospheric pressure (hPa)	988	989	989	990	993

Simultaneously, maximum daily concentrations are characterised by a higher dynamics with time. Therefore, the percentage of the errorneous predictions of daily concentration is relatively higher compared to the same predictions of average daily concentrations.

In the calculations, we take into account only the data from winter seasons (544 days), when the dust concentration in the air is relatively high. The input data of the model are:

the concentration of PM_{10} in the air,
maximum and minimum (extreme) daily air temperatures,
daily rainfall,
daily Sun radiation,
wind velocity,
velocity of vertical air flow, the direction of motion,
average daily atmospheric pressure.

The previous testing of neural models was used in terms of the optimisation of structures and the usability of models [10]. The optimisation means the possibility of simplifying the model by:

a) the qualitative and quantitative selection of input vector structure, including the assessment of transformation effects based on the Method Principal Component Analysis (PCA),

b) the minimisation of the model internal structure in relation to a number of layers and hidden neurons and weights (in the models of the MLP type as well as in a number of the centres in the RBF models),

c) finding the proportion of a quantity of a training group to a testing group.

Table 2

Characteristics of input data used in air quality classification in terms of average PM_{10} concentration during the day. The results obtained on the basis of data from cool seasons I, II, III, XI and XII (2004–2007)

Parameter	Classes of PM_{10} concentration (μg/m^3)				
	I	II	III	IV	V
Range of classes (μg/m^3)	1–25	25.01–50	50.01–75	75.01–100	>100
Number of cases	92	214	118	77	43
Average maximum concentration during day (μg/m^3)	19.4	38.1	60.9	85.1	145.3
Average daily rainfall (mm)	2.5	0.84	0.60	0.37	0.11
Average daily radiation (W/m^2)	617	1092	1257	1271	1491
Average daily wind velocity (m/s)	4.5	3.4	2.9	2.7	2.2
Average daily vertical velocity (m/s)	0.01	–0.1	–0.1	–0.1	–0.1
Average maximum daily temperature (°C)	4.6	3.0	2.5	0.6	–0.9
Average daily minimum temperature (°C)	0.4	–1.2	–2.3	–4.5	–7.4
Average daily atmospheric pressure (hPa)	986	990	989	991	992

Finally, a three-layer MLP model with four hidden neurons and RBF network with four centres were used. For both neural networks tested, the input vectors were as follows: the data of PM_{10} dust concentration and the values of the meteorological parameters (without transformation of the data using the PCA method).

In the construction of the model, the number of results to be achieved were the same or nearly the same as that of weights in each model and variant. This allows us to compare the results obtained using the model selected and the variants of calculations. The measurements of dust pollutant concentration were grouped into five classes, depending on the concentration value (separately for maximum and average daily concentrations). The ranges of classes were declared in accordance with the effective standards of air quality (and multiplication factor of these standards, tables 1 and 2).

The analysis of the data included in the tables confirms the effect of meteorological factors on air pollution. To each class of PM_{10} concentration it is possible to ascribe its own characteristics set of meteorological parameters. In the winter season, higher concentrations are observed in sunny days (relatively high total radiation) at higher atmospheric pressure, higher velocities of the vertical air flow (directed to the ground), lower wind velocities and lower temperatures of the air and higher daily amplitudes of the air temperature.

Relatively low values of dust PM_{10} concentrations occur in the days with dynamic advection of the air mass controlled by a low pressure system. In the days with such a type of circulation and weather, clouds and rainfall as well as strong winds occur. This cool season is characterised by relatively high temperatures with relatively low daily amplitudes of temperature. Vertical motion of the air is directed upwards. Such meteorological conditions contribute to the dispersion of air pollutants. Simultaneously, they substantially impede the development of the urban island of heat and urban breeze.

For each calculation variant, at the outlet of neural network, the air quality class prediction for $n + 1$ day (for tomorrow) was obtained (in terms of maximum or average daily concentration). For each kind of network, two variants of calculations were performed. Those variants differed in the scope of the input data in terms of a previous n day PM_{10} concentration. The analysis of auto-correlation indicated that the concentrations in $n + 1$ day depend on the values of the concentrations from n day (67% on average).

The following way of coding the air quality class modelling was assumed:

- MLP/RBM: ANN type,
- average 1: the input vector of PM_{10} concentration is daily average value for the day n,
- average 2: the input vector of PM_{10} concentration is daily average value for the day n and maximum daily one-hour average value for the day n;
- max 1: the input vector of PM_{10} concentration is maximum daily one-hour average value for the day n,
- max 2: the input vector of PM_{10} concentration is maximum daily one-hour average value for the day n and daily average value for the day n.

4. RESULTS OF MODELLING

The basic criterion of the effectiveness of the model for predicting the air class quality was the estimation of the difference in quantity of a class number between the real and predicted states. The results of forecasting the air quality class were defined in a three-stage arrangement:

- I stage – good results: the difference between a calculated class and a real class equals 0 (the forecast is in strict conformity with reality),
- II stage – acceptable results (correct): the difference between a calculated class and a real class equal +/– 1 (the forecast differs from reality by one concentration class),
- III stage – no acceptable results (erroneous): the difference between a calculated class and a real class is greater than +1 and smaller than –1 (the forecast differs from reality by more than one concentration class).

Table 3

Results of forecasting the air quality class for average daily PM_{10} concentration in Łódź during cool seasons (XI–III, 2004–2007)

Calculation case	Rate of results in test series (%)					
	Good		Acceptable		Erroneous	
	Training	Test	Training	Test	Training	Test
MLP-mean 1	61.6	58.3	37.0	38.0	1.4	3.7
MLP-mean 2	52.9	48.1	38.6	44.4	8.5	7.5
RBF-mean 1	51.3	54.6	45.5	43.5	3.2	1.9
RBF- mean 2	57.2	53.7	37.9	42.6	4.9	3.7

The results of predicting the air quality class in Łódź may be regarded as highly satisfactory. In optimally constructed models, the minimum rate of erroneous results was 1.9% in the case of average daily concentration forecasting and 7.4% in the forecast of maximum daily concentration. The average (from various models and variants) values of the rate of erroneous results of air quality class forecasting in terms of average daily PM_{10} concentration were 4.5% in the training series and 4.2% in the test series. On forecasting the classes of the air quality in terms of maximum daily PM_{10} concentrations, the average rates of erroneous results were 4.0% in the training series and 9.2% in the test series. The detailed results of neural forecasting of the air quality classes in Łódź in cool season are presented in tables 3 and 4.

The optimisation of neural networks enabled the models of sparse structure to be built. The number of the input vectors, layers, neurons, weights and centres were limited to minimum, hence the procedures of neuron networks were effective and satisfactory. This effectiveness is corroborated by minor differences between the forecast results obtained in the training and test series.

Table 4

Results of forecasting the air quality class for the daily maximum PM_{10} concentrations in Łódź during cool seasons 2004–2005

Calculation case	Rate of results in test series (%)					
	Good		Acceptable		Erroneous	
	Training	Test	Training	Test	Training	Test
MLP-max 1	61.6	58.3	35.4	31.5	3.0	10.2
MLP- max 2	59.8	55.6	37.5	37.0	2.7	7.4
RBF-max 1	56.3	57.4	39.1	32.4	4.6	10.2
RBF- max 2	54.9	56.5	39.5	34.3	5.6	9.2

5. CONCLUSIONS

In this study, the neural models for predicting the air quality classes in cities were presented. Two kinds of ANN were developed and tested, namely the MLP type and the RBF type. In constructing the neural models, the authors' experience was applied to optimise the structure of the network and input vector. The modelling results confirm the usefulness of artificial intelligence methods to asses and predict the air quality.

It has been proved that the neural models allow us to create the accurate forecast of air quality, both in terms of average daily concentrations and maximum daily concentrations (with a small number of erroneous predictions). Furthermore, they may be considered to constitute an essential element of the air quality management in cities

The effective use of neural models requires several conditions to be met. Neural models may only be used in the cities with well developed environmental monitoring. For each monitoring station the neural network training has to be conducted. In addition, the procedures of neural network architecture optimisation have to be implemented to minimise a number of the input vectors, layers, neurons, centres and weights.

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NEURONOWE MODELE PREDYKCJI JAKO NARZĘDZIA ZARZĄDZANIA JAKOŚCIĄ POWIETRZA W MIASTACH

Badano możliwości rozszerzenia prognostycznych metod zarządzania jakością powietrza w dużych miastach. Działania skoncentrowano na opracowaniu neuronowych modeli predykcji klas jakości powietrza (w odniesieniu do stężeń pyłu PM_{10}). Prognozowano klasę jakości powietrza na dzień następny w odniesieniu do średnich oraz maksymalnych stężeń dobowych. Testowano modele typu MLP oraz RBF. Uzyskane wyniki są satysfakcjonujące. W optymalnie skonstruowanych modelach odsetek prognoz błędnych (w seriach testowych) wynosił zaledwie 1,9% w przypadku prognozowania średnich stężeń dobowych oraz 7,4% w odniesieniu do dobowych prognoz stężeń maksymalnych. Niski poziom błędów predykcji potwierdza, że modele neuronowe mogą stanowić efektywny instrument zarządzania jakością powietrza w miastach.