

Used Some Modelling Applications in Air Pollution Estimates

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Received September 22, 2016; Accepted December 28, 2016

Abstract: Air Pollution is produced by airborne Sulphur dioxide (SO₂), particulate matter (PM), nitrogen oxides (NO_x) and ozone (O₃) of pollutants in the environment and defined as the level that will have a negative impact on human health. This pollution disrupts natural processes in the atmosphere and affects public health and comfort. In the developing world, industry and human population growth poses a risk in terms of environmental pollution. Therefore, it is important to estimate air pollution and measures taken in advance. Some modelling applications used for this purpose include the commonly used Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference System models. In this study; compared different modelling programs with some gases which cause air pollution were estimated. The results were compared and try to select the most suitable modelling program.

Keywords: *Air pollution, modelling, ANN, ANFIS, ATDL.*

Introduction

One of the most significant concerns of the today's world is air pollution along with water and soil pollution. When the environmental consequences of air pollution are considered, importance of it is getting increase. Human and environmental health is directly or indirectly affected from air pollutants (Boube *et al.*, 1994). So many factors lead to air pollution emissions the main ones are originating from industrial development and personal activities and classified as anthropogenic sources (Boube *et al.*, 1994; Dursun *et al.* 2015). The main source of air pollution emitted by industrial process is raw materials in manufacturing processes. For instance, dust and SO₂ emissions from mining activities, gases and impurities of coal from coking of coal dust, SO₂ and various volatile metals such as Hg, As, Pb, Cd, from metal smelting process and HCl, HF, H₂S, NO_x, NH₃, HC_s, VOC from chemical industry are the main emissions of industrial processes (Boube *et al.*, 1994). Moreover, facilities like thermal treatment plants convert energy in order to produce electricity. As a result of this procedure, huge amounts of CO₂, Nitrous and Sulphur oxides are emitted to the atmosphere. Furthermore, mobile vehicles, furnaces and stoves in homes, barbeque grills, and burning of leaves in open area that are main human activities cause emission of major air pollutants such as SO₂, NO_x and CO₂ (Boube *et al.*, 1994, Dursun *et al.* 2015).

Particulate matter, sulphur compounds, nitrogen compounds, carbon compounds, and halogen compounds are the primary air pollutants causing significant effect on human health and environment (Zannetti, 1990). Also, atmospheric chemical reactions cause the conversion of primary pollutants to secondary ones like transformation of SO₂ gas to SO₄²⁻ (Zannetti, 1990). The main effects of these compounds on the human health are the respiratory illnesses, cardiovascular system problems, reproductivity system deterioration and neurological problems (Dursun *et al.* 2015, Curtis, 2006). In addition to human health impact of air pollutants, they can give harm to environment, vegetation and animals. Especially SO₂ emissions play an important role into ecosystem change. The huge amounts of SO₂ emissions cause the depletion of ozone layer and climate change. Oxidation reaction between hydroxyl ion (OH⁻) which is produced in higher layers of the atmosphere and ozone (O₃) is used for its' formation and the other gases which have greenhouse effect is the main reason of climate change (Hussain, 2011).

Because of the negative impacts of air pollutants, it is clearly seen that their emissions to the atmosphere is very significant. In order to establish preventive precautions, establish emission control legislations, control air pollutant episodes, and assess present air pollutant sources and their responsibility in future events, the prediction of air pollutants has to be achieved (Zannetti, 1990). There are many modelling techniques used for prediction such as neural networks, fuzzy logic, genetic

algorithms (Pham, 1999). Artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS) and atmospheric turbulent diffusion laboratory (ATDL) are some of them.

ANN uses the computational features of human brain by creating interconnected units which are working in parallel structure named as neurons (Pham, 1999). There are many applications of neural networks used for problem solving in engineering point of view such as clustering, optimisation prediction, classification and pattern recognition and signal processing (Pham, 1999). Multilayer perceptron the mostly known neural network is used for applications in the field of air quality prediction according to recent researches (Dursun *et al.*, 2015). In perceptron modelling feedforward network in which inputs and outputs are connected with each other in a single line of signals is used (Pham, 1999).

Performance of fuzzy logic is certainly related to inference mechanism with cognitive uncertainty. Moreover, neural networks have many useful features like parallelism, learning, and generalization of data sets, adaptation and fault tolerance. These special features of neural networks are used to reduce uncertainties in the fuzzy logic by the incorporation between neural networks and fuzzy logic. As a result, neuro-fuzzy network, hybrid system, is produced (Dursun *et al.*, 2015; Fuller, 1995; Taylan, 2013). Adaptive neuro-fuzzy inference system (ANFIS) gives more accurate response against the approximation of highly nonlinear functions than the traditional statistical models (Dursun *et al.*, 2015; Jang *et al.*, 1997; Rawat & Burse, 2013; Moumeni *et al.*, 2013).

ATDL model is one of the well-known box models which based on the assumption of the uniform mixture of pollutants in the fixed volume of air. ATDL models are extensively used for determine the average concentrations of pollutants which do not react with each other on large areas with long averaging times. These models may work with very small amount of input data and very easy to apply (Sauter, 1976). ATDL models working principle is based on the wind speed in the selected area. Uniform wind speed is used in ATDL models in every location of grid system. Furthermore, in this model the topography of the domain is neglected while pollution concentrations are tried to estimate. For the winter months like December and January prediction of ATDL model is getting higher because the atmospheric conditions during this period of the year is more stale with respect to low wind speeds (Dib, 2011).

In this study, the performances of artificial neural networks and adaptive neuro-fuzzy inference system were compared in accordance with different gases such as SO₂, NO_x, Ozone and PM. The results taken by these models were evaluated in order to determine which model gives the best prediction performance with the selected gases.

Materials and Methods

Data Collection

For all air pollution models, proper collection is very important in order to decrease errors and increase model performance. There are so many techniques developed to collect air pollution data properly. There are three main fields in which air pollution monitoring could be applied such as ambient air pollution monitoring, stack monitoring and experimental analysis. The gases which are mostly monitored as an ambient air pollutants are SO_x, NO_x, CO, PM, HC, O₃. For measuring ambient air pollutants, different types of automated stations are used. Type of the monitoring station depends on the features such as traffic density, building types, industrial activities of the location in which station will be built (Url 1). Furthermore, stacks monitoring is important to understand air pollution amount from industrial facilities. For sampling mobile devices including probe, filter, manometer, thermometer, ice bath, pitot tube are used. Owing to these devices, it is possible to measure many pollutants such as HC, H₂S, SO₂, N₂O, NO₂, NH₃, CH₄, CO₂, and O₃ from stacks (Url 1). The last monitoring process is applied at laboratories with manual measurements. Most of the gaseous pollutants may be monitored with various measurement principles such as gravimetric method for PM, atomic absorption spectrometry for metalloid elements (Pb, Hg, Zn), chemiluminescence for SO₂ and O₃, gas chromatography for VOC and Fourier transform infrared spectroscopy for VOC, CO and CH₄ (URL 1). Moreover, majority of the air pollution models use the meteorological data as input variables. This data may be provided from automatic meteorological observation stations (AMOS) if the device used for air pollution monitoring does not have the ability of measuring meteorological parameters.

Data Preparation

After the data collection process, they should be prepared for the modelling. First step of data preparation is organizing the data according to requirements of the model. The miscellaneous data should be eliminated and too high and low values should not be integrated to the model in order to decrease the error. The second step of data preparation is normalization because if the data includes different aspects with different units, then they should be normalized and be closer to each other. Most of air pollution model requires data and input variables with small standard deviation. There are many different types of normalization methods. The mostly used ones for air pollution models are max-min and z-scores normalization method (Öztürk & Dursun, 2016). The equation (1) gives the definition of max-min normalization and (2) gives the z-score normalization.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (\text{Eq 1})$$

Where: $z_i \rightarrow$ normalized value, $\min(x) \rightarrow$ Min. value of x data, $\max(x) \rightarrow$ Max. value of x data, $x_i \rightarrow$ Value of i^{th} in x data

$$z = \frac{x - \mu}{\sigma} \quad (\text{Eq 2})$$

Where: $z \rightarrow$ z-score of value, $\mu \rightarrow$ Mean, $\sigma \rightarrow$ Standard deviation, $x \rightarrow$ Value

The determination of normalization method depends on the data and the structure of model. However, it is not necessary to apply normalization to the data for all air pollution models because sometimes without normalization very good results can be taken.

Artificial Neural Networks

ANN uses complex problem solving ability of biological networks (Rozlach, 2015). Many interconnected neurons transfer information using parallel structure (Wang, 2013). The classification of ANN is done according to type of the learning algorithm, purpose of modelling, flow direction of the information and connectivity degree of the neurons. The mostly known ANN models are hopfield networks, adaptive resonance theory networks, kohonen networks, backpropagation networks, counter propagation networks, and radial basis function networks (Basheer & Hajmeer, 2000). Back propagation (BP) feedforward algorithm is the most famous learning algorithm used in ANN models. Error is searched by back propagation using gradient descent points. Iterations in BP include forward step in which solution is provided and backward step in which error is computed for modifying weights (Basheer & Hajmeer, 2000). To train multilayer networks, back propagation algorithm is used (Haykin, 2001). Multilayer neural networks consist of input layer, hidden layer and final layer including neurons (Wang, 2003). In Figure 1 the architecture of simple multilayer neural network is given.

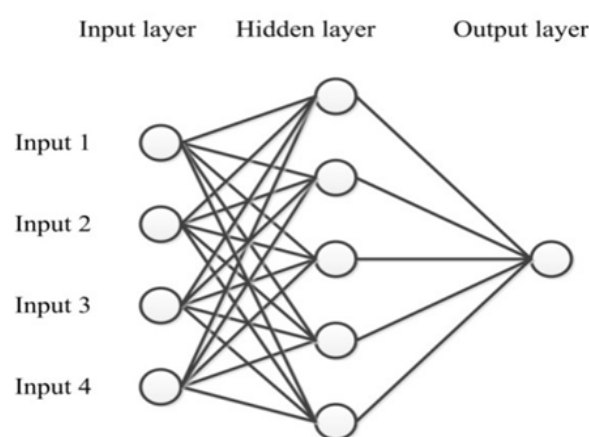


Figure 1. The architecture of simple multilayer neural network (Dehkordi, 2012).

In order to build an ANN model, there are some basic steps which should be followed. In Figure 2 these steps are summarized. Determination of the number of input and output variables is the first step. Only one hidden layer is enough for most of the nonlinear functions (Hornik *et al.* 1989). Furthermore, number of neurons in the hidden layer is determined with training and error approach (Sarle, 1997). Corresponding parameters are connected with activation functions. There are many activation

functions which can be used for modelling purposes such as sigmoidal, hyperbolic and tangent. The type of activation function depends on environmental problem (Öztürk *et al.*, 2015). The selection of optimum learning parameter is important for improving the learning ability of the model. Gradient descent method is used for computing back propagation algorithm which increase or decrease the convergence of errors (Battiti, 1992; Rumelhart & McClelland, 1995). The initialization of weights and bias of ANN is significant before start of the training process. The fast training process can be achieved with the appropriate starting values of weights and free parameters. The usage of random numbers with known range is helpful for decreasing errors (Wasserman, 1989) The last step of developing ANN model is training, testing and validation processes. Data is divided into three set and majority of the data is used in training data set. When error minimization is provided on the test data set, training is stopped. Then, the model prediction is evaluated with validation data set (Gardner & Dorling, 1998).

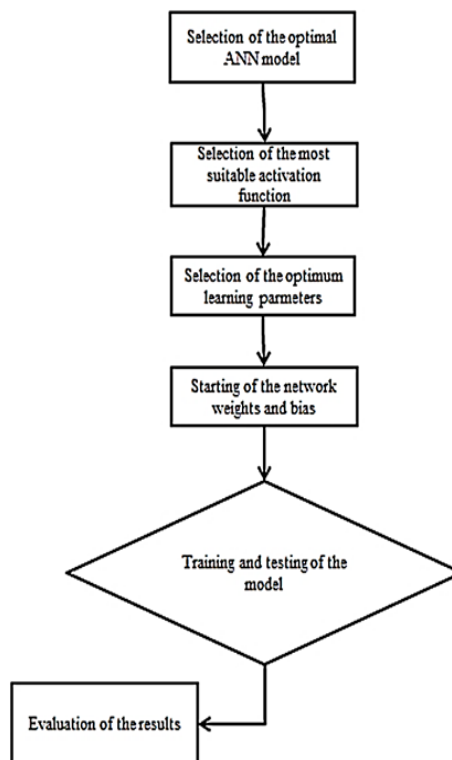


Figure 2. ANN Model Building Approach (Öztürk *et al.*, 2015).

Adaptive Neuro-Fuzzy Inference System

ANFIS model is a hybrid artificial intelligence method that combines the parallel computation capability of artificial neural networks and the inference feature of fuzzy logic. Moreover, ANFIS uses hybrid learning algorithm which is a mixture of least square method and back propagation learning algorithm. Learning rule determines the update mechanisms of the parameters in order to minimize assumed error accuracy. Error accuracy shows the difference between the expected output and the actual output. Sugeno type fuzzy inference system is used in ANFIS. In this system, the outputs of the rules are first order polynomial but it could be any linear function in case the output of the rules completes their process (Bonissone, 2002).

Adaptive systems consist of connected nodes which represent the operation units. Connection between them shows the relevance which value is not certain. ANFIS may assign all possible rules for the problem working on or make it possible to assign all rules manually (Bonissone, 2002). The rule set representing the working principle of ANFIS with 2 input and 1 output is showed in (Eq. 3).

$$\begin{aligned}
 &\text{IF } (x_1 \text{ is } A_1) \text{ AND } (x_2 \text{ is } B_1) \text{ THEN } f_1 = p_1x_1 + q_1x_2 + r_1 \\
 &\text{IF } (x_1 \text{ is } A_2) \text{ AND } (x_2 \text{ is } B_2) \text{ THEN } f_2 = p_2x_1 + q_2x_2 + r_2
 \end{aligned}
 \tag{Eq. 3}$$

The fuzzy logic includes IF-THEN rules. In this equation x_1 and x_2 represents the input parameters, A and B values represent the fuzzy sets for x_1 and x_2 memberships function, and p, q, r values represent the ultimate parameters. Therefore, one output is obtained for each rule (Özgana et.al., 2009).

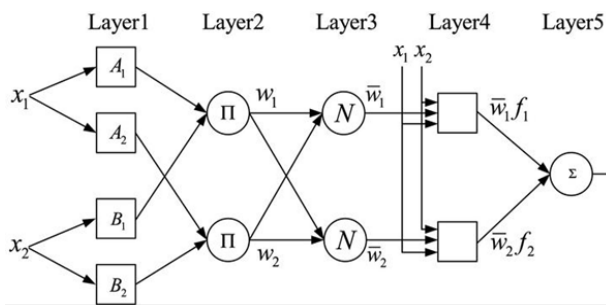


Figure 3. The architecture of simple ANFIS Model with two input parameters (Yechea *et al.*, 2015)

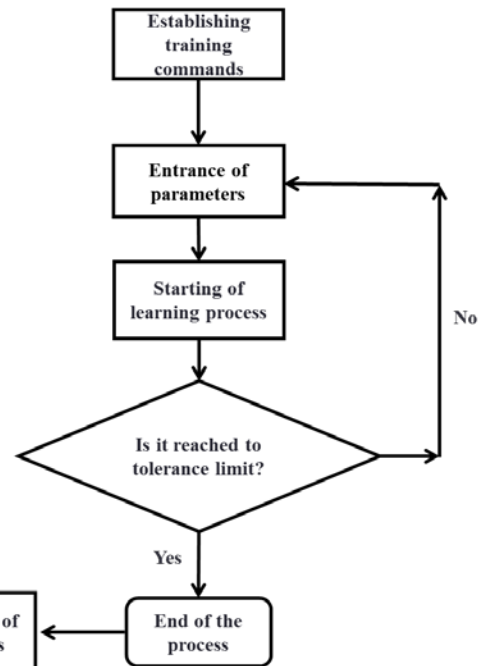


Figure 4. ANFIS Model Building Approach (Dib *et al.*, 2011)

In Figure 3 the architecture of ANFIS with 2 inputs and 1 output is given. Layer 1 is named as fuzzification layer and it separates the input parameters to the subsets. Gaussian activation function is used as a membership function in this layer. The output of each node consists of membership degrees depending on input parameters and membership function. Layer 2 is the rule layer and each rule in this layer represents the rules produced with respect to sugeno type fuzzy logic system and the number of them. The output of rule nodes represents the firing degree of each rule. Layer 3 is the normalization layer. Each node in this layer accepts all parameters coming from rule layer as an input parameter and calculates the normalized value of the rules. Layer 4 is the defuzzification. In this layer the weighted result value is calculated for each rule. Layer 5 is the total layer which sums the output values coming from layer 4. The result gives the output value of the ANFIS model (Özgana *et al.*, 2009).

The simple building approach for ANFIS system is given in the Figure 4. After establishment of ANFIS architecture for the problem, the training commands are determined. In ANFIS as a learning algorithm, mixture of least square method and back propagation learning algorithm is used. In the next step, input parameters are loaded to the system and the learning is started. When the tolerance limit is reached, the process is stopped (Dib *et al.*, 2011). The tolerance limit is determined according to the subject. Mostly the average errors, R^2 value and mean square error are used as evaluation criteria for prediction models.

Results

The mostly known air pollution prediction models ANN and ANFIS were compared with respect to their application to the air pollutants (SO_2 , NO_x , Ozone and PM). The results of previous studies related to ANN and ANFIS modelling are shown in the Table 1. According to this table, there are so many studies which have been done on these models in literature. The main evaluation criteria in order to understand prediction performances of the models are correlation factor which means match ratio between actual and predicted values. Almost all models have seen in Table 1 use meteorological parameters as input parameters. Performance of the models changes with respect to many factors such as duration of data collection, types of input parameters, time range between measurements, types of activation functions, percentages of data sets and other factors affecting model development stage.

According to these results, ANN models have given results nearly 70% and ANFIS models have given results nearly 85% for prediction of SO₂, NO₂, O₃ and PM. Therefore, the results illustrated that ANN models offer a valuable prediction performance for air pollution management but predictions of ANFIS model are found more accurate and reliable. Artificial intelligence and its applications to the air pollutants is relatively new subject and with more effort more accurate predictions may be achieved with different methods.

Table 1. Comparison of ANN and ANFIS models with respect to previous studies

ANN Models					
Ref.	Input Parameters	Predicted Pollutant(s)	Evaluation Criteria	Results	
Dursun <i>et al.</i> , 2015	Temperature, moisture, wind speed, atm. pressure, rainfall, NO ₂ , O ₃	SO ₂	Aver. Error	9.79	
Savic <i>et al.</i> , 2013	Wind speed, humidity wind direction, temperature	SO ₂	R ²	0.20	
Polat, 2011	Temperature, humidity, pressure, wind velocity	SO ₂	MSE	7.278	
Akkoyunlu <i>et al.</i> , 2010	Daily temperature, relative humidity, cloudiness, average daily wind speed	SO ₂	MSE	0.0042634	
Chelani <i>et al.</i> , 2001	Wind speed, temperature, relative humidity, wind direction index	SO ₂	R ²	0.70	
Asadollahfardi <i>et al.</i> , 2016	Temperature, NO, NO ₂ , NO _x , CO, SO ₂ and PM ₁₀	PM _{2.5}	R ²	0.92	
Demir <i>et al.</i> , 2008	Temperature, humidity, solar irradiation, amount of cloud, wind speed, wind direction, dust, amount of rain, pressure	O ₃	R ²	0.8903	
ANFIS Models					
Ref.	Input Parameters	Predicted Pollutant(s)	Evaluation Criteria	Results	
Dursun <i>et al.</i> , 2015	Temperature, moisture, wind speed, atm. pressure, rainfall, NO ₂ , O ₃	SO ₂	Aver. Error	2.81	
Savic <i>et al.</i> , 2013)	Wind speed, humidity wind direction, temperature, SO ₂	SO ₂	R ²	0.526	
Yıldırım & Bayramoğlu, 2016	Meteorological factors	SO ₂ , PM	R ²	0.89, 0.65	
Rafetia <i>et al.</i> , 2014	NO _x , Temperature, Wind speed Wind direction	O ₃	R ²	0.949	
Hanafy <i>et al.</i> , 2015	NO ₂ , SO ₂ , wind speed, wind direction, temperature	O ₃	MSE	8.505	
Prasad <i>et al.</i> , 2016	Temperature, visibility, pressure, wind speed, relative humidity, dew point, and precipitation	CO, NO ₂ , PM ₁₀ , SO ₂ , O ₃	R ²	0.77, 0.85, 0.89, 0.71, 0.65	
Polat, 2011	Temperature, humidity, pressure, wind velocity	SO ₂	MSE	13.855	

Conclusions

Air pollutants and their effects on human, environment and other living organisms is very important. These pollutants are reached to human body by accumulating on the soil and vegetation. They cause severe effects on the human such as respiratory problems, cancer and destruction of immune system. In order to take precautionary actions against harmful air pollutants, their prediction is one of the best options. In this study the main applications of ANN and ANFIS estimation models on some of air pollutants such as SO₂, NO₂, O₃ and PM was investigated. Also, model development steps of the two mostly known models were given. According to the results of previous studies, ANN and ANFIS show high prediction performances.

ANN models have many advantages which are training large amount of data, small time requirement owing to parallel structure of the model, applicability on the nonlinear and complex problems. However, the uncertainties are the main problem in the ANN modelling which cannot interpret relationship between input and output parameters. There are some methods developed for

solving this problem (Öztürk et.al, 2015). Furthermore, main advantages of ANFIS are the ability of excellent expression with fuzzy rules, usage of all data related to problem and expert experience together, toleration against unknown data, modelling nonlinear functions, good generalization and fast and correct learning (Özgana et al., 2009).

Although the advantages and disadvantages of the models, their success mostly depends on the data that can be improved with longer measurement periods, hourly or daily measurement, selection of appropriate data preparation technique and construction of correct path. Also, the investigation of the selected area before modelling is very important. The identification of pollution sources and designation of predominant wind direction are some points that should be considered.

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