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Artificial neural network approach for determination of mixing height

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***Abstract*— Artificial neural networks (ANNs) are one of the areas of artificial intelligence that includes systems that model the way the brain works. In this paper, ANN Model use to determine mixing height from surface meteorological parameters by using MATLAB tools. Weather data for Qena city between 2009 and 2013 are used for training the neural network, while data of 2014 are used for testing. The results of this study indicated high correlation coefficient (R=0.82) between the measured and predicted output variables. Therefore, the model developed in this work has an acceptable generalization capability and accuracy. As a result, the neural network modeling could effectively simulate and predict mixing height.**

***Index Terms*— Artificial neural network, mixing height, prediction model, simulation model.**

I. INTRODUCTION

The human brain is arguably one of the most exciting products of evolution on Earth. It is also the most powerful information processing tool so far. Learning based on examples and parallel signal processing lead to emergent macro-scale behavior of neural networks in the brain, which cannot be easily linked to the behavior of individual micro-scale components (neurons). Artificial intelligence (AI) has been established as the area of computer science dedicated to production software capable of sophisticated, intelligent, computations similar to those that the human brain routinely performs. It includes methods, tools and systems devoted to simulate human methods of logical and inductive knowledge acquisition, reasoning of brain activity for solving problems [1]. Artificial neural networks (ANNs) are one of the areas of artificial intelligence that includes systems that model the way the brain works.

ANNs were studied as early as the 1940s by McCulloh and Pitts [2]. However, they did not become popular until around 1985 when the method of backpropagation for training ANNs was introduced by Rumelhart et al. [3]. Hundreds of papers were published during the early 90s, [4]. Nowadays neural models are enjoying resurgence and there is a substantial amount of research in the area of neural networks, because of their ability to represent nonlinear relationships, useful in making function approximation, forecasting, and recognizing patterns [5]. An ANN is a collection of neurons, which are the basic information-processing entities of the biological brain, highly interconnected by synapses. An ANN is a computational-based, nonlinear empirical model, inspired on the biological. ANN can "learn" complex dynamic behaviors of physical systems. An ANN acts as a black box and learns to predict the value of specific output variables given sufficient input information.

In this paper, ANN Model use to determine mixing height from surface meteorological parameters like as temperature and relative humidity. The concentration of atmospheric pollutants is affected by atmospheric flows and by dispersion within the atmospheric boundary layer (ABL). ABL, being the lower part of the troposphere, is governed by the influence of the earth's surface through friction, convective heating during the day, and radiative cooling of the ground during the night, as shown in Figure 1 [6]. The height of ABL or mixing height (MH) is a fundamental parameter that characterizes the structure of the lower atmosphere.

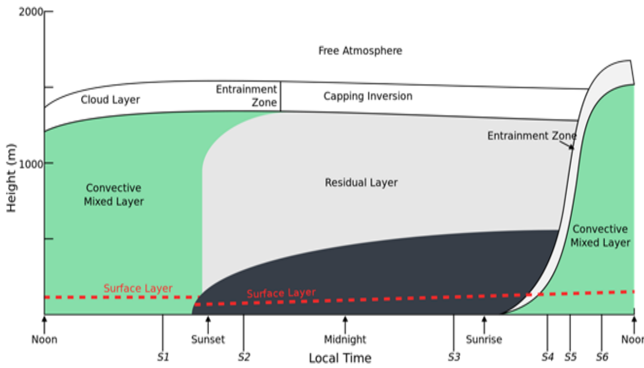

Figure 1: The diurnal evolution of the boundary layer over a plain in fair weather during summer. (Stull, 1988).

Mixing height determines the volume available for the dispersion of pollutants by convection or mechanical turbulence and it is used in environmental monitoring and prediction of air pollution [7]-[10]. Topographical features and climatological conditions also influence the mixing height and evolution of stable and unstable ABL. The use of mixing height data of one particular site for another will be unjust and unwise when dealing with the dispersion models which require site-specific mixing height and stability class data [11]. In addition to latitudinal variation [12], meteorological parameters may also affect the mixing height. Spurr [13] stated that the pollutants discharged into the atmosphere depend upon the meteorological conditions prevailing in the earth's atmospheric boundary layer. The main objective of this study development of an artificial neural network (ANN) model for the prediction mixing height for air pollution modelling.

II. METHODS AND DATA COLLECTION

A. Model of Artificial Neural Network

ANN is an information processing system that is inspired by the way such as biological nervous systems e.g. brain. The objective of a neural network is to compute output values

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from input values by some internal calculations [14]-[15]. Neural network is trained to perform a particular function by adjusting the values of the connections, which called weights, between elements. This training continues based on a comparison of the output and the target until the network output matches the target. Other words, the neural network can predict the correct outputs for a given set of inputs, as shown in Figure 2 [16].

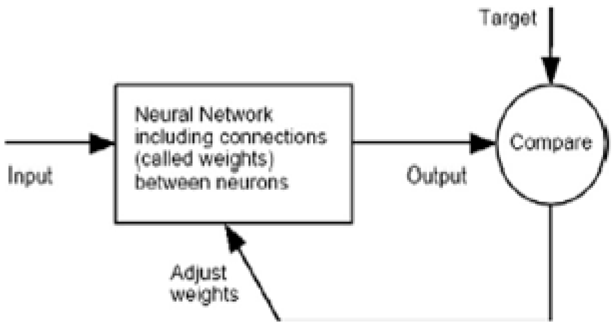

Figure 2: Neural networks training structure.

The following diagram represents the general model of ANN followed by its processing as shown in Figure 3. For the above general model of artificial neural network, net input has to be calculated in the following way:

$$y_{in} = x_1.w_1 + x_2.w_2 + x_3.w_3 \dots\dots\dots\dots\; x_m.w_m$$

i.e., Net input $y_{in} = \sum_i^m x_i.w_i$

The output can be calculated by applying the activation function over the net input.

$Y = F(y_{in})$

Output = function (net input calculated)

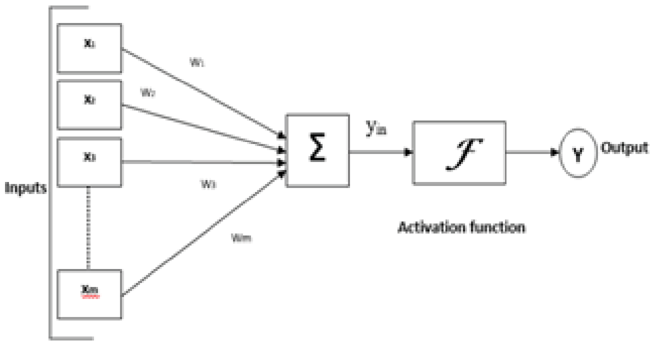

Figure 3: Diagram represents the general model of ANN followed by its processing.

The function to be applied over the net input is called activation function [17]. The activation function can transform the ANN's net input in a linear or non-linear manner. Three types of commonly used activation functions are as follows [18]:

1- Sigmoid activation function:

$$f(x) = \frac{1}{1 + e^{-x}} \qquad 0 \le f(x) \le 1$$

2- Hyperbolic tangent activation function:

$$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad -1 \le f(x) \le 1$$

3- Linear activation function:

$$f(x) = x \qquad -\infty < f(x) < +\infty$$

The ANN's output is found by performing one of these functions on the ANN's net input.

ANN is trained to perform complex functions in various fields, including pattern recognition, identification, classification, and speech, vision, and control systems. It is also trained to solve problems that are difficult for conventional computers or human beings.

There are many different types of training algorithms. One of the most common classes of training algorithms for Feed Forward Neural Networks FFNNs is called Back Propagation BP [19].

B. Mixing height determination

In dispersion models, the mixing height is a key parameter needed to determine the turbulent domain in which dispersion takes place. Air pollution climatology is concerned with the aggregate of weather as it may affect the atmospheric concentrations of pollutants. The mixing layer is the depth of the atmospheric layer which is characterized by strong turbulent and convective mixing. Accurate representation of mixing depth plays an essential role in the ability of models to predict pollutant concentrations [20]-[21]. There are several methods currently available for the estimation of mixing heights [22]-[25]. Each method has its own advantages and limitations, and different methodologies give rise to differences in mixing heights. These differences are the results of the physical limitations of each method and the assumptions used as to which variable most accurately defines the depth of the mixed layer. Figure 4 shows a schematic diagram of Vertical air temperature and dry-adiabatic profile.

Many Studies in Egypt were concerned about determination of mixing height. Some of these studies depend on the data of radiosonde (upper air data) [26]. Due to the high cost of monitoring in the upper atmosphere, so that, other studies have been estimated through theoretical or empirical models based on metrological surface data. These data are often available in most meteorological stations [27]. In this study, an attempt is made to use artificial neural network to determine the mixing height. The inputs of this ANN model are metrological surface data such as temperature, humidity and wind speed.

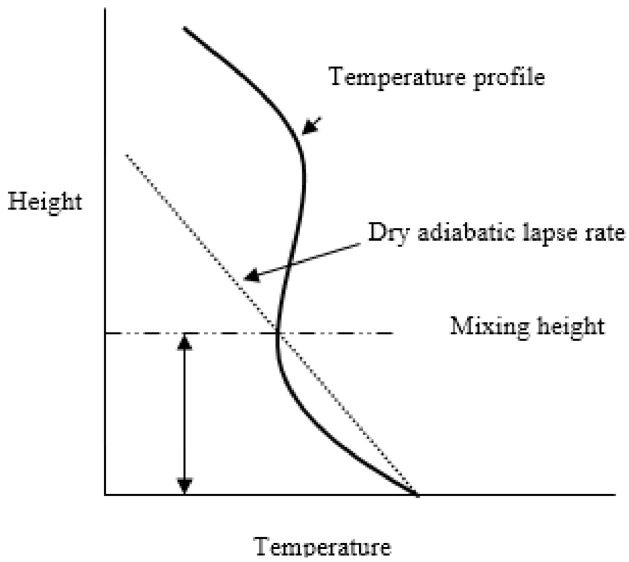

Figure 4: A schematic diagram of Vertical air temperature and dry-adiabatic profile

C. Data collection and study area

As a case study, this paper was performed at Qena (26.2°N, 32.7°E, and 96 m above mean sea level). Qena is located in Upper Egypt, about 600 km to the south of Cairo. The dataset used in this study was collected at the South Valley University-Meteorological Research Station (SVU-MRS), located at Qena, which is one of the guide stations of the Egyptian Meteorological Authority (EMA). The SVU and the EMA established SVU-MRS at Qena. Scientific advice and instrument calibrations for SVU-MRS are provided by the EMA. However, the instruments are also calibrated yearly against the World Radiometric Reference (WRR) maintained at Davos, Switzerland [28]-[30]. The data included surface hourly and daily values of "Temperature (°C)", "Relative Humidity (%)" and "Wind speed (m/sec)", during the period (2009-2013). In addition to the upper air data at the same period.

D. Developing ANN models

Figure 5 summarizes five basics steps for developing ANN models. A simple summary of each step as follows:

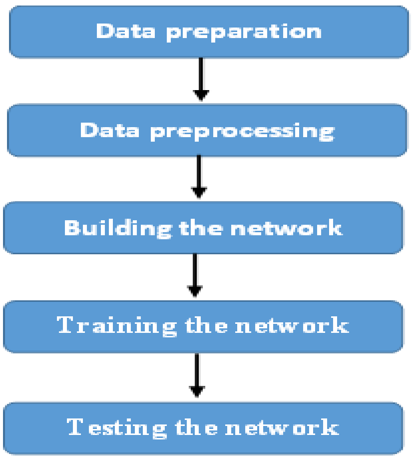

Figure 5: A Sketch of five basics steps for designing ANN models.

i. **Data preparation:** Collecting and preparing sample data is the first step in designing ANN models. As it is outlined in above section c, measurement data of temperature (°C), wind Speed (m/s), relative humidity (%) for Qena city was collected through the NCMS.

ii. **Data preprocessing**: Three data preprocessing procedures are conducted to train the ANNs more efficiently. These procedures are: (1) solve the problem of missing data, (2) normalize data and (3) randomize data. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [31], [32].

iii. **Building the network:** At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this paper, Feed Forward Neural Networks (FFNN) are used.

iv. **Training the network:** During the training process, the weights are adjusted in order to make the actual outputs (predicated) close to the target (measured) outputs of the network. In this study, 5-year data period from 2009 to 2013 are used for training.

v. **Testing the network:** The final step is to test the performance of the developed model. Unseen data are exposed to the model. In this paper, surface data for 2014 have been used for testing the ANN models. In order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models, statistical analysis involving the coefficient of determination (R^2), the root mean square error (RMSE), and the mean bias error (MBE) were conducted.

In this paper MATLAB (R2008b) is used to develop ANN models and performance functions for calculating the model performance error statistics. Figure 6 shows the flowchart procedural steps to develop the ANN models. Finally, the output results were exported to excel file.

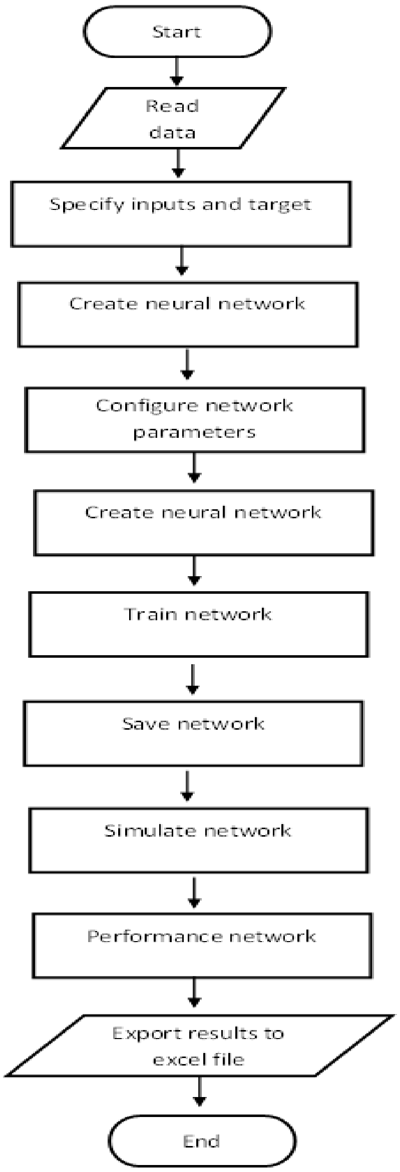

Figure 6. Flowchart for developing of ANN using MATLAB.

III. RESULTS AND DISCUSSION

Figure 7 shows the mean monthly plot of the three measured weather predictors namely, temperature T, wind speed WS, relative humidity RH, as well as the mean monthly mixing height MH, dependent model variable for Qena city between 2009 and 2013. These plots can help examine the correlation between the output variable MH and the three weather predictors.

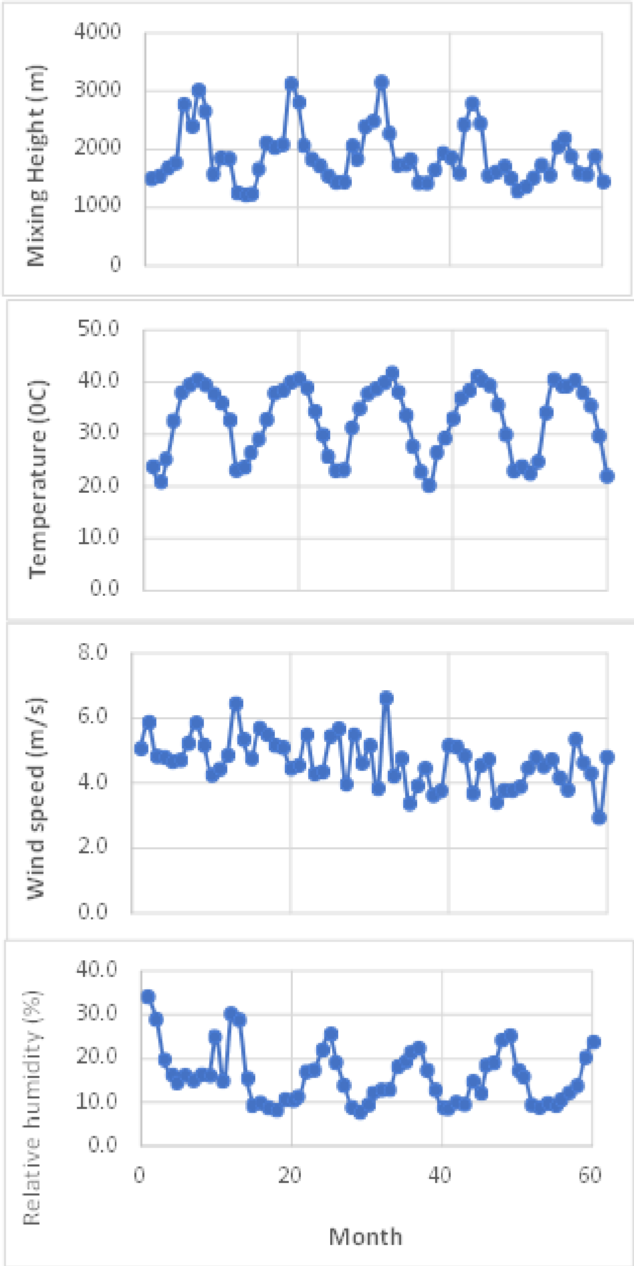

Figure 7. Monthly mean of MH, T, WS and RH for Qena city between 2009-2013

Various network architectures were investigated in order to determine the optimal ANN architecture (i.e. the highest coefficient of determination, the lowest root mean square error and the lowest mean bias error). Different training algorithms were used with changes in the number of neurons and hidden layers. In addition, different transfer functions including the tangent sigmoid, log sigmoid and linear functions in the hidden layer were also investigated.

Figure 8 shows a screen caption of opened window of the network

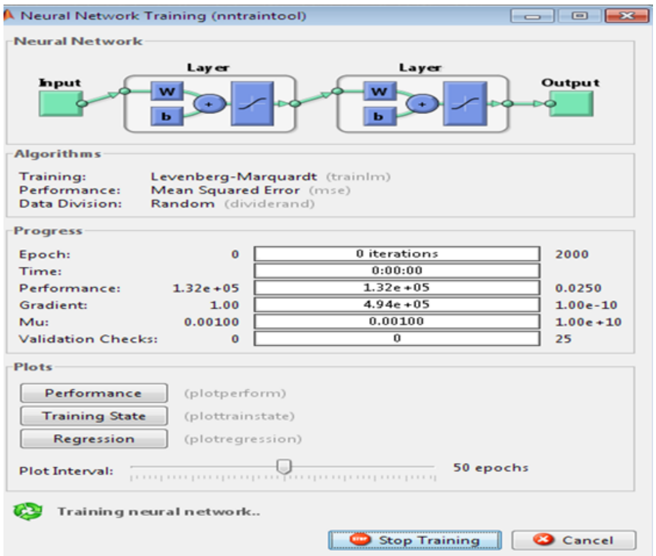

Figure 8. The network during training

during training. This window displays training progress and allows the user to interrupt training at any point by clicking stop training. The regression button in the training window performs a linear regression between the network outputs and the corresponding targets. Figure 9 shows screen caption of the results. It is observed that the output tracks the targets very well. Table 1 Summarizes the value of regression coefficients.

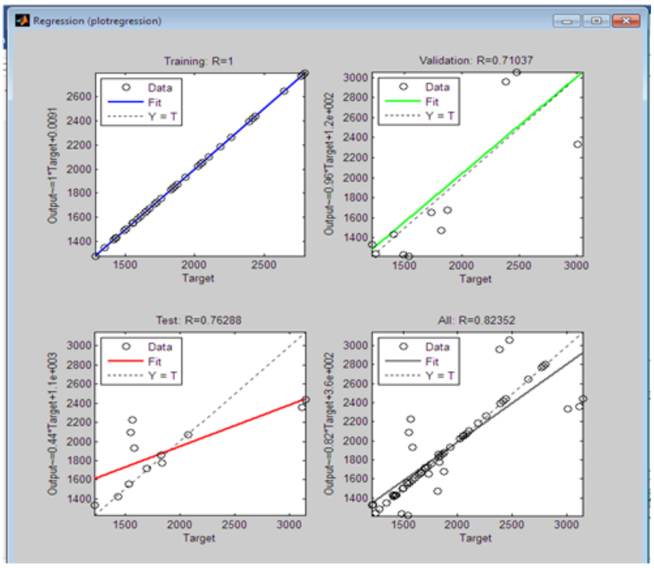

Figure 9. Network regression

Regression Coefficients			
R-Training	R-Validation	R-Test	R-All
1	0.71037	0.76288	0.82352

Table 1. Summary values of network regression coefficients.

From these values the network response is satisfactory, and simulation can be used for entering new inputs. The results of simulation are presented in Figures 10 & 11 by plotting the relation between calculated mixing height and predicted output.

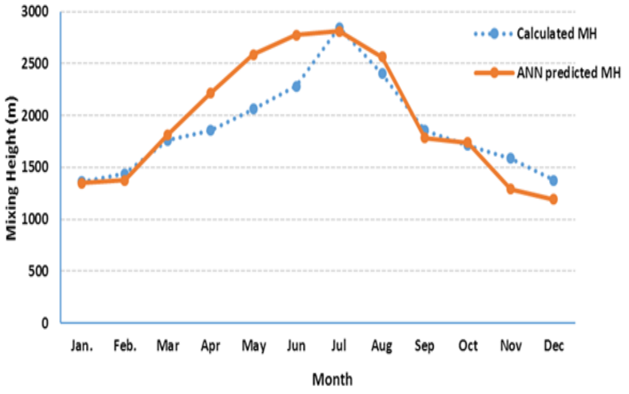

Figure 10. Comparison between measured data and predicted ANN model.

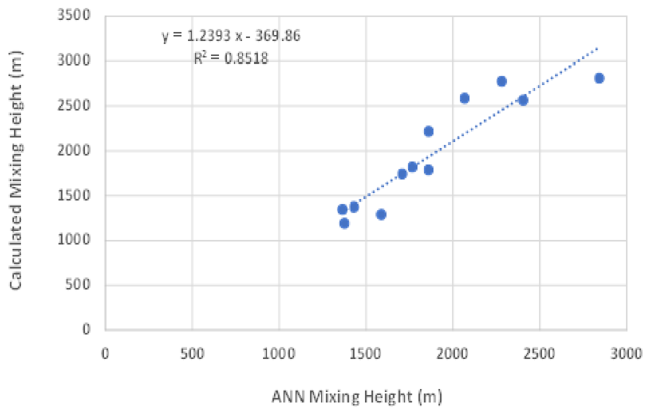

Figure 11. Correlation between calculated and ANN mixing height as results of network simulating

IV. Conclusion

This work discusses the development of an artificial neural network model for predicting the mixing height from weather surface data. MATLAB tools are used to develop this network by using five years' data for Qena city in period from 2009 to 2013. The results of this study indicated high correlation coefficient (R-value) between the measured and predicted output variables as shown in table 1 and figures 10 & 11. Therefore, the model developed in this work has an acceptable generalization capability and accuracy. As a result, the neural network modeling could effectively simulate and predict mixing height.

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