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Forecasting of Ground Level Ozone around Chennai by Artificial Neural Network

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Abstract:
The aim of this research was to develop pure predictive models to provide short–term prediction of near surface ozone concentration for the Chennai capital city of Tamilnadu. The short–term prediction of near surface ozone levels is very important due to the negative impacts of ozone on human health, climate and vegetation. A new method for short-term prediction is presented using the neural network technique. Due to increase in industrial and anthropogenic activity, air pollution is a serious subject of concern today. Ground level ozone prediction using the technique of adaptive pattern recognition is developed. The model can predict the mean surface ozone based on the parameters like wind speed, temperature and % Relative Humidity. The Mean absolute Percentage of error of the data during testing is 8.647%. The model can perform well both in training and independent periods.

Keywords: Air pollution; artificial neural network; Ground Level Ozone; Short term Forecast; Tamilnadu

1. Introduction:
The analysis and forecasting of air quality parameters are important topics of atmospheric and environmental research. In many of the applications, data are generated in the form of a time series. Therefore, time series analysis is a major task in forecasting average ozone concentrations, where one tests and predicts known or estimated observations for past times using them as input into the model to see how well the output matches the known observations. Many studies [Ramaswamy and Bowen, (1994); Rajeevan, (1996); Bojkov,(1983)] suggest that an increase in tropospheric ozone leads to the warming in surface temperature. Ground-level ozone (O3) is one of the air pollutants; it is an irritating and reactive component in atmosphere that has negative impacts on human health, climate, vegetation and materials [Pires, J.C.M].

Ground-level ozone is a highly reactive oxidant and is unique among pollutants because it is not emitted directly into the air [Ozdemir, H., Demir, G. (2008)]. It is a secondary pollutant that results from complex chemical reactions in the atmosphere. In the presence of the sun's ultraviolet radiation (RAD), oxygen (O_2), nitrogen dioxide (NO_2), and volatile organic compounds (VOCs) react in the atmosphere to form ozone and nitric oxide (NO) through the reactions given in (1) and (2)

$$NO_2 + hv \longrightarrow NO + O \qquad (1)$$
$$O_2 + O \longrightarrow O_3 \qquad (2)$$

The non-linear relationship of surface ozone with solar radiation has been mentioned by [Bravo et al. (1996)]. There is a value of solar radiation for which ozone concentration has a maximum. This effect may be due to days with high solar flux having little atmospheric pollution, with little ozone formation and high atmospheric transparency [Bravo et al., (1996)]. The problem of short term modeling in complex terrain is discussed in details by [Bonzar et al. (1993)]. They have also shown that in the case of stable atmosphere and of thermal inversions the failure of dispersion model and the inadequacy of this model for controlling emissions. In this regard they have applied the neural network technique for short term prediction. The results obtained by them are significantly better than those obtained from conventional models.

Neural network techniques have recently become the focus of much attention as they can handle the complex and non-linear problems better than the conventional statistical techniques. Neural network is simple mathematical input/output model which learns the relationship (linear or non-linear) between the input and output during the training period. Neural network model brings out the maximum information available within the data during the training period and reflects these in the independent period. Present paper aims to develop a simple model using neural network technique based on the data which are easily available.

2. Area of Study and data

The study area is Choolaimedu, one of the main city of Chennai (13.0628°N 80.2275°E). It is locating nearby Koyambedu.The most important entry-exit point of the city, the terminus has a capacity to handle over 200,000 passengers a day.

The following parameters were used to develop the model:

(1) Customary(%) Relative Humidity as predictor.
(2) Wind Speed as predictor.
(3) Mean temperature as predictor.
(4) Ground level ozone concentration as response

3. Method of data measurement

Ground level ozone concentration along with wind speed ,temperature and Rh measurements were carried out in the city Choolaimedu. A portable Aeroqual series S200 ozone monitor was used. A gas sensitive semiconductor (GSS) type sensor is described in www.aeroqual.com. The data sampling collected from the period from august 2011 to July 2012.

Wind speed is calculated using a wind vane. Wind velocity is measured using AM-4201digital Anemometer. Measurement in range 0.4 – 3 m\s has resolution 0.1 m\s of accuracy ± (2% + 0.2 m\s). The ambient temperature and humidity are measured by Thermo Hydrometer. Temperature accuracy ± 0.1^{o}C and humidity accuracy ± 5%. Sampling was carried out august 2011 to July 2012.

4. Artificial Neural Networks

Artificial Neural Networks (ANN) is a special approach in the creation of Intelligent Systems as they neither use knowledge representation nor they adopt specially designed search algorithms. Artificial Neural Network is based on biological models uses structures and processes similar to the ones of the human brain. The computing power of Artificial Neural Network is achieved through their massively parallel distributed structure and their ability to learn and therefore generalize [Haykin, S., (1999)]. The application areas of ANN are expanded but not limited to various Engineering, Financial and Environmental domains to provide smart solutions towards forecasting or clustering. The concepts of neural networks are initiated by [Hebb, D.O., (1949)] and [Rosenblatt, F., (1959)]. It has been extended by [Hopfield, J., (1982)], [Feldman, J. A., & Ballard, D. H., (1982)], Rumelhart and McClelland [Rummelhart, D. and McClelland, J., (1986)] and Lippmann [Lippmann, R. P.,(1987)] through the development of new topologies and algorithms.

4.1.1 Description

The Artificial Neural Network technology is familiar in many disciplines like mathematics, physics, statistics, and several branches of engineering. Enormous successful applications of this can be found in so many diverse fields due to their ability to learn from input data either in supervised or in unsupervised mode. Artificial Neural Network has been inspired from studies of biological nervous systems which have interconnected elements of networks. Fig. 4.1 depicts a typical biological nervous system. This network consists of units that have a very limited computing capability. But still the complete network is capable of performing a very complicated task, as many of the above units are connected to each other. They have the ability to adapt, learn, generalize, cluster or organize data. The actual power of ANN is due to their massively parallel distributed structure.

4.1.2 The Nature and Structure of Input Data

In Artificial Neural Network (ANN) defining the problem plays a vital role. For example, in the problem of predicting the present value of the time series, by giving a set of its past values. A good selection of a set of values of time series as input (as past values) results a better corresponding succeeding value (as present values) of time series. A set of input and corresponding output parameters actually represent the problem. The next step is to select a network that suits our problem. This can be carefully being carried out from the knowledge of literature survey. Last but not the least choosing the simplest training algorithm returns a better output. The training or the test set must be a complete representative of the problem with some of the input and corresponding output sets chosen. Once the training session gets over choose remaining input and corresponding output sets and test the trained network whether it produces correct output for every input in testing set. The design and development of an Artificial Neural Network model that estimates the Ground level Ozone when the values of temperature, wind speed, Relative Humidity are used as predictors.

4.1.3 Designing the Optimal Artificial Neural Networks

There are many structures of Artificial Neural Networks. To name a few: Percepton, Madaline, Adaline, Kohonen, Back Propagation and many others. Of these Back Propagation Artificial Neural Network is the most commonly used, as it is very simple to implement and effective.

The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. There may be one or more intermediate *hidden layers*.

The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN *learns* the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

The activation function of the artificial neurons in ANNs implementing the back propagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \qquad (3)$$

We can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function:

$$O_j(\bar{x}, \bar{w}) = \frac{1}{1+e^{A_j(\bar{x},\bar{w})}} \qquad (4)$$

The sigmoidal function is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. This allows a smooth transition between the low and high output of the neuron (close to zero or close to one). We can see that the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights.

Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron:

$$E_j(\bar{x}, \bar{w}, d) = \left(O_j(\bar{x}, \bar{w}) - d_j\right)^2 \qquad (5)$$

We take the square of the difference between the output and the desired target because it will be always positive, and because it will be greater if the difference is big, and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E(\bar{x}, \bar{w}, \bar{d}) = \sum_j \left(O_j(\bar{x}, \bar{w}) - d_j\right)^2 \qquad (6)$$

The back propagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of *gradient descendent*:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \qquad (7)$$

This formula can be interpreted in the following way: the adjustment of each weight (Δw_{ji}) will be the negative of a constant eta (η) multiplied by the dependance of the i previous weight on the error of the network, which is the derivative of E in respect to w .The size of the adjustment will depend on η, and on the contribution of the weight to the error of the function. This is, if the weight contributes a lot to the error, the adjustment will be greater than if it contributes in a smaller amount. (7) is used until we find appropriate weights (the error is minimal). If we do not know derivatives, don't worry, we can see them now as functions that we will replace right away with algebraic expressions. If we understand derivatives, derive the expressions ourself and compare our results with the ones presented here. If we are searching for a mathematical proof of the back propagation algorithm, we are advised to check it in the suggested reading, since this is out of the scope of this material. So, we "only" need to find the derivative of E in respect to w_{ji}. This is the goal of the back propagation algorithm, since we need to achieve this backwards. First, we need to calculate how much the error depends on the output, which is the derivative of E in respect j to O (from (5)).

$$\frac{\partial E}{\partial O_j} = 2\left(O_j - d_j\right) \quad (8)$$

And then, how much the output depends on the activation, which in turn depends on the weights (from (3) and (4)):

$$\frac{\partial O_j}{\partial w_{ji}} = \frac{\partial O_j}{\partial A_j}\frac{\partial A_j}{\partial w_{ji}} = O_j(1 - O_j)x_i \quad (9)$$

And we can see that (from (8) and (9)):

$$\frac{\partial E}{\partial w_{ji}} = \frac{\partial E}{\partial O_j}\frac{\partial O_j}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1 - O_j)x_i \quad (10)$$

And so, the adjustment to each weight will be (from (7) and (10)):

$$\Delta w_{ji} = -2\eta\left(O_j - d_j\right)O_j(1 - O_j)x_i \quad (11)$$

We can use (11) as it is for training an ANN with two layers. Now, for training the network with one more layer we need to make some considerations. If we want to adjust the weights (let's call them v_{ik}) of a previous layer, we need first to calculate how the error depends not on the weight, but in the input from the previous layer. This is easy, we would just need to change x_i with w_{ji} in (9), (10), and (11). But we also need to see how the error of I k the network depends on the adjustment of v_{ji}. So:

$$\Delta v_{ik} = -\eta\frac{\partial E}{\partial v_{ik}} = -\eta\frac{\partial E}{\partial x_i}\frac{\partial x_i}{\partial v_{ik}} \quad (12)$$

Where:

$$\frac{\partial E}{\partial w_{ji}} = 2\left(O_j - d_j\right)O_j(1 - O_j)w_{ji} \quad (13)$$

And, assuming that there are inputs u_k into the neuron with v_{ik} (from (9)):

$$\frac{\partial x_i}{\partial v_{ik}} = x_i(1 - x_i)v_{ik} \quad (14)$$

If we want to add yet another layer, we can do the same, calculating how the error depends on the inputs and weights of the first layer. We should just be careful with the indexes, since each layer can have a different number of neurons, and we should not confuse them. For practical reasons, ANNs implementing the back propagation algorithm do not have too many layers, since the time for training the networks grows exponentially. Also, there are refinements to the back propagation algorithm which allow a faster learning.

The Back Propagation Artificial Neural Networks contain one or more layers each of which are linked to the next layer. The first and the last layers are known as input and output layer. The layers between these two are known as hidden layers as shown in fig. 4.2. An ANN is a collection of units (Neurons or Nodes or Processing Elements) that are connected in some pattern which allows communication among them. Neurons are simple processors whose computing ability is typically restricted to a rule for combining input signals and an activation rule that processes the combined input signal and calculates the output signal [Callan R., (1999)]. The hidden layer is the place where the data is being processed and it may consist of one or more sub-layers.

The role of the hidden layer is to propagate the previous layer's outputs to the next layer and (back) propagates the following layer's error to the previous layer. The selection of the proper ANN model always requires the performance of several training experiments. Training is the process of adapting or modifying the connection weights according to the stimuli being presented at the input buffer or optionally at the output buffer. A typical Back Propagation Artificial Neural Network is as shown in fig. 4.3. The nodes on the extreme left are the initial inputs. Generally two phases involves in the training. In the first phase, the inputs are propagated forward to compute the outputs for each output node. Then, each of these outputs is subtracted from its desired output, causing an error (an error for each output node). In the second phase, each of these output errors is passed backward and the weights are fixed. These two phases is continued until the sum of square of output errors reaches an acceptable value.

An action presented at the output buffer corresponds to a desired response to a given input is so called "supervised learning". The requirements of a supervised learning strategy are a suitable weight adjustment mechanism and suitable error functions. Output signals are transmitted among Neurons through connections known as weights. The weights excite or inhibit the signal according to the case and the desired result. A typical computational element takes the weighted sum of the input links and passes the result through a transfer function. The transfer function used here is the sigmoidal function,

$$Y = \left[1 + e^{(-ax+b)}\right]^{-1}$$

where 'a' determines the slope of the sigmoid and 'b' is the threshold. The process of learning the training set of patterns means the determination of the optimum weights which minimize the mean square error between the outputs in the output layer and the desired values. The good performance of an ANN in the Training phase is a strong indication of its ability to produce reliable results. The reliability of the ANN is measured in terms of its ability to generalize. Artificial Neural Network is considered to be successful only when they are able to generalize [Haykin, S., (1999)]. Generalization refers to their ability to produce reasonable output for inputs not encountered during the training phase [Haykin, S., (1999)]. Once the network learns the training set of patterns well enough it can be used for determining the output values (testing) for the pattern with unknown outputs. Fig. 4.4 illustrates the structural representation of the ANN model used.

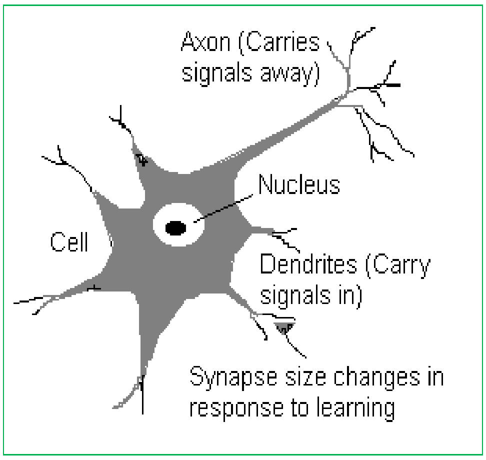

Fig 4.1: A typical biological nervous system

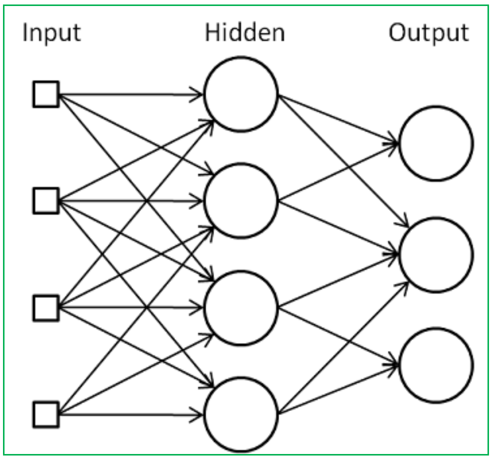

Fig 4.2: Three layer Back Propagation Architecture

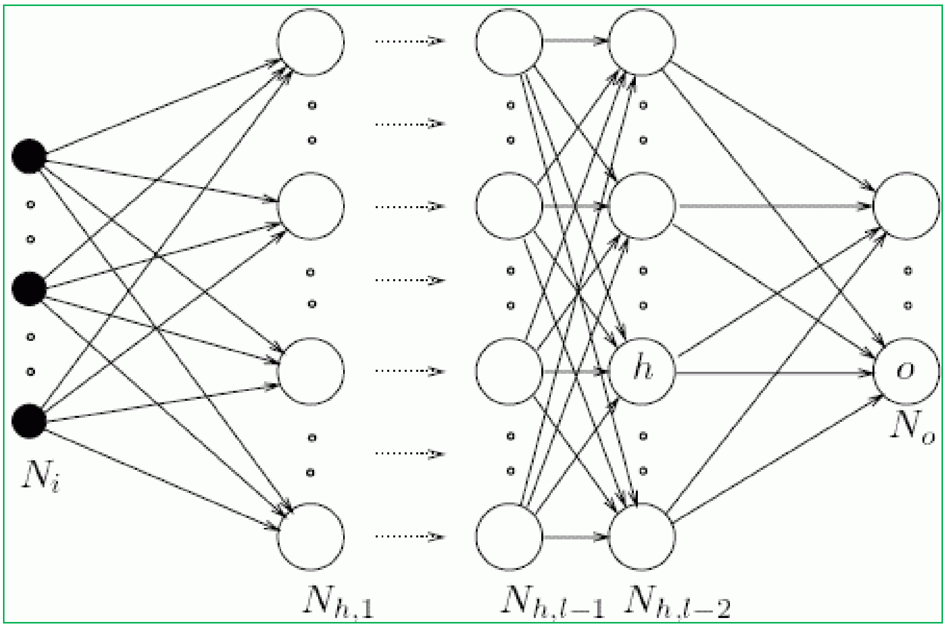

Fig 4.3: Back Propagation Artificial Neural Network

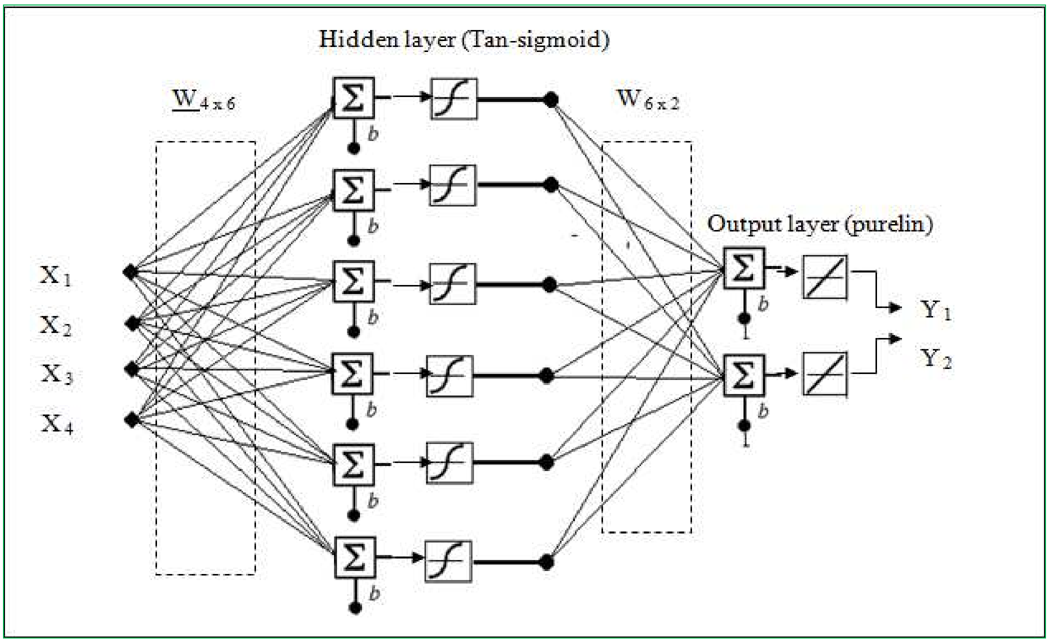

Fig 4.4: Structural representation of the ANN model used

The data obtained is tabulated in Table 1.

Date	Ozone (ppm)	temp (^{O} c)	Relative Humi %	wind speed (m/s)
01-Au-11	0.0131	30.4400	58.5000	0.5700
2-Aug-11	0.0129	30.0500	57.3000	0.8000
3-Aug-11	0.0136	30.1200	54.2000	0.4000
4-Aug-11	0.0183	30.3300	58.2000	1.1000
5-Aug-11	0.0167	30.6400	56.4000	1.2300
6-Aug-11	0.0136	30.0700	62.1000	0.6800
7-Aug-11	0.0183	31.0700	57.7000	1.4600
8-Aug-11	0.0152	30.9700	55.4000	1.0900
9-Aug-11	0.0190	32.1600	59.8000	0.8300
10-Au-11	0.0159	32.6200	61.4000	0.4000
11-Au-11	0.0198	29.3900	66.7000	1.3500
12-Au-11	0.0149	29.7000	66.3000	1.7300
13-Aug-11	0.0159	30.3200	59.7000	1.9100
14-Aug-11	0.0129	30.4800	60.0000	0.7400
15-Aug-11	0.0143	30.1200	58.4500	0.6600
16-Aug-11	0.0141	30.2100	58.6700	0.7400
17-Aug-11	0.0125	30.3400	59.4300	0.4000
18-Aug-11	0.0128	30.4300	55.3000	1.1000
19-Aug-11	0.0134	29.6700	58.1200	1.2300
20-Aug-11	0.0131	30.1800	57.1100	0.9000
21-Aug-11	0.0141	29.9800	59.1800	1.4000
22-Aug-11	0.0137	31.1000	54.2300	1.8000
23-Aug-11	0.0130	30.1100	70.7000	0.8700
24-Aug-11	0.0180	29.7500	68.1000	0.8900
25-Aug-11	0.0144	29.4600	69.8000	0.8400
26-Aug-11	0.0126	28.6900	69.3000	1.7600
27-Aug-11	0.0068	29.8000	68.6000	5.6200
28-Aug-11	0.0130	29.8300	60.8000	5.3900
29-Aug-11	0.0071	30.6700	58.2000	2.7910
30-Aug-11	0.0317	32.0700	55.8000	4.1300
31-Aug-11	0.0155	32.7400	55.1000	5.2500
1-Sep-11	0.0149	30.8400	62.0000	4.9000
2-Sep-11	0.0103	30.7000	61.5000	4.4800
3-Sep-11	0.0125	30.4800	63.0000	4.5600
4-Sep-11	0.0199	30.6500	57.5000	3.3300
5-Sep-11	0.0092	32.9600	57.6000	2.0000
6-Sep-11	0.0216	30.3750	59.0000	1.6714
7-Sep-11	0.0202	30.5700	60.2000	1.5000
8-Sep-11	0.0190	30.1800	57.2222	1.5000
9-Sep-11	0.0183	30.5100	62.2000	1.3700
10-Sep-11	0.0173	30.0900	63.5000	0.6700
11-Sep-11	0.0177	30.0000	66.4000	0.7900
12-Sep-11	0.0157	29.8000	63.6000	0.6333
13-Sep-11	0.0160	30.2100	59.9000	1.8500
14-Sep-11	0.0114	30.5000	59.3333	0.5889
15-Sep-11	0.0170	29.8900	54.3700	1.4600
16-Sep-11	0.0154	29.7300	61.8000	0.9600
17-Sep-11	0.0146	29.1800	67.7000	0.8200
18-Sep-11	0.0192	29.9000	63.9000	1.2980
19-Sep-11	0.0251	27.3800	64.2000	1.4900
20-Sep-11	0.0098	28.2400	72.0000	0.3300
21-Sep-11	0.0166	29.2700	64.0000	0.8100
22-Sep-11	0.0327	30.1500	59.3000	1.1600
23-Sep-11	0.0193	31.2900	53.6000	3.1200
24-Sep-11	0.0192	29.9700	62.7000	0.7700
25-Sep-11	0.0163	29.8556	63.7778	1.5111
26-Sep-11	0.0190	30.4000	60.6000	0.8700
27-Sep-11	0.0149	30.3500	67.2000	0.3600
28-Sep-11	0.0469	30.1900	58.8100	2.3000
29-Sep-11	0.0205	29.2800	67.5000	0.7300
30-Sep-11	0.0428	30.0200	67.9000	0.9100
1-Oct-11	0.0142	27.2700	54.6000	0.4000
2-Oct-11	0.0222	31.0200	60.0000	0.6800
3-Oct-11	0.0239	29.6000	65.1000	0.7900
4-Oct-11	0.0173	29.0750	63.5000	2.8625
5-Oct-11	0.0165	29.9000	64.2500	0.6625
6-Oct-11	0.0143	29.9100	66.2000	0.9000
7-Oct-11	0.0185	29.7000	63.9000	0.6800
8-Oct-11	0.0145	29.9500	65.2000	1.2700
9-Oct-11	0.0111	29.6600	39.5400	0.4700
10-Oct-11	0.0140	29.9667	64.0000	0.1333
11-Oct-11	0.0105	29.7500	67.6250	0.6750
12-Oct-11	0.0114	29.4300	68.7000	1.3600
13-Oct-11	0.0209	27.4667	67.0000	0.7667
14-Oct-11	0.0098	29.7467	65.4000	0.5967
15-Oct-11	0.0128	26.4700	63.6000	0.7100
16-Oct-11	0.0111	26.9556	69.3333	1.2000
17-Oct-11	0.0115	29.8600	69.1000	0.2900

18-Oct-11	0.0220	29.5875	68.6250	0.3875
19-Oct-11	0.0146	26.5100	56.0000	0.3500
20-Oct-11	0.0177	29.5800	66.0000	0.5200
21-Oct-11	0.0128	27.4700	60.1000	0.3100
22-Oct-11	0.0117	30.2900	65.9000	0.1200
23-Oct-11	0.0090	30.4433	65.2111	0.1356
24-Oct-11	0.0131	29.6400	61.5100	0.1300
25-Oct-11	0.0063	27.9889	75.5556	0.2444
26-Oct-11	0.0079	24.1000	68.1250	0.1625
27-Oct-11	0.0121	27.0700	79.7000	0.0600
28-Oct-11	0.0117	28.7333	75.6667	0.5333
29-Oct-11	0.0090	32.8933	77.7667	0.4433
30-Oct-11	0.0213	30.1125	74.8750	3.1500
31-Oct-11	0.0097	27.9100	78.7000	0.2333
1-Nov-11	0.0097	27.9100	78.7000	0.2333
2-Nov-11	0.0078	26.9500	78.0000	0.1300
3-Nov-11	0.0101	27.1111	80.6667	0.0889
4-Nov-11	0.0094	27.2900	82.6000	0.2500
5-Nov-11	0.0086	28.0700	79.0000	0.1200
6-Nov-11	0.0132	27.5222	77.8889	0.2000
7-Nov-11	0.0154	27.7556	70.4444	0.2667
8-Nov-11	0.0115	27.9667	65.3333	0.2000
9-Nov-11	0.0188	27.7200	56.2000	0.7100
10-Nov-11	0.0171	27.8700	62.5000	0.5600
11-Nov-11	0.0184	28.1100	64.8000	0.3400
12-Nov-11	0.0148	28.3600	61.2000	0.4556
13-Nov-11	0.0127	28.4600	63.0000	0.8000
14-Nov-11	0.0130	28.6300	61.1000	0.4100
15-Nov-11	0.0134	28.4750	63.1250	0.6125
16-Nov-11	0.0159	28.1600	63.7500	0.4143
17-Nov-11	0.0095	28.6900	75.2000	0.1333
18-Nov-11	0.0097	27.3600	74.5000	0.4000
19-Nov-11	0.0240	28.0667	60.4444	0.7500
20-Nov-11	0.0141	27.7000	63.3333	0.2889
21-Nov-11	0.0207	29.3111	56.9000	0.6667
22-Nov-11	0.0109	28.3571	57.0000	0.3571
23-Nov-11	0.0313	28.8556	56.0000	0.5375
24-Nov-11	0.0098	28.3600	66.8000	0.3200
25-Nov-11	0.0178	27.3000	75.3333	0.4250
26-Nov-11	0.0093	27.4667	78.2222	0.3750
27-Nov-11	0.0105	23.8588	76.8750	0.2714

28-Nov-11	0.0313	28.8556	56.0000	0.5375
29-Nov-11	0.0087	26.9700	75.8000	0.4300
30-Nov-11	0.0086	27.1167	76.6000	0.5286
1-Dec-11	0.0087	28.5200	70.5000	0.1300
2-Dec-11	0.0121	28.8900	69.5100	0.2800
3-Dec-11	0.0132	27.6200	70.5600	0.6780
4-Dec-11	0.0137	27.9900	68.9000	0.1100
5-Dec-11	0.0109	28.8100	68.1000	0.4200
6-Dec-11	0.0131	28.6400	67.0000	0.4000
7-Dec-11	0.0300	28.0900	0.5300	0.5300
8-Dec-11	0.0199	27.9500	60.8000	0.5000
9-Dec-11	0.0100	28.5500	70.0000	0.4900
10-Dec-11	0.0106	28.8600	65.6000	0.3700
11-Dec-11	0.0097	29.6800	65.6000	0.3800
12-Dec-11	0.0112	30.0000	61.3000	0.5000
13-Dec-11	0.0125	28.9600	60.2000	0.4200
14-Dec-11	0.0154	27.5800	61.5000	0.3800
15-Dec-11	0.0233	28.1540	68.3000	0.2400
16-Dec-11	0.0134	28.3110	61.6000	0.5400
17-Dec-11	0.0151	28.1000	55.9000	0.3800
18-Dec-11	0.0145	26.9700	59.9000	0.3100
19-Dec-11	0.0149	27.0100	59.3000	0.3000
20-Dec-11	0.0155	26.5500	60.2000	0.2100
21-Dec-11	0.0165	26.7800	59.1000	0.3400
22-Dec-11	0.0186	26.5200	58.7000	0.2900
23-Dec-11	0.0145	26.1400	59.6000	0.4700
24-Dec-11	0.0137	27.2300	60.6000	0.2500
25-Dec-11	0.0176	27.2600	60.8000	0.2520
26-Dec-11	0.0132	26.7000	62.6000	0.3200
27-Dec-11	0.0175	26.6900	57.9000	0.4800
28-Nov-11	0.0313	28.8556	56.0000	0.5375
29-Nov-11	0.0087	26.9700	75.8000	0.4300
30-Nov-11	0.0086	27.1167	76.6000	0.5286
1-Dec-11	0.0087	28.5200	70.5000	0.1300
2-Dec-11	0.0121	28.8900	69.5100	0.2800
3-Dec-11	0.0132	27.6200	70.5600	0.6780
4-Dec-11	0.0137	27.9900	68.9000	0.1100
5-Dec-11	0.0109	28.8100	68.1000	0.4200
6-Dec-11	0.0131	28.6400	67.0000	0.4000
7-Dec-11	0.0300	28.0900	0.5300	0.5300
8-Dec-11	0.0199	27.9500	60.8000	0.5000

9-Dec-11	0.0100	28.5500	70.0000	0.4900
10-Dec-11	0.0106	28.8600	65.6000	0.3700
11-Dec-11	0.0097	29.6800	65.6000	0.3800
12-Dec-11	0.0112	30.0000	61.3000	0.5000
13-Dec-11	0.0125	28.9600	60.2000	0.4200
14-Dec-11	0.0154	27.5800	61.5000	0.3800
15-Dec-11	0.0233	28.1540	68.3000	0.2400
16-Dec-11	0.0134	28.3110	61.6000	0.5400
17-Dec-11	0.0151	28.1000	55.9000	0.3800
18-Dec-11	0.0145	26.9700	59.9000	0.3100
19-Dec-11	0.0149	27.0100	59.3000	0.3000
20-Dec-11	0.0155	26.5500	60.2000	0.2100
21-Dec-11	0.0165	26.7800	59.1000	0.3400
22-Dec-11	0.0186	26.5200	58.7000	0.2900
23-Dec-11	0.0145	26.1400	59.6000	0.4700
24-Dec-11	0.0137	27.2300	60.6000	0.2500
25-Dec-11	0.0176	27.2600	60.8000	0.2520
26-Dec-11	0.0132	26.7000	62.6000	0.3200
27-Dec-11	0.0175	26.6900	57.9000	0.4800
28-Dec-11	0.0283	26.0710	53.6000	0.7800
29-Dec-11	0.0125	25.2900	67.7000	0.4700
30-Dec-11	0.0121	24.8100	1.1400	1.1300
31-Dec-11	0.0140	26.5000	78.1000	0.3500
1-Jan-12	0.0116	26.9160	77.2000	0.2200
2-Jan-12	0.0105	27.1500	78.4000	0.1700
3-Jan-12	0.0082	27.9600	77.0000	0.3400
4-Jan-12	0.0073	28.3000	71.8000	0.2444
5-Jan-12	0.0109	29.4200	70.3000	0.2300
6-Jan-12	0.0182	28.4100	69.7000	0.2000
7-Jan-12	0.0101	29.9200	62.0000	0.5400
8-Jan-12	0.0093	31.0100	62.7000	0.3222
9-Jan-12	0.0221	28.5500	68.7700	0.3000
10-Jan-12	0.0119	28.8300	68.9000	0.2700
11-Jan-12	0.0087	30.1800	57.8000	2.1200
12-Jan-12	0.0119	30.3800	56.6000	3.2700
13-Jan-12	0.0096	29.3800	59.6000	1.0400
14-Jan-12	0.0161	26.8800	53.1000	2.1400
15-Jan-12	0.0063	27.5100	49.8000	1.9800
16-Jan-12	0.0192	25.7000	55.0000	2.3500
17-Jan-12	0.0147	25.8200	54.7000	2.8000
18-Jan-12	0.0162	27.4630	55.4000	0.9500
19-Jan-12	0.0147	25.9600	59.6000	1.2500
20-Jan-12	0.0135	27.4100	57.8000	0.9600
21-Jan-12	0.0110	27.2500	60.6000	0.2700
22-Jan-12	0.0132	27.7300	55.7000	0.3500
23-Jan-12	0.0125	28.2300	55.2000	0.3700
24-Jan-12	0.0126	27.2000	57.8000	0.1900
25-Jan-12	0.0124	27.4700	54.0000	0.1900
26-Jan-12	0.0124	26.6000	57.7000	0.3200
27-Jan-12	0.0124	27.8500	57.7000	0.6300
28-Jan-12	0.0440	27.8900	58.2000	0.2500
29-Jan-12	0.0121	27.4000	57.4000	0.6000
30-Jan-12	0.0144	28.2500	56.0000	0.4600
31-Jan-12	0.0131	28.0000	57.9000	0.2700
1-Feb-12	0.0154	27.8000	55.6000	0.2600
2-Feb-12	0.0151	27.2000	57.5000	0.2400
3-Feb-12	0.0136	29.0000	52.9000	0.3900
4-Feb-12	0.0164	27.1800	54.8000	0.3400
5-Feb-12	0.0137	27.6500	56.0000	0.2600
6-Feb-12	0.0156	29.6600	55.8000	0.2700
7-Feb-12	0.0106	28.4600	58.1000	0.2900
8-Feb-12	0.0117	27.9700	62.0000	0.1800
9-Feb-12	0.0108	28.2700	61.5000	0.3500
10-Feb-12	0.0123	28.5100	63.2000	0.1900
11-Feb-12	0.0089	28.5400	63.5000	0.2700
12-Feb-12	0.0114	28.6900	60.5000	0.2400
13-Feb-12	0.0087	29.1000	57.6000	0.3760
14-Feb-12	0.0088	29.1800	59.0000	0.3600
15-Feb-12	0.0097	29.0500	59.3000	0.2400
16-Feb-12	0.0123	28.2300	60.9000	0.5500
17-Feb-12	0.0110	28.9000	60.6000	0.2600
18-Feb-12	0.0122	29.4800	61.3000	0.3300
19-Feb-12	0.0218	27.9400	60.3000	0.4500
20-Feb-12	0.0115	28.6700	59.4000	0.2600
21-Feb-12	0.0138	26.1100	64.6000	0.2700
22-Feb-12	0.0101	27.9700	60.7000	0.2700
23-Feb-12	0.0106	29.1900	44.9000	0.5100
24-Feb-12	0.0112	28.4600	42.1000	0.4900
25-Feb-12	0.0159	28.5900	38.7000	0.5000
26-Feb-12	0.0116	28.5400	43.1000	0.3800
27-Feb-12	0.0099	29.1500	47.7000	0.3600
28-Feb-12	0.0136	31.3900	55.4000	0.4300

29-Feb-12	0.0120	29.0400	63.9000	0.3900
1-Mar-12	0.0141	29.4200	63.3000	0.2300
2-Mar-12	0.0156	29.4700	65.7000	0.2700
3-Mar-12	0.0154	29.9800	63.5000	0.3200
4-Mar-12	0.0182	30.4000	62.0000	0.3000
5-Mar-12	0.0155	30.4800	62.3000	0.2900
6-Mar-12	0.0180	29.8000	61.6000	1.3600
7-Mar-12	0.0208	29.4100	60.3000	1.2500
8-Mar-12	0.0184	29.8800	59.9300	2.5500
9-Mar-12	0.0145	29.8200	59.5000	0.2800
10-Mar-12	0.0152	29.3900	65.7000	0.3900
11-Mar-12	0.0162	29.7300	60.1000	0.3300
12-Mar-12	0.0154	29.4900	63.6000	0.3800
13-Mar-12	0.0148	29.8100	64.0000	0.9600
14-Mar-12	0.0161	30.4800	59.5000	0.3500
15-Mar-12	0.0154	30.5600	60.1000	0.4300
16-Mar-12	0.0150	30.3200	60.7000	0.4100
17-Mar-12	0.0158	30.0500	62.5000	0.3300
18-Mar-12	0.0159	29.8900	65.1000	0.2700
19-Mar-12	0.0152	29.7200	62.0000	0.2300
20-Mar-12	0.0140	29.8650	58.7000	1.0300
21-Mar-12	0.0161	29.6500	59.8000	######
22-Mar-12	0.0151	30.5100	55.1000	0.3800
23-Mar-12	0.0150	30.0700	58.8000	0.3200
24-Mar-12	0.0146	29.6900	55.7000	0.2700
25-Mar-12	0.0121	29.1700	55.8000	0.2700
26-Mar-12	0.0163	29.3600	56.7000	0.4600
27-Mar-12	0.0129	29.6200	58.2000	0.5480
28-Mar-12	0.0134	30.1900	60.9000	0.2500
29-Mar-12	0.0129	30.1100	60.1000	0.5100
30-Mar-12	0.0191	31.8000	60.9000	0.3600
31-Mar-12	0.0172	30.5000	62.4000	0.3400
1-Apr-12	0.0158	30.0000	62.1000	0.5100
2-Apr-12	0.0151	30.0900	56.1000	1.2600
3-Apr-12	0.0156	31.0200	55.1000	1.3900
4-Apr-12	0.0145	31.1200	59.3000	0.9700
5-Apr-12	0.0153	30.3300	56.1000	1.2000
6-Apr-12	0.0156	31.0200	54.7000	1.3800
7-Apr-12	0.0181	30.9500	61.2000	1.0000
8-Apr-12	0.0145	30.9000	60.7000	1.1100
9-Apr-12	0.0170	30.8700	61.4000	0.8800
10-Apr-12	0.0190	31.1400	60.6000	1.1100
11-Apr-12	0.0171	30.8900	58.1000	0.6111
12-Apr-12	0.0144	30.8900	58.9000	0.4600
13-Apr-12	0.0178	30.6000	61.8000	1.0400
14-Apr-12	0.0171	31.0800	59.9000	0.4889
15-Apr-12	0.0171	30.9400	60.7000	0.4000
16-Apr-12	0.0140	30.5100	62.9000	1.1900
17-Apr-12	0.0152	30.8800	60.6000	0.8700
18-Apr-12	0.0164	31.0800	63.3000	0.8100
19-Apr-12	0.0151	30.7400	63.5000	0.6600
20-Apr-12	0.0149	27.8100	65.6000	0.7000
21-Apr-12	0.0164	31.4000	59.6000	0.7300
22-Apr-12	0.0150	31.1100	58.4000	0.6600
23-Apr-12	0.0187	30.9200	63.7000	0.5900
24-Apr-12	0.0158	31.1400	61.5000	0.2800
25-Apr-12	0.0173	31.1200	62.7000	0.5800
26-Apr-12	0.0124	31.6700	61.1000	0.3400
27-Apr-12	0.0163	33.1300	59.4000	2.6500
28-Apr-12	0.0138	33.1300	59.4000	2.6500
29-Apr-12	0.0155	32.2600	60.5000	2.4900
30-Apr-12	0.0144	32.2600	60.5000	2.4900
1-May-12	0.0151	32.0000	57.5000	1.5700
2-May-12	0.0146	31.8100	57.5000	1.7600
3-May-12	0.0141	31.6000	55.6000	0.7400
4-May-12	0.0156	32.3400	58.0000	1.6300
5-May-12	0.0158	32.7800	52.4000	0.8400
6-May-12	0.0152	31.9600	55.9000	1.5300
7-May-12	0.0163	31.4100	54.7000	1.8300
8-May-12	0.0151	32.4200	61.6000	1.5100
9-May-12	0.0153	31.6800	59.1000	2.0900
10-May-12	0.0144	31.6800	59.1000	2.0900
11-May-12	0.0172	31.1000	54.0000	1.9900
12-May-12	0.0151	31.3200	59.1000	2.7800
13-May-12	0.0190	31.3100	58.9000	1.1700
14-May-12	0.0153	31.8800	61.0000	1.7300
15-May-12	0.0142	32.2900	58.9000	2.3900
16-May-12	0.0173	32.2111	52.6667	0.3667
17-May-12	0.0233	31.8300	54.1000	1.0300
18-May-12	0.0174	33.1400	50.7000	1.0800
19-May-12	0.0211	33.7500	54.5000	6.6100
20-May-12	0.0181	32.7300	50.3000	0.7700

21-May-12	0.0166	32.8600	53.5000	0.9100
22-May-12	0.0156	33.1500	50.3000	1.0300
23-May-12	0.0179	33.0300	49.6000	2.4800
24-May-12	0.0158	33.8500	48.7000	2.2400
25-May-12	0.0161	34.2800	42.1000	2.4200
26-May-12	0.0185	32.3100	42.7000	1.8900
27-May-12	0.0147	33.7400	82.5000	1.0200
28-May-12	0.0161	34.4700	42.3000	4.9500
29-May-12	0.0155	33.2300	45.1000	2.2200
30-May-12	0.0171	34.4600	43.8000	2.6700
31-May-12	0.0220	33.8500	41.4000	2.9400
1-Jun-12	0.0175	34.1000	37.9100	1.9100
2-Jun-12	0.0145	33.4600	37.5000	2.2200
3-Jun-12	0.0158	33.4111	38.6000	1.9000
4-Jun-12	0.0149	33.8300	45.3000	1.9400
5-Jun-12	0.0164	32.7200	44.7000	1.2900
6-Jun-12	0.0176	33.3400	44.3000	1.5600
7-Jun-12	0.0152	33.2100	43.5000	1.6000
8-Jun-12	0.0154	33.5900	42.8000	1.3200
9-Jun-12	0.0150	32.8600	40.4000	1.5800
10-Jun-12	0.0148	32.7700	41.7000	5.0300
11-Jun-12	0.0172	32.8800	38.7000	1.2800
12-Jun-12	0.0158	32.9200	38.6000	1.4700
13-Jun-12	0.0158	32.0800	43.8000	0.9800
14-Jun-12	0.0156	31.9600	48.0000	1.1200
15-Jun-12	0.0174	33.3300	47.6000	1.1800
16-Jun-12	0.0158	31.5000	46.5556	1.0333
17-Jun-12	0.0161	31.1900	45.3000	1.1800
18-Jun-12	0.0145	30.8300	45.9000	0.7800
19-Jun-12	0.0181	31.0500	46.5000	1.3100
20-Jun-12	0.0171	31.7100	44.3000	2.2200
21-Jun-12	0.0144	31.5400	42.0000	1.6600
22-Jun-12	0.0160	31.9500	44.5000	2.0300
23-Jun-12	0.0162	32.1800	45.1000	1.3300
24-Jun-12	0.0147	32.1000	46.8000	1.1200
25-Jun-12	0.0151	31.6100	47.8889	0.6800
26-Jun-12	0.0135	31.3800	48.3000	1.1300
27-Jun-12	0.0131	30.8700	52.8000	1.3700
28-Jun-12	0.0095	31.8400	59.6000	0.3600
29-Jun-12	0.0103	33.1500	59.1000	0.3600
30-Jun-12	0.0092	31.9000	52.3000	1.3000
1-Jul-12	0.0165	31.8000	2.8500	0.6000
2-Jul-12	0.0147	29.2900	53.4000	0.9200
3-Jul-12	0.0143	31.2100	46.5000	2.2300
4-Jul-12	0.0125	31.3900	43.7000	1.7300
5-Jul-12	0.0151	32.0000	44.4000	1.2700
6-Jul-12	0.0148	31.7700	48.2000	1.1000
7-Jul-12	0.0145	32.2500	47.9000	0.4700
8-Jul-12	0.0129	31.7000	47.5000	0.9230
9-Jul-12	0.0140	30.4400	58.1000	0.6500
10-Jul-12	0.0161	30.9700	56.0000	1.1000
11-Jul-12	0.0162	30.7200	55.7000	1.0500
12-Jul-12	0.0135	29.7200	62.3000	0.6000
13-Jul-12	0.0143	27.7900	56.3000	0.5000
14-Jul-12	0.0131	29.2600	65.4000	0.6000
15-Jul-12	0.0118	28.6700	65.2000	0.4500
16-Jul-12	0.0114	29.5200	61.0000	0.5200
17-Jul-12	0.0150	29.4000	65.8000	0.8300
18-Jul-12	0.0156	29.0100	64.6000	1.1200
19-Jul-12	0.0131	30.2000	61.6000	0.5600
20-Jul-12	0.0128	30.1100	53.7000	1.4200
21-Jul-12	0.0121	30.2600	55.8000	1.3400
22-Jul-12	0.0142	31.3400	53.4000	1.2400
23-Jul-12	0.0140	31.7300	51.7000	1.5900
24-Jul-12	0.0149	31.6200	48.4000	0.9900
25-Jul-12	0.0140	31.8000	53.9000	0.8000
26-Jul-12	0.0115	31.5300	50.9000	1.0500

Date	Actual	Forecasted ANN	Error	ABS Error	% Error
27/7/12	0.0129	0.01466	-0.0018	0.0018	13.660
28/7/12	0.0159	0.01469	0.0012	0.0012	7.6348
29/7/12	0.0120	0.01291	-0.0009	0.0009	7.5855
30/7/12	0.0136	0.01551	-0.0019	0.0019	14.079
31/7/12	0.0159	0.01594	0.0000	4E-05	0.2769

5.0 Findings:

The data is separated for training of the network and the network was trained. The weight values were fixed. Remaining data was used for testing of the network. **The Mean absolute Percentage of error of the data during testing is 8.647%.** The above results validate the proposed model. Hence it is concluded that the above model can be used for predicting surface ozone concentration with wind speed, temperature, % relative humidity as predictors.

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