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DISPERSION PATTERN OF VEHICULAR CARBON MONOXIDE NEAR BUSY ROAD JUNCTION IN COIMBATORE CITY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In urban air quality, Automobile sources are considered to be threatening issue. Profuse expansion of Coimbatore city has resulted in a drastic increase of air pollution. The main objective of this study is to model the dispersion pattern of vehicular carbon monoxide near busy road junction in Coimbatore city using ANN model. Two consecutive days in every month of 2011 have been chosen to calculate 8-hour average CO concentration at six receptor points. ANN modeling Technique has been used to predict air pollution concentrations in the urban environment. The model calculate pollution concentrations due to observed traffic, meteorological and pollution data after an appropriate relationship has been obtained empirically between these parameters. The predicted CO concentration at the receptor points are then compared with the observed concentrations of CO. ANN method is used to evaluate the model performance by comparing the predicted and observed CO concentration.

KEYWORDS: Air Quality Modelling, ANN - Artificial Neural Network, CO Concentration, CO Prediction

INTRODUCTION

Rapid growth of motor vehicles ownership and activities in indian cities are causing serious health, environmental and socio economic impacts (**Badami et al., 2009**). In urban air quality, automobile sources are considered to be threatening issue. The rapidly growing vehicle fleet, distance travelled by each vehicle and change in land use pattern are some of the primary causes of vehicular air pollution and consequently urban air pollution (**Mayer et al., 1999**). The motor vehicle population in India has increased from nearly 0.3 million in 1951 to 115 million in 2009, of which, two wheelers accounted for approximately 70% of the total vehicles (**CPCB**).

The pollutants include respirable suspended particulate matter (RSPM), especially $PM_{2.5,}$ Nitrogen dioxide (NO_2), CO and hydrocarbons (HC). Vehicular pollution is the major contributor of urban air pollution in most of the cities of India and estimated to account for approximately 70% CO, 50%HC, 30-40% NO_X, 30% of SPM and 10% of SO_2 of the total pollution load of which two third is contributed by two wheelers alone(**Sharma et al, 2005**). The city of coimbatore is no exception. Because of the city is experiencing an exponential industrial and population growth, it has a high potential for vehicular air pollution. Further, the meteorological conditions prevailing in the city are unfavourable for the dispersion of pollutants. The most affected group of people is urban inhabitants especially the people residing in the vicinity of urban roadways as well as pedestrians. The situation further deteriortae at urban roads, where the ventilation is insufficient for dispersion of pollution. Therefore, the prediction of pollutants emitted in the vicinity of urban roadway is of foremost importance in order to improve ways to mitigate vehicular pollution effect.

METHODOLOGY

Study Area

Coimbatore city is a rapidly developing city and it experiences an exponential growth in the vehicular usage and subsequently high fuel consumption. Also the presence of industrial activities on a large scale in and around Coimbatore tends to have a strong impact on the environmental quality of the city. Transportation is the prime source of mobility in urban society. It not only provide a fast, convenient and economical mode or carrier to meet multifarious activities of citizens but vitiates the environment in the process by emanating obnoxious and toxic pollutants in the surrounding atmosphere and there by poses serious health hazards to human and biotic community. It has been found that the vehicular exhaust accounts for the part of the pollution from all sources put together in all major road junctions in Coimbatore city in India. Hence, it was decided to monitor the air quality in some selected locations. In the current study, sampling locations were selected based on the traffic density. The concentrations of CO in the ambient air were estimated.

Sites were chosen in respect of maximum vehicular usage as the basis. Six sampling stations were selected for monitoring ambient air concentration of CO over Coimbatore city viz,

- **Site 1:** Ukkadam
- **Site 2:** Railway station
- **Site 3:** Hope college Junction – Peelamedu
- **Site 4:** Gandipuram-Corporation Bus terminal
- **Site 5:** Mettupalayam road bus terminal
- **Site 6:** Lawly road

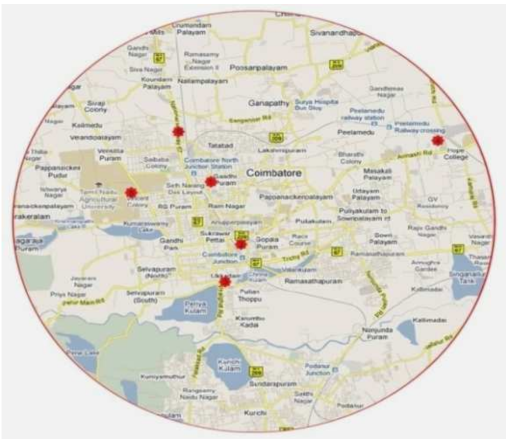

Figure 1: Location of Six Sampling Stations

Architecture of Neural Networks

The basic components of neural network architecture are shown in figure 2. It consist of an input layer with the number of processing elements equal to the predictor variables and an output layer with the number of processing element equal to the predicted variables. In between the input and output layers, there are hidden layers and the number of processing elements in each hidden layers will be fixed on trial and error and depend on the desired accuracy of the model.

The number of neurons in the input layer equals the number of input variables (i.e. in the present work meteorological and traffic characteristics are variables). The output layer consists of one neuron, i.e. the pollutant concentration. The number of neurons in the hidden layer depends upon the number of training patterns, the number of input/output neurons, the amount of CO in the data, the network architecture, the type of activation function used in the hidden layer and the training algorithm (Alsugair and Al-Qudrah, 1998; Sarle, 1997). One hidden layer is sufficient to approximate any nonlinear function in addition to input and output layers (Hornik et al., 1989). The number of neurons in the hidden layer is obtained by training several networks and estimating the corresponding errors on the test data set. A few neurons in the hidden layer produce high training and testing errors due to under-fitting and statistical bias. On the contrary, too many hidden layer neurons lead to low training error, but high testing error, due to over fitting and high variance (Sarle, 1997). In the past, researchers used 'rule of thumb' to find the number of neurons (H) in the hidden layer, as described below

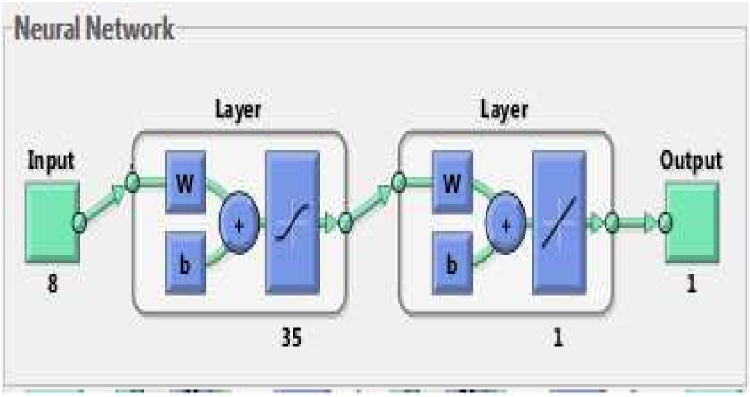

Figure 2: Neural Network Architecture

Feed Forward Back Propagation Networks

The most suitable ANNs to interpret environmental processes (and among them the pollution one) are those known as feed-forward back propagation because they map inputs to outputs non deterministically (like the natural process they describe past experience without copying it) by optimizing forecasting of the learning section. It is possible to reach evidence of the ANNs to generalize classical models, by writing input/output analytical formation of network.

Formulation of the Network

The neural network configuration is developed in the following stages.

- Selecting input vector
- Selecting Output vector
- Configuring hidden layer
- Normalizing input output parameters
- Presenting training pairs
- Testing the network architecture
- Organizing training set

Selection of Input Layer Nodes

The input layer has to be configured taking into account the possible parameters that may influence the output. Although the network is supposed to map unknown additional relationship between the input and output parameters. The performance for unseen problems, is dependent on input parameters. The selection of input layer parameters becomes more important for problems like approximation and for mapping a complicated non-linear relation. Whenever it is possible, the use of binary type of input is recommended instead normalized continuous-valued input. The network is found to have performed in such a condition. This style increases the number of nodes in an input, which are justified cases if the piece of information to be provided is of vital importance.

Selection of Output Layer Nodes

The selection of output layer nodes is the simplest task in the net development. Normally the number of output parameters is decided automatically by a number of desired output parameters. But sometimes it may be required to provide a node for a parameter which is not desired, to facilitate easy mapping in the functional relationship between the input and output parameters. The redundant node in the output layer may be neglected.

Configuring Hidden Layers

The selection of the number of hidden layers, the number of nodes in the hidden layers is the most challenging part in the total network development process, Moreover, there are no fixed guidelines available for this purpose, and this has to be trail and error method. Though some investigators tired to arrive an approximate formula, still there is no reliable method. Therefore, generally, the decision about this takes longer time, it may take weeks to train the neural network. It is proves that with a sufficient number of nodes, any functional relationship can be mapped using the neural network having single hidden layer. However, an increase in the number of hidden layers may improve the generalized capacity. The number of hidden layers as well as the nodes were altered to achieve the accuracy and to improve generalized capacity.

Selection of Initial Weights

Before starting ANN training, initialization of ANN weights and the bias (free parameters) are required. A good choice for the initial values of the synaptic weights and bias of the network can be very helpful in obtaining fast convergence of training process. If no proper information is available, then all free parameters of the network are set to random numbers that are uniformly distributed at a small range of values. When the weights associated with a neuron grow sufficiently large, neuron operates in the region within which the activation function approaches limits (in sigmoid function 1 or 0). With this, derivative of activation function (DAF) will be extremely small. When DAF approaches zero, the weight adjustment (made through Feed Forward back-propagation) also approaches zero, which results in ineffective training.

Normalization of the Training Data Set

In many ANN softwares, normalization (rescaling input data between 0 and 1) of training data set is required before presenting it to the network for its learning, so that it satisfies the activation function range14. Normalization is also necessary if there is a wide difference between ranges of input values. Normalization enhances learning speed of network and avoids possibility of early network saturation.

Activation Function

The non-linear relationship between input and output parameters in any network requires a function, which can appropriately connect and/or relate the corresponding parameters (Sarle, 1997). Past air pollution related studies by Gardner and Dorling (1999, 2000), demonstrated that the hyperbolic sigmoid activation function is faster and efficient in mapping the nonlinearity among the hidden layer neurons than the logistic sigmoid activation function (Comrie, 1997; Rege and Tock, 1996). Hence, in the present study the hyperbolic tangent function has been used for hidden layer neurons. Further, the input and output layer neurons use the ‘identity function’ for their respective target values (Gardner and Dorling, 2000).

Training and Testing

The neural networks are mostly trained using the ‘supervised’ learning algorithm. It is accomplished by providing known input and output data in an ordered manner to the network (Rumelhart and McClelland, 1995). Training involves finding the set of network weights thus enabling the model to represent the underlying patterns in the training data. It is achieved by minimizing the model error for all the input and associated output patterns (Gardner and Dorling, 1998). The ‘under-training’ of the network ‘traps’ the training algorithm in ‘local’ minima and ‘over-training’ results in high model prediction errors (Gardner and Dorling, 1998, 1999; Comrie, 1997). The over training can be avoided by training the network on a subset of inputs and outputs to determine weights and subsequently tested on the remaining (quasi-independent) test data to assess accuracy of the model predictions (Comrie, 1997).

Therefore, the number of training epochs is decided avoiding under- and/or over-training of the network. The back-propagation learning algorithm is most suitable for air-quality modelling studies (Gardner and Dorling, 1998; Comrie, 1997). This algorithm divides the data into three partitions namely, the ‘training data set’, the ‘test data set’ and the ‘evaluation data set’. The ‘training data set’ forms the bulk of the data used for the training purposes; the ‘test data set’ is used to check the generalization performance of the trained neural network model. The training is stopped when the performance on the ‘test data set’ results into minimum model error. Finally, the ‘evaluation data set’ is used to validate the model (Gardner and Dorling, 1998). The step-by-step procedure of the back-propagation training

Meteorological and Traffic Characteristic Variables

The ANN models were developed for respectively, using daily average meteorological and traffic characteristics as predictor variables. Several hundred experiments were performed to determine the best combination of the number of hidden layers, the learning algorithm and the transfer function. The guidelines were considered for choosing the optimum the number of hidden layers, the learning algorithm and the activation function.

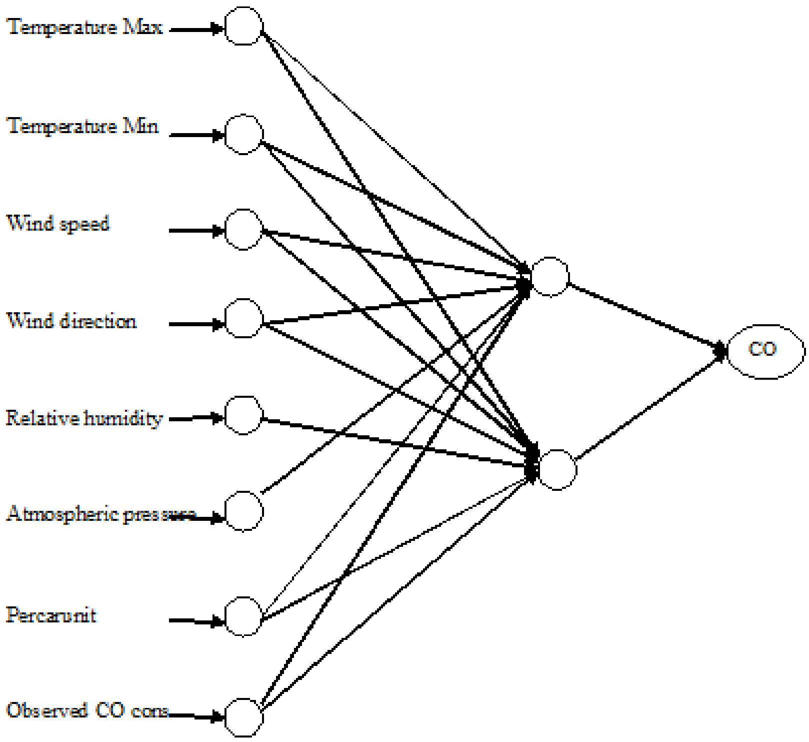

Figure 3: Structure of ANN-Based CO Model

The inputs to these runs were the meteorological and traffic characteristic variables in the input layer, the output was in terms of only pollutant concentration, i.e. CO. The number of neurons in the hidden layer were varied from 2 to 34. The descriptive statistics test, i.e. '*d*' value and RMSE (Willmott, 1982) were used to arrive at optimum number of neurons in the hidden layer. As a result, a fully connected feed-forward neural network with 17 neurons in the input layer, a single hidden layer, with five hidden neurons and a single neuron in the output layer shows best prediction on the 'test data set'. Table 1 shows the statistics of 24 h average ANN-based CO models with the number of neurons in the hidden layer. Tables lists the performance of the ANN model during generalization on 'test data set' and. After repeated experiments, the best model prediction on the test data set was achieved at 150 training epochs with 'η' = 0.01 and 'μ' = 0.7 at model prediction was achieved after 250 training epochs with 'η' = 0.001 and 'μ' = 0.3. Figure 2 shows the architecture of the models with predictor variables.

Data Base Construction

The monitored data on pollutant and meteorological parameters from a time series. The surface temperature, wind speed(m/s), wind direction (degree), Relative pressure(hpa), Pcu value (pas car equivalent) were considered as the predictor variables for each of the pollutant namely CO. The outliers have not been eliminated, as there is a enhance of extreme events being omitted. To facilitate the comparison of models between stations, a uniform database was created from the pollutants and met data.

Training the Network

After deciding the number of elements in the input layer and output layer, the numbers of hidden layers and the number of elements in the hidden layers have been chosen by trial and error. The learning parameter, number of cycles and the error tolerance has given as input. The iterations continue by training the network with the training input data set.

The weights are initially set to random values. The inputs are then propagated forward in the network until they eventually reach the output layer. With the given learning parameter, the nodel tries to capture the non-linear complex relationships between the weather parameters and pollutants concentration.

The inputs are then propagated forward in the network until they actually reach the output layer. In each iteration the error between the observed and predicted values gets propagated back into the whole network and weights get adjusted accordingly to reduce the error in each iteration.

Testing the Network

The trained network is fed with the testing data that is un exposed to the architecture. The weight at the final iteration is assigned to the input parameters of the architecture and the output is obtained. The difference between the observed and predicted concentrations denotes the accuracy of the model.

Files Used for ANN Modeling

Train Weight.dat File

The initialized weights for the choosen architecture of the network in this file. During training phase. These weights are updated after completion of one cycle and finally the updated weights are stored in the same for computing the output of the test data.

Training.dat File

This file stores both the input parameters as well as the corresponding observed output parameter, constituting one exemplar pair of training set. Number of such pairs will be presented to the network to learn the behavior of data. Tables 1 were the training data set before normalization for the CO models for all stations.

Table 1: Training Data Set for CO Prediction Model-Gandhipuram

Temperature Max	Temperature Min	Wind Speed (m/s)	Wind Direction (Degree)	Relative Humidity	Atmospheric Pressure	PCU	CO
28.8	20.6	0.98	128.3	76.2	960.5	50054	710
29.2	20.6	0.95	158.6	81.5	959.7	50054	653
29.5	20.3	0.92	141.7	83.2	960.4	50054	710
26.7	17.8	1.06	183.5	86.8	961.5	50054	653
29.7	20.9	1.62	127.2	76.9	961.3	50054	710
27	19.4	1.61	67.4	79.7	960.9	50054	653
29.1	20.4	1.41	94.1	70.4	961	50054	710
30.3	18.7	0.96	141	71.7	960.2	50054	653
31	21.7	0.98	103.1	77.6	959.2	50054	710
30.3	20.2	0.86	187.8	77.6	960.1	50054	653
30.1	19	0.83	172.1	75.8	961	50054	710
31.3	15.4	0.79	252.8	66.8	961.1	50054	653
30.3	14.5	0.94	172.4	67.3	961.1	50054	710
30.4	13.8	1.19	169.2	57.9	961.9	50054	653
29.7	14.9	1.24	153.3	59.5	962.5	50054	710
29.6	20	1.68	53.4	66.4	963.1	50054	653
29.4	19.5	1.37	131.3	74.5	962.3	50054	710
30.5	20.1	1.25	102	71.2	962.3	50054	653
30	15.9	1.58	79.4	62.5	962	50054	710
30.4	15.4	1.23	137.6	57.8	961.8	50054	653
31	16.9	1.44	146.9	61.5	962.7	50054	710
30.6	19.1	1.93	57.9	66.7	962.9	50054	653

Table 1: Contd.,

29	19.5	2.03	37.8	65.2	964	50054	710
29	18.4	2.29	42.4	62.5	964.7	50054	653
29.1	18.8	2	58	62.5	964.2	50054	710
28.7	18.8	1.86	68.1	67.7	964	50054	653
29.1	21	2.23	46	69.6	964.8	50054	710
29.9	19.7	1.83	51.3	70.5	964.5	50054	653
30.8	20.4	1.51	72.6	65.4	963.8	50054	710
31.2	16	1.82	92	64.4	962.7	50054	653
30.9	17.7	1.8	129.1	59.8	963.1	50054	710
31.2	16.7	1.52	121.3	57.8	963.5	51635	734
31.6	15.2	1.64	158.8	52.8	963.6	51635	779
30.1	17	2.01	114.4	47.7	963.1	51635	734

Table 2: Training Data Set for CO Prediction Model-Gandhipuram

Temperature Max	Temperature Min	Wind Speed (m/s)	Wind Direction	Relative Humidity	Atmospheric Pressure	PCU	CO	Trained
28.8	20.6	0.98	128.3	76.2	960.5	50054	710	653
29.2	20.6	0.95	158.6	81.5	959.7	50054	653	653
29.5	20.3	0.92	141.7	83.2	960.4	50054	710	653
26.7	17.8	1.06	183.5	86.8	961.5	50054	653	653
29.7	20.9	1.62	127.2	76.9	961.3	50054	710	653
27	19.4	1.61	67.4	79.7	960.9	50054	653	653
29.1	20.4	1.41	94.1	70.4	961	50054	710	653
30.3	18.7	0.96	141	71.7	960.2	50054	653	653
31	21.7	0.98	103.1	77.6	959.2	50054	710	653
30.3	20.2	0.86	187.8	77.6	960.1	50054	653	653
30.1	19	0.83	172.1	75.8	961	50054	710	653
31.3	15.4	0.79	252.8	66.8	961.1	50054	653	653
30.3	14.5	0.94	172.4	67.3	961.1	50054	710	653
30.4	13.8	1.19	169.2	57.9	961.9	50054	653	653
29.7	14.9	1.24	153.3	59.5	962.5	50054	710	653
29.6	20	1.68	53.4	66.4	963.1	50054	653	734
29.4	19.5	1.37	131.3	74.5	962.3	50054	710	734
30.5	20.1	1.25	102	71.2	962.3	50054	653	734
30	15.9	1.58	79.4	62.5	962	50054	710	734
30.4	15.4	1.23	137.6	57.8	961.8	50054	653	734
31	16.9	1.44	146.9	61.5	962.7	50054	710	734
30.6	19.1	1.93	57.9	66.7	962.9	50054	653	734
29	19.5	2.03	37.8	65.2	964	50054	710	734
29	18.4	2.29	42.4	62.5	964.7	50054	653	734
29.1	18.8	2	58	62.5	964.2	50054	710	734
28.7	18.8	1.86	68.1	67.7	964	50054	653	734
29.1	21	2.23	46	69.6	964.8	50054	710	734
29.9	19.7	1.83	51.3	70.5	964.5	50054	653	734
30.8	20.4	1.51	72.6	65.4	963.8	50054	710	734
31.2	16	1.82	92	64.4	962.7	50054	653	752
30.9	17.7	1.8	129.1	59.8	963.1	50054	710	752
31.2	16.7	1.52	121.3	57.8	963.5	51635	734	752
31.6	15.2	1.64	158.8	52.8	963.6	51635	779	752
30.1	17	2.01	114.4	47.7	963.1	51635	734	752

Out.dat File

This file stores the results calculated by using the updated weight matrix test data. For the given input vector the output vector is stored in this file.

Table 3: Observed Value and Predicted Output of the Model-Gandhipuram

Sl. No.	CO Observed	CO Predicted
1	710	710.0649
2	653	654.4631
3	710	709.5967
4	653	653.3889
5	710	710.7085
6	653	652.9867
7	710	710.4571
8	653	653.3889
9	710	709.2723
10	653	652.8523
11	710	709.0186
12	653	654.3043
13	710	710.2696
14	653	651.3681
15	710	710.4919
16	653	652.9141
17	710	710.0867
18	653	652.3663
19	710	711.6306
20	653	654.9144
21	710	708.832
22	653	653.8305
23	710	710.6737
24	653	651.9546
25	710	707.9869
26	653	653.4111
27	710	708.6143
28	653	653.1165
29	710	710.573

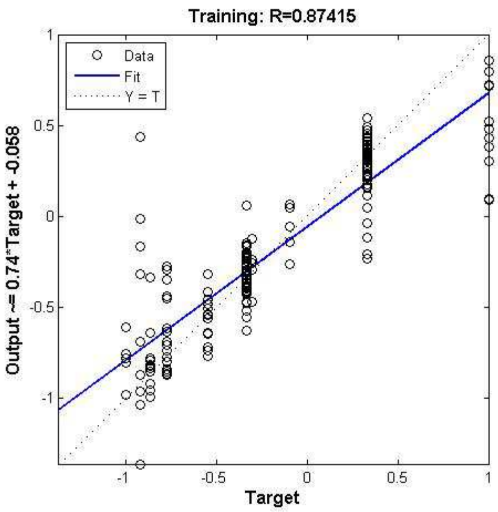

Figure 4: CO Concentration of Ukkadam

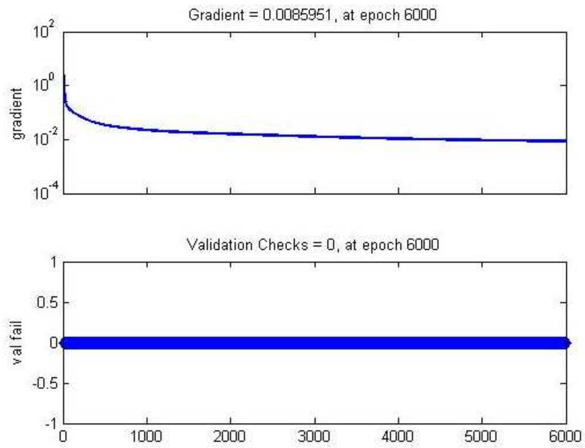

Figure 5

RESULTS AND DISCUSSIONS

Ann model is validated against measured CO concentrations, which is further applied in predicting of the pollutant. Randomly selected data from the same measured traffic and meteorological data as represented in 2-7 and Table-2 respectively. The values predicted by Ann are compared with the measured values. The emission factors as calculated for the mentioned motorised vehicles from Dhakal et al., 1998. Composite emission factors i.e. weighted average emission factor considering individual numbers of vehicles of every category are calculated based on traffic volume data. A 16 spoke Wind rose is generated by Lakes Environmental WRPLOT View tool **(Jain et al., 2006)**, based on the same dataset for study area.

In order to validate the Ann model for CO in study area, measured CO concentrations of days are selected. With the help of mentioned meteorological condition and meteorological and emission data and traffic volume data, Ann is run. The linear regressions between CO concentrations measured and predicted by Ann are plotted and are represented in Figure 4 to 5. Table-3 lists the performance statistics of the Ann model predictions of CO concentrations on the, six sampling station in Coimbatore. The r^2 value for Ukkadam, Railway station, Hopes College, Gandhipuram, MTP Road and Lawly Road are found to be 0.821, 0.985, 0.985, 0.971 respectively. It indicates that the model perform better at all the above stations. Further the prediction of CO concentration are also closely matching with the observed CO concentration. Figure 4-5 shows observed versus predicted CO concentration for all the six sampling stations.

Table 4: The Performance Statistics of the ANN Model

S. No	AAQ Station	R^2
1	Ukkadam	0.87415
2	Railway station	0.89751
3	Hopes College	0.88015
4	Gandhipuram	0.86208
5	MTP road	0.89241
6	Lali road	0.90595

CONCLUSIONS

The study deals with an approach for validation and application ANN model for a busy road juctions in Coimbatore city for CO. It has been inferred that ANN model prediction is more accurate as it resembles the real scenario ideally and exhibits better correlation with measured values (r^2 being 0.82 to 0.99). The study also shows a typical example pollutant contour around the study area, based on spatial data prediction. This approach of modelling thus would be helpful for air quality planning for the city of Coimbatore where spatial distribution of air quality is required to estimate. The present work provides vital statistics and guidelines on the choice of the ANN-parameters, e.g. 'when to stop' the training process and determination of the learning parameters in Feed forward back propagation learning algorithm. Multilayer neural network technique has been used to develop short-term ANN-based Co model for the air-quality prediction purposes at a traffic intersection and arterial road in the Coimbatore city.

The daily time series of Co concentration, meteorological and traffic characteristic variables, collected for the years from 2011, Jan to Dec, have been used for training, testing and evaluation of the ANN-based models. The models have been formulated following input data sets, with both meteorological and traffic input data. The regression coefficient for all the prediction models are nearly 0.8 these values are slightly away from the ideal value of one, they are found appreciable as for as the air quality models are concerned. These models can be implemented at Ukkadam, Railwaystation, Hope college junction, Gandipuram bus terminal, Mettupalayam road, Law lyroad. The prevailing meteorological parameters the selected monitoring stations is one of the reasons for improved efficiency of the models. Since the modeling technique is simple to the models can be developed for shor term application using the data over a short period during which chance of occurrence of cycles trends of pollutants concentration is implausible.

REFERENCES

1. Attri S D, Singh S, Mukhopadhyay B & Bhatnagar A K, Atlas of hourly mixing height and assimilative capacity of atmosphere in India, Met Monograph No. Environment Meteorology-01/2008, Indian Meteorological Department, New Delhi, Govt of India.
2. Badami M.G, Urban transport policy as if people and the environment mattered: padestraian accessibility the first step, Economic & Political Weekly, 44(33) (2009).
3. CPCB, Status of the vehicular pollution control programme in India. Central Pollution Control Board, Ministry of Environment and Forest New Delhi, Govt. of India, 2010.
4. Dhakal, S. 1998. Transportation and Environmental Issues: A case study of Nepal. Reprint of paper presented at International Students' Seminar on Transport Research, 26-27 November, 1998, Chiba, Japan.
5. Jain, Parida M, Rastogi A & Mittal N, Performance evaluation of air pollution models for Delhi city, J Instn Engrs India Pt En, 87(9) (2006) 16-26.
6. The JL, The CL, Johnson MA (2007) User's Guide, CALROADS View Air dispersion Models for roadways, Lakes Environmental Software.
7. Mayer H, Air pollution in cities; Atmos Environ, 33 (1999) 4029-4037.
8. Potoglou, D. and Kanaroglou, P. S. 2005. Carbon monoxide emissions from passenger vehicles: predictive mapping with an application to Hamilton, Canada. *Transportation Research Part D* 10, 97-109.
9. Sharma N, Chaudhry K K & Rao C V C, Vehicular pollution modelling in India, J Instn Engrs India Pt En, 85 (2005) 46- 53.

10. Alsugair, A.M., Al-Qudrah, A.A., 1998. Artificial neural networkapproach for pavement maintenance. J. Comput. Civil Eng. ASCE 2 (4), 249–255.

11. Aitkenhead, M.J., McDonald, A.J.S., Dawson, J.J., Couper, G.,Smart, R.P., Billett, M., Hope, D., Palmer, S., 2003. A novel method for training neural networks for time-series prediction in environmental systems. Ecol. Model. 162 (1–2), 87–95.

12. Barciela, R.M., Garcia, E., Fernandez, E., 1999. Modelling primary production in a costal embayment affected by upwelling using dynamic ecosystem models and artificial neural networks. Ecol. Model. 120 (2–3), 199–211. Battiti, R., 1992. First and second order methods for learning between steepest descent and Newton's method. Neural Comput.4, 141–166.

13. Berry, T., Linoff, J., 1997. Data Mining Techniques. JohnWiley and Sons, NY.Bose, N.K., Liang, P., 1998. Neural Network Fundamentals with Graphs, Algorithms and Applications. Tata McGraw Hill Publishing Company Limited, New Delhi, India.

14. Boznar, M., Lesjak, M., Malker, P., 1993. A neural network based method for short-term predictions of ambient SO2 concentrations in highly polluted industrial areas of complex terrain.

15. Atmos.Environ. 27B (2), 221–230. Brosse, S., Guegan, J.F., Tourenq, J.N., Lek, S., 1999. The use of artificial neural networks to assess fish abundance and spatial occupancy in the littoral zone of a mesotrophic lake.

16. Ecol. Model. 120 (2–3), 299–311.Chen, T., March, C.F., 1971. Effect of highway configurations on environmental problems dynamics of highway associated air pollution. In: Englund, H.M., Berry, T. (Eds.), Second International Clean Air Congress. Academic Press, NY, pp. 35–40.Chon, T.S., Park, Y.S., Moon, K.H., Cha, E.Y., 1996. Patternizing communities by using an artificial neural network. Ecol. Model.90 (1), 69–78. Comrie, A.C., 1997. Comparing neural networks and regression model for ozone forecasting. J. Air Waste Manage. Assoc. 47, 653–663.