FORECASTING CARBON MONOXIDE CONCENTRATION USING ARTIFICIAL NEURAL NETWORK MODELING

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ABSTRACT:
Air pollution has emerged as a serious problem affecting health and environment. Out of many pollutants Carbon Monoxide (CO) gas is considered as a silent and lethal killer. In large urban areas such as Delhi, the CO emissions from the Transport sector pose unprecedented risks to the commuters and inhabitants. In order to eradicate the adverse impact of CO pollution, there exists a need for an early warning system, which may be of immense help to manage and regulate ambient CO concentrations. In this research paper an attempt is made to forecast CO gas based on historical data using artificial neural network (ANN). Real time 8 hourly average CO emission data of eleven years (1996-2006), day time (14.00hrs-22.00hrs) from ITO square of Delhi has been used for modelling and simulation study. Results of ANN studies show that these models are better suited to provide efficient and closer-to-reality forecasting in order to initiate policy measures which can be helpful to alleviate the excessive CO accumulations. Based on ANN modelling, an appropriate short-term management measures such as a pre-warning mechanism for air pollution episodes may be developed.

Keywords:- Concentration, Forecasting, Artificial Neural Network (ANN), Real time analysis, Modelling

1. INTRODUCTION
Air pollution as one of the major environmental concern, is a primary cause of adverse health effects on human beings (Elsom and Longhurst, 2004; Marshall et al., 2005). In big cities the concentration of air pollutants particularly carbon monoxide (CO) gas is increasing mainly because of burning of the fossil fuels in various applications concerned to the energy production in Domestic, Industrial, and Transportation sectors (EEA, 2000). As CO gas is the core (criteria) air pollutant resulting from the insufficient burning of fossil fuels (EPA, 2007a) and is called an invisible killer being colorless, odorless, and tasteless. CO can be lethal to human beings within minutes at high concentrations exceeding 12,800 parts per million (ppm) (Davis and Cornwell, 1998). EPA (1999) has given the summary of CO emissions by sources based on the most recent inventory and it states that as much as 95 percent of the CO in typical cities comes from mobile sources. The problem of CO emission could be of special concern in countries like Delhi where the number and use of vehicles has increased drastically (Bener et al., 1999). Gasoline powered vehicles are the major sources of CO in urban atmosphere. The contributions of various sources of air pollution in the ambient air of Delhi are as listed in table 1.1

Table 1.1: Trends in the Pollution Sources

	Source	1970-71	1980-81	1990-91	2000-2001
1	Industrial	56%	40%	29%	20%
2	Vehicular	23%	42%	64%	72%
3	Domestic	21%	18%	7%	8%

Carbon monoxide (CO) gas is a relatively non reactive pollutant and needs a better representation for its temporal and spatial distribution and also an effective diagnosis for atmospheric dispersion patterns. A high residence time of CO in the air (20-23 hrs.) and a high atmospheric life time of about 440.9 day light hours and its dispersion conditions are sensitive to meteorological changes (NRC Report, 2003). The air quality standards have evolved differently in different countries depending on the exposure condition, socio-economic situation and importance of other health related problem. The guiding values and periods of time-weighted average of CO exposures as given in table 1.2, have been determined in such a way that the carboxyhaemoglobin level of 2.5% is not exceeded, even when a normal subject engages in light or moderate exercise.

A series of policy measures have been undertaken over the last decade to address the increasing vehicular air pollution problems in Indian cities, but without any effective improvements in the urban air environment. The air quality forecasting (AQF) method are required to alleviate the air pollution problem using best method for identification and control, contemporary policy and planning intervention etc. An effective AQF system requires modern tool capable of providing pollution assessment due to emission scenario, traffic conditions, land use pattern etc. Models are valuable tools for regulatory purposes, policymaking and research applications. AQF could be best done using pre-warning (forecasting) system based on the modeling the past realizations of air pollution data. In the present study CO gas has been forecasted based upon ANN modeling which is the most efficient method for making use of both the measurements and modeling techniques.

2. LITERATURE REVIEW
Many CO models have been developed to forecast its concentration and health effect. These CO forecast models can be broadly classified into six major categories, viz. statistical, deterministic, numerical, stochastic, soft computing and hybrid. However, EPA has recommended three types of models to be used to demonstrate attainment of the CO NAAQS: rollback (or statistical rollback), Gaussian dispersion, and numerical predictive models (NRC, 2003). The earliest available study of CO data has been done by Colucci and Begeman (1969), who compared CO concentrations in Detroit, New York and Los Angeles and found that Los Angeles' high levels are related to frequent atmospheric temperature inversions and lower wind speeds. The various statistical and deterministic models though have greatly improved, but still have disadvantages in representing the actual influences of the traffic flow characteristics on the pollutant concentrations (Yang et al., 2007). Advances in soft computational modus operandi endow with techniques like the GIS, ANN, Genetic Algorithm etc. can be used for modeling and simulation of CO pollution event.

Table:-1.2 Ambient Air Quality Standards of CO ($\mu g/m^3$)

Air Pollutants	Time Weighted Average	WHO, 1999	India, 1994			USEPA 1997	UK 1997	Japan
			Industrial	Residential	Sensitive			
Carbon monoxide CO (Non-dispersive infrared Spectroscopy)	Annual average			100				
	24 Hrs			400				
	8 hrs	10000	5000	2000	1000	10000	10 ppm	
	1 hrs	30000	10000	4000	2000	40000		22900
	30 min	60000						
	15 min	100000						

The initial attempt to incorporate neural network and fuzzy in CO forecast was made by Tanaka et al., (1992 and 1995). A neural network based model has been developed by Drozdowicz et al. (1997) to predict the CO concentration in the urban areas of the Rosario, Argentina. Nagendra and Khare (2002) presented a detailed review of vehicular exhaust emission models including ANN based models. Nagendra and Khare (2004) developed an ANN-based line source model to forecast CO concentrations. Yang et al., (2007), presented an ANN technique to forecast real time short cut roadside CO and CO_2 conc., considering the effects of traffic flow and road conditions.

3. METHODOLOGY

The CO dispersion process in an urban area is a complex and non-linear process. The ambient CO concentration is affected by many and often inter related factors Such as Temperature, wind velocity, rainfall events, geomorphologic characteristics of study area / road, i.e. size, shape, slope, land use and vegetation type and Traffic Conditions (vehicle population and type, traffic flow and speed, etc. (Yang et al., 2007). An ANN is a quite efficient tool for modelling and forecasting such a non linear CO air pollution time series with less effort, provided that efficient architectures are available. An ANN models take into account various factors to predict the CO concentrations. An ANN models for now casting of CO concentrations at any time t + Δt, depend on its previous concentrations (fig. 3.1) and on the other external information e.g. meteorological data, solar radiation, traffic information and chemical precursors (Benvenuto and Marani, 2000).

The purpose of developing a neural model is to produce a formula that captures essential relationships in data. Once developed, this formula is used to interpolate from a new set of inputs to corresponding outputs. In neural net structuring, this is called generalization. In a neural network each neuron has an activation function which specifies the output of a neuron to a given input. Neurons are switches that output a "1" when they are sufficiently activated and a "0" when not. The sigmoid activation functions $f(x) = 1/(1+e^{-x})$ is used in the design of neural network architecture in the study. There are two levels of data preprocessing required when trying to build a neural model.

- The first level is domain-dependent preprocessing in which relevant features are derived from the raw collected data.
- In the second problem-dependent preprocessing level, which is generic in nature and is used to transform and shape the data into a useful form for interfacing with the neural net. Here modeler decides the degree of preprocessing oriented to the application demand.
- Available data is divided into three set: training / learning set, validating set and testing set. The neural network layers (Input: Hidden: Output) developed to output the forecasting results are detailed in table in section 5.

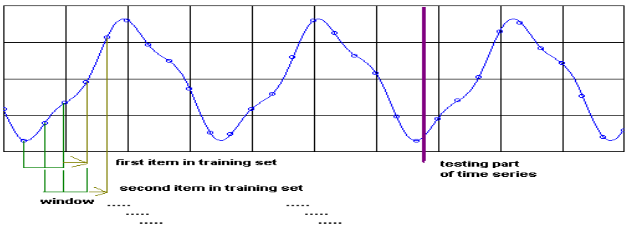


Fig. 3.1: Creating NN Data Sets

4. STUDY AREA

The ITO square of India's Capital city Delhi (Latitude**:** 28°40'12"N and Longitude**:** 77°12'36"E with Time zone: UTC+5:30 hours) is selected for study of spatial CO concentration data. The ITO areas has continuously shows increasing sign of CO pollution stress owing to rapid increase in numbers of vehicles, loss of open space, traffic congestion etc. Delhi has an extreme climate which is very cold in winter and terribly hot in summer. The diurnal moisture varies from dry to wet. A strong radiative inversion occurs during winter when the nights are long and the air is dry and cloud free. Because of all the above, during some days in winter the pollutants get stuck in a layer very close to the surface, not higher than 200 meters.

5. RESULT & DISCUSSION

For the present study mid day 8 hourly average carbon monoxide concentration data (14.00 – 22.00 hrs) for the year 1996 – 2006 (except for the year 1998) is used. In the Figures- 5.1 annual CO values are represented by their mean, median, mode, standard deviation (S.D.) and sample mean (SM+ and SM-) with 95% confidence level. The larger values of sample mean in comparison to the mode and median values is indicative of larger dispersion of data which is further supported by the higher standard deviation in the data. The higher mode value during the year 2002 is the indication of the exceptionally large frequency of few higher CO concentrations.

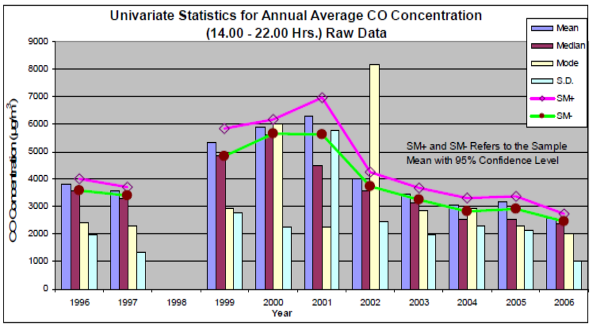


Fig 5.1: Elementary Statistics of Av. (8 Hr) CO data

A trend analysis of 8 hourly average annual CO concentrations has been plotted as shown in figure 5.2. The graph clearly indicates the changing pattern of CO concentration. It is obvious from the graph that there is sudden rise in ambient CO levels after the year 1999 till the year 2001. After the year 2000 with the enforcement of several pollution control norms there has been a marked decrease in the CO levels but not to the satisfactory level since concentration was not below the norms 2000 µg/m^3.

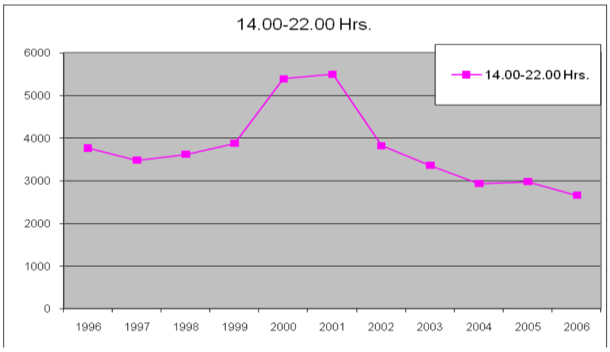


Figure 5.2: Trends in Yearly Average CO Conc.

Based upon the analysis of CO trend the analysis of data is classified into three groups (stages) as listed in the table 5.1 below. Accordingly, between the years 1996-2000 (the pre intervention period) the air pollution control regulations have been forced to be adopted by all the concerned. With the time the stringent enforcement of pollution control measures have resulted in improved air quality after the year 2003.

Table 5.1: Classification of CO data for ANN Analysis

Group	Duration	Data Length (years)	Reason for Classification
A	Jan. 1996 – Dec. 1999	4	Pre Intervention Period
B	Jan. 2000 – Dec. 2002	3	Transition Phase
C	Jan. 2003 – Dec. 2005	3	Post Implementation duration
D	Year 2006 data is exclusively used only for model forecast purposes		

The number of observation with exceedance from a particular CO concentration (i.e. 2000 µg/m^3) each year for the unrefined data in study area are computed and plotted on 8 hourly basis for the years 1996-2006 as shown in the figure 5.3. It is obvious that in almost all the years under consideration the CO concentrations have attained the level higher than the prescribed limits especially during the winter months. The highest value was obtained during the year 2000. It is evident that though mean CO levels are reduced after the year 2001 but the events of CO exceedance are higher enough not to stop our effort to control CO emissions.

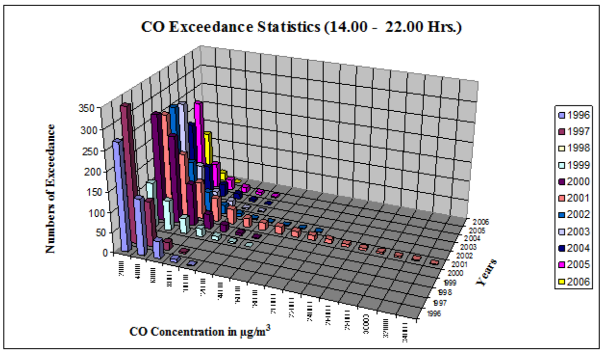


Fig- 5.3: CO (8 Hr Av.) Exceedance Frequency

5.1 ANN Architecture and Forecasts

For neural net design data set is divided into training set (70%), test set (30%) and validation set (100%) by random selection inherent to the software capabilities. The training data for each model contains the input variables and the corresponding observed (output variable) target that constitutes one paradigm of the test set. A number of such paradigms have been stored and has been fed to the NN program. Table 5.2, gives details of ANN design (learning) parameters and selected architectures, for forecasting of mid day (14.00 – 22.00 Hrs) 8 hourly CO observations at the same time, one day and two day advance (Lag 0, 1 and 2) periods. In the table 5.2 abbreviations are as NNA = Neural Network Architecture, I:H:O = Input:Hidden:Output layer Architecture, R is the correlation coefficient with its absolute value as net R. Absolute maximum and average absolute values of forecasted data are given with root mean square (RMS), forecast efficiency and 95% confidence level (CL).

The forecasts are made for the months of Oct. to Mar.(year 1999 and 2002) and Jan. to Oct. (year 2006) and graphically presented in figure 5.4.. Forecasting is done for the winter months since the weather remains moderately stable for CO spread. During summer and monsoon months highly unstable and wash out conditions inherits better forecast as is obvious in the forecasting curve of the year 2006, where too much higher and lower CO concentrations are observable. For most of the time the forecasted values are in tune with the observed CO conc. in trends and pattern. It is found that the NN perform absolutely well for lag zero (L=0) forecasting with around 99% accuracy followed by the one day (L=1) and two days (L=2) ahead forecasts with 70-80% and 80-50% accuracy respectively. It is also conferred that NN model perform best for the moderate CO concentrations values, at extremely low and high values the forecast results do not shown perfect agreement with the observed data.

5.2 Statistical Evaluation of NN Forecasts

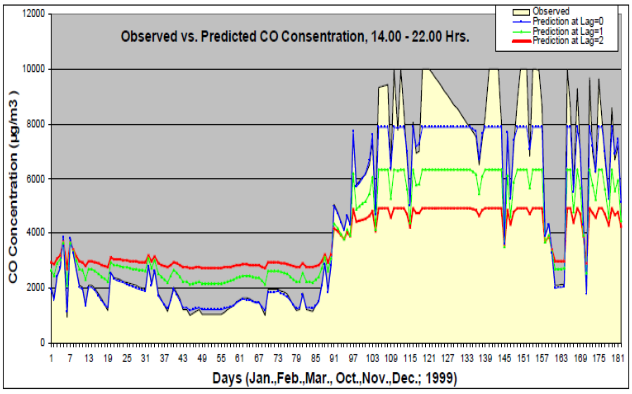
The global fit statistical evaluation studies of models results have been done for forecasted results as recommended by Willmott and Matsuura (2005) and Schlink et al. (2006). Table 5.3 lists values of performance parameters and errors corresponding to the various neural network model forecasts. In the table 5.3 O and P are the Observed and Predicted CO concentrations. MPE, MBE, MAE and NMSE are the Mean Percentage Error, Mean Biased Error, Mean Absolute Error and normalised mean square error respectively.

Table 5.3:- Statistical Evaluation of Model Forecasts

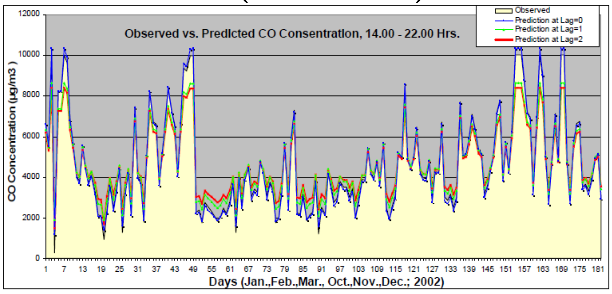
SN	Duration	Lag	Errors				CD	IA	FB
			MPE	MBE	MAE	NMSE			
1	Jan., 1999	L=0	0.0006	-38.6	62.5	0.0011	0.997	0.996	0.018
		L=1	-0.0083	566.6	592.2	0.0652	1.000	0.563	-0.229
		L=2	-0.0124	843.7	866.5	0.1316	0.991	-0.270	-0.323
2	Dec., 1999	L=0	0.0027	-556.4	654.0	0.0237	0.981	0.956	0.089
		L=1	0.0071	-1444	1647.	0.1137	0.986	0.750	0.249
		L=2	0.0108	-2181	2481.	0.3006	0.972	0.229	0.401
3	Jan., 2002	L=0	-0.0002	33.79	144.3	0.0018	0.998	0.998	-0.007
		L=1	-0.0003	49.9	508.9	0.0163	0.999	0.979	-0.011
		L=2	-0.0002	25.06	603.7	0.0213	1.000	0.972	-0.005
4	Dec., 2002	L=0	-0.0001	21.8	141.2	0.0007	1.000	0.999	-0.004
		L=1	0.0017	-323	526.1	0.0123	0.999	0.973	0.054
		L=2	0.0022	-414	632.5	0.0179	1.000	0.960	0.070
5	Jan., 2006	L=0	0.0002	-21.6	29.6	0.0002	1.000	0.999	0.007
		L=1	-0.0014	121.4	483.8	0.0345	0.999	0.844	-0.041
		L=2	-0.0018	159	595.2	0.0522	0.998	0.716	-0.054
6	Oct., 2006	L=0	0.0001	-12.3	19.6	0.0001	1.000	1.000	0.004
		L=1	-0.0014	122.7	400.1	0.0240	0.999	0.848	-0.042
		L=2	-0.0019	165.3	498.7	0.0373	0.998	0.714	-0.056

Table:- 5.2 NN Design Parameters for CO Concentration Series (14.00-22.00 Hrs.)

SN	Input	Output	NNA I:H:O	Time Lag	Data Set	R	Net R	Avg. Abs.	Max. Abs.	RMS	Accuracy	95% CL	Record
1	Jan. –Mar., & Oct. - Dec.; 1996 -1998	Jan. – Mar., Oct., - Dec., 1999	1:5:2		All	0.998	-0.995	66.3	374.4	89.1	1.0	174.7	182.0
					Train	0.998	-0.995	63.9	374.4	85.3	1.0	167.8	127.0
					Test	0.998	-0.995	71.9	362.7	97.4	1.0	194.5	55.0
				L=0	Valid	0.998	-0.995	66.3	374.4	89.1	1.0	174.7	182.0
			1:5:2	L=1	All	0.815	0.815	658.0	3255.8	870.4	0.7	1705.6	182.0
					Train	0.806	0.806	666.1	3255.8	888.2	0.7	1746.6	127.0
					Test	0.839	0.839	639.3	2141.1	827.7	0.8	1652.7	55.0
					Valid	0.815	0.815	658.0	3255.8	870.4	0.7	1705.6	182.0
			1:0:3	L=2	All	0.749	0.749	795.3	3186.1	999.7	0.7	1959.0	182.0
					Train	0.754	0.754	786.8	3186.1	991.3	0.7	1949.3	127.0
					Test	0.746	0.746	815.1	2621.1	1019	0.7	2034.3	55.0
					Valid	0.749	0.749	795.3	3186.1	999.7	0.7	1959.0	182.0
2	Jan. –Mar., & Oct. - Dec.; 2000-2001	Jan. – Mar., Oct., - Dec., 2002	1:2:3	L=0	All	0.997	-0.964	175.9	1095.4	304.0	1.0	593.4	365.0
					Train	0.997	-0.964	175.7	1095.4	303.8	1.0	594.0	255.0
					Test	0.997	-0.964	176.3	1095.4	304.6	1.0	600.1	110.0
					Valid	0.997	-0.964	175.9	1095.4	304.0	1.0	593.4	365.0
			1:2:3	L=1	All	0.763	-0.750	1688.6	10472	2344	0.8	4574.5	365.0
					Train	0.755	-0.741	1746.5	10472	2374.	0.8	4641.4	255.0
					Test	0.782	-0.775	1554.3	9144.4	2272.	0.8	4476.9	110.0
					Valid	0.763	-0.750	1688.6	10472	2344	0.8	4574.5	365.0
			1:16:2	L=2	All	0.728	-0.715	1897.2	8517.6	2494	0.8	4867.3	365.0
					Train	0.726	-0.710	1940.0	8517.6	2514	0.8	4914.3	255.0
					Test	0.737	-0.731	1797.9	7632.6	2447	0.8	4821.8	110.0
					Valid	0.728	-0.715	1897.2	8517.6	2494	0.8	4867.3	365.0
3	Jan. –Mar., & Oct. - Dec.; 2003-2005	Jan. –Oct., 2006	1:4:2	L=0	All	0.998	-0.986	54.8	543.5	117.0	1.0	228.0	511.0
					Train	0.998	-0.986	55.0	543.5	117.6	1.0	229.6	357.0
					Test	0.998	-0.986	54.4	528.2	115.5	1.0	226.6	154.0
					Valid	0.998	-0.986	54.8	543.5	117.0	1.0	228.0	511.0
			1:2:2	L=1	All	0.556	-0.552	1229.2	5113.2	1539.	0.7	3000.2	511.0
					Train	0.541	-0.536	1256.3	5020.7	1555.	0.7	3036.0	357.0
					Test	0.593	-0.592	1166.4	5113.2	1500.	0.8	2944.2	154.0
					Valid	0.556	-0.552	1229.2	5113.2	1539	0.7	3000.2	511.0
			1:8:2	L=2	All	0.460	-0.459	1325.5	5286.9	1643.	0.7	3203.6	511.0
					Train	0.472	-0.472	1315.2	5286.9	1635	0.7	3190.8	357.0
					Test	0.432	-0.430	1349.6	4644.6	1663	0.7	3263.9	154.0
					Valid	0.460	-0.459	1325.5	5286.9	1643	0.7	3203.6	511.0



Among the model performance measures we used Coefficient of Determination (CD), Index of Agreement (IA) and Fractional Bias (FB). The forecasts exhibit most excellent correlation in terms of the coefficient of determinations where values of the performance of NN models are found the best at the Lag = 0 followed by the forecasts at Lag =1 and Lag=2. In terms of index of agreement the forecasts for the year 1999 are poor enough to represent the model suitability; the reason is that for the three months the CO levels were very low compared to the other three months where the average levels were upto 5 times higher. The index of agreement is excellent for CO forecasts at lag 0, however with increased delay in forecasting exhibits poor IA. The performance of model with respect to the factors FB, is fluctuating over a wide range from negative values of FB to about 30% above or below the desirable standard value. The variations in MPE and NMSE are within ± 2 % and 13% and the error criteria that MBE should be less than MAE hold good indicating error are within acceptable limits. Therefore, based upon the statistical evaluation of forecast the developed neural network architecture can be assigned excellent grade for the CO forecast purposes.



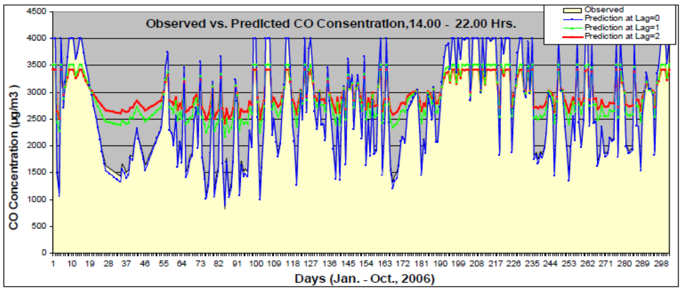


Fig -5.4: CO Concentration Forecasts Using Neural Network for the years (1999, 2002, and 2006)

6. CONCLUSION

In this study the optimum ANN model was obtained after trying different structures in terms of hidden layer node numbers. The neural network methods are highly capable to simulate air pollutant (CO) dispersion as an optimal network structuring uses the former knowledge inherent in the data. The error of forecasting which increases for the time ahead forecasts, can be improved with the amplification and stability of data. The Performance of NN model is found excellent in capturing the trends of pollution dispersion and predicting the mean levels of CO. The general trend in forecasts is over predictive except at few peaks of observed high CO levels. In an optimal network (with minimum operating layers) a close to ideal values of statistical performance measure guarantees the reliability and generalization ability of NN.

The control of carbon monoxide concentration is not an easy task in comparison of other pollutants as there is no efficient technology available to avert its production during the use of fossil fuels. Also there is no economical substitute to fossil fuels. The production of CO gas and its dispersion in atmosphere is a dynamic, non linear and complex site dependent phenomenon which can be efficiently modeled using neural network methods as evident by the present study. The ANN forecasts results can be used for real time pollution warning for roadside traffic regulations and prevention of commuters with the intense exposure.

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