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Evaluation and forecasting of PM_{10} air pollution in Chennai district using Wavelets, ARIMA, and Neural Networks algorithms

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ABSTRACT: The advent of advanced features of soft computing can be used to solve complex problems which are more non-linear and messy. Many of the applications have been analysed and validated by the researchers through soft computing approach in the past.Neural Networks (NN) with appropriate selection of training parameters is implemented apart from conventional mathematical model. In this paper, analysis is made on the estimation of PM_{10} air quality in selected regions of Chennai district by wavelet approach with energy spectrograms. After analysing the results, NN of multilayer feed forward back propagation algorithm forecasts the air quality of selected regions. Discrepancies in selecting the training parameters of NN's have been overcome by trial and error basis. This work will be helpful in proving the powerful tool of NN to forecast short term nonlinear parameters and the predicted results will give us the clear design of existing problem and thecontrol measures need to be implemented.

Keywords: Air pollution, Wavelet analysis, Neural Networks forecast, PM_{10}Chennai.

INTRODUCTION

According to Central Pollution Control Board report says that the detrimental air pollution in Chennai district is severe in recent days. It is a significant problem in Chennai. Due to severe air pollution people sufferedfrom respiratory problems and other relentless health effects (Nyberg F et al., 2000; Sunyer et al., 1997). Except other metropolitan cities, Chennai district is facing a different scenario on pollution harm effects. The monsoon and sea breeze of the coastal regions, makes the peak of the harmful effects to be in moderation. Even when it exceeds the critical level, the coastal air in Chennai helps the situation to be under control (Guttikunda et al., 2015).It is very dangerous to breathe polluted air and research needs to be incorporated in areas of factors involving in air pollution. Chennai was reported to have high risk in traffic and air pollution. Air quality monitoring needs to be addressed since it is a health hazard. (The Hindu, July 16, 2015). Recent research reveals that there is a mean risk of 0.4 percent to 0.5 percent per 10 μg/m3 increase in PM_{10} concentration (HEI, 2004). There were 3.5 million people suffered with Acute Respiratory Infection (ARI) as reported by the National Health Profile (2015). According to World Health Organisation report, India has the highest rate of death from respiratory disease in the

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world. The rate of mortality in respiratory disease was 159 per 100,000 in 2012 which is about 10 times than that of Italy five times that of UK and twice the amount numbered than that of China (The Guardian, 2015). Chennai also experiences pollution as its population has increased drastically recent years (Figure 1).

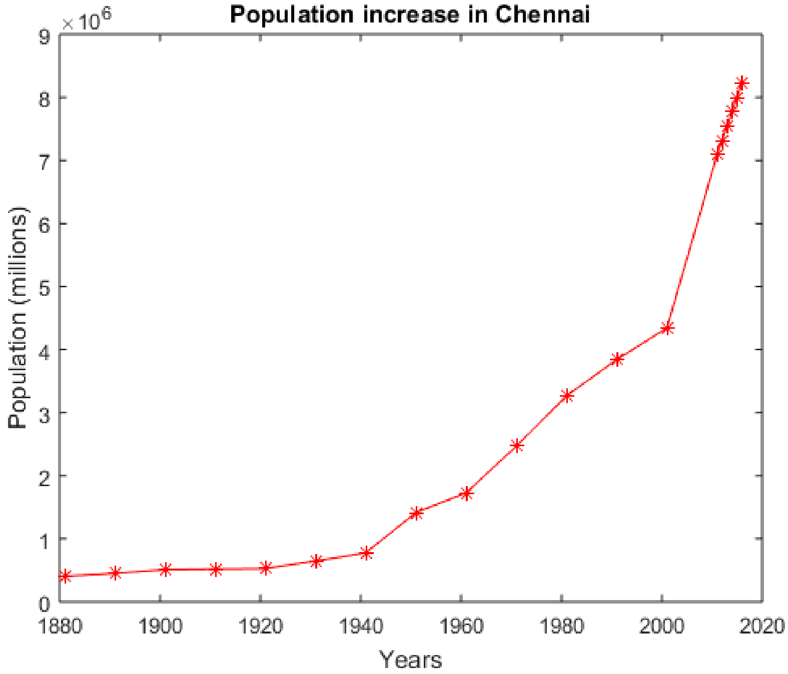


Fig. 1. Population growth in Chennai from 1881-2016
(Source: http://www.indiaonlinepages.com/population/chennai-current-population.html)

The worst affected regions lie in the northern and central part of Chennai. Northern part of Chennai has many petrochemical factories, car factories, coal industries which are very close residential areas.Delhi tops the usage of vehicles with 7.3million unit followed by Chennai which is 3.7 million unit. In terms of vehicle density Chennai tops the list with 2093 followed by Pune (1260) and Mumbai (1014), Hyderabad (723), Kolkata (355) and Delhi (245). (Times of India, 2015)

MATERIALS AND METHODS

Air pollution causes adverse health effects in human beings in states of specific mortality and morbidity (Dockery et al., 1993; Samet et al., 2000). Most health effects related to air pollution has been reported earlier viz., Pope & Dockery (2006) research provides persuasive evidence of adverse health effects on cardiopulmonary health when exposed to fine particulate matter. Brook et al. (2010) provides a comprehensive review of the new evidence on connecting particulate matter exposure with cardiovascular disease. Ruckerlet al. (2011) reviewed health effects on particulate air pollution. Health effects would be different with different geographical conditions across various seasons noticed all over the world (Bell et al., 2004, 2005; Ito et al., 2005, Levy et al., 2005). In the perspective of urban population air pollution often makes the aggressive effects (Smoyer at al., 2000; Kinney et al., 2008).

In this context, it is necessary to analyze the air quality in Chennai district and a non-retrospective approach has been taken to approach it. Several artificial intelligence techniques have been used by the previous researchers for modelling urban air pollution forecasting. Forecasting using Artificial

Neural Networks has been applied by Harri Niska et al., 2004, Support Vector Machines by Lu&Wang, 2005 and fuzzy logic (FL) by Francesco Carlo Morabito& Mario Versaci, 2003. Specific components involved in air pollution such as carbon dioxide (CO_2) predicted by Chelani & Devotta, 2007; Ming Caiet al., 2009; Patricio Perez et al., 2004, sulfur monoxide (SO) by Brunelliet al., 2007. Though there are certain drawbacks due to the overfitting, generalisation problems when applying support vector machine method (Lu &Wang, 2005), the network with certain training parameters with adjustable qualities will make the NN to perform better.Considerable increase in developing better models has been tried by various researchers (Gardner & Dorling, 1999; Kolehmainenet al., 2001; Kukkonenet al., 2003).

Particulate Matter (PM) consists of large amount of complex and various mixtures of gases and particles with approximate size which exist in the atmosphere because of natural and human activities. The sources for producing PM are factories, industries, vehicles, fires and dusts and the sizes of$PM_{2.5}$ and PM_{10} are particulate or suspended matter is about 2.5 and 10 micrometer diameter respectively. The particles which are lesser than 0.1 µm are ultra fine particles, fine particles are smaller than 1 µm and coarse particles are particles larger than 1 µm. The particle size PM_{10} is determined on the size of the particle, which enters the upper respiratory tract and the fine and ultra fine particles are able to reach the alveoli of the lungs. The mixture of PM varies based on the absorption of other pollutants including metal, organic compounds, material or biological components. Evidences show that the fine and coarse particles will make adverse harmful effects than large particles (Kampa & Castanas, 2008).

Lot of respiratory problems results in inhaling the polluted air due to long term exposure or concentration of pollutant. Particulate Matter that enters the lung alveoli leads to throat irritation that subsequently results in bronchoconstriction and dyspnoea which may cause asthma (Ghio & Huang, 2004). Chronic exposure will reduce the lung functions (Rastogi at al., 1991; Tager et al, 2005, Brunekreef & Holgate, 2002; Norris et al., 2000). In the worst case, severe problems will occur on continuous exposure like severe asthma, emphysema and even lung cancer (Kuo et al., 2006; Nawrot et al., 2006). Apart from having lung problem, particulate matter makes changes in blood coagulation (Riediker et al., 2004). Air pollution that stimulates lung problems and blood clotting affects the blood vessels, leading to angina or myocardial infarction (Vermylen et al., 2005). It also affects the developing foetus, reduced size at birth, advanced sexual maturation, distorted hormone levels related to thyroid regulation and other physiological problems (Schell et al., 2006).

Here in this research paper, four pollution monitoring station data were taken for analysis viz., Anna Nagar, Adyar, T. Nagar and Kilapuk of Chennai district. Based on the pollution data base available at the stations for the last 7 years (2007-2013). Location map of monitoring station is shown in Figure 2.

Anna Nagar (13.0846° N, 80.2179° E) is located in the north-western part of Chennai. It is one of the prime residential areas in the city equipped with transportation and all amenities. It is a fully flourished and well established traffic zone of Chennai.

Adyar River bounded with Buckingham canal to the west, Tiruvanmiyur to the south and Besant Nagar to the east. It is also one of the prime residential localities surrounded with enough buildings and well furnished bridges and roads. So there is no way of avoiding pollution in this area. It is very nearer to the coastal area (Besant Nagar Beach).

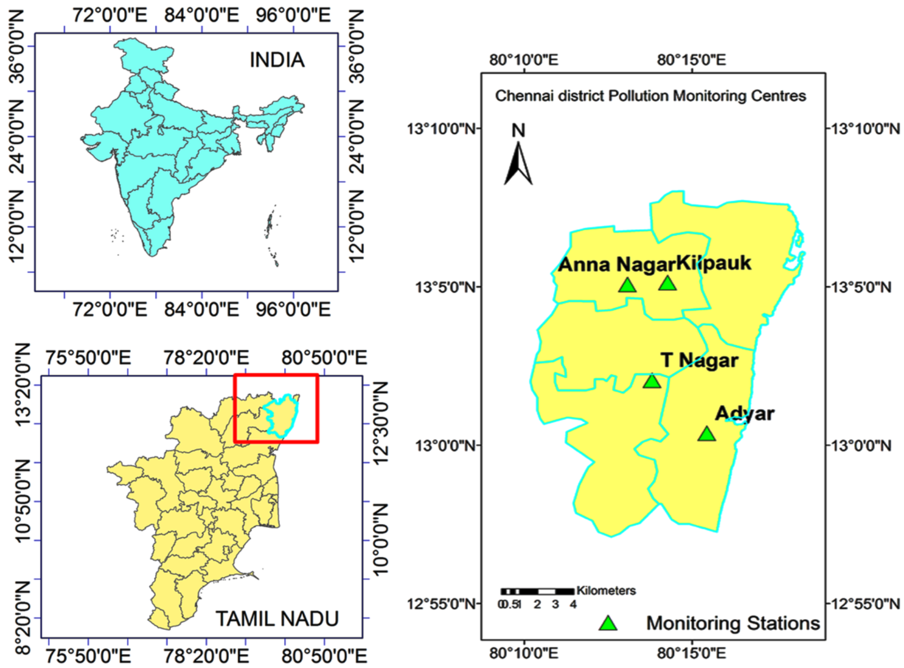


Fig. 2. Location of Air pollution monitoring centres in Chennai district, Tamil Nadu, India

Thiyagaraya Nagar also called as T.Nagar (13.0342° N, 80.2301° E) is located to the east of Teynampet and Saidapet to the south and southwest and Kodambakkam to the northwest and Nungambakkam to the north. It is one of the prime shopping localities of the Chennai city and located at the heart of the city. This paves way for congested traffic in and around the region. During the festive seasons it becomes crowded and the pollution level keeps on increasing.

Kilpauk (13.0856° N, 80.2379° E) is located in Poonamalle high road to the west and includes Chetpet, Egmore, Anna Nagar and Purasawalkam. It is a slowly developing region of Chennai district and hence pollution levels are increasing gradually.

RESULTS AND DISCUSSION

Wavelet transform plays major role in analysing the data in broad spectrum of time-frequency. Event related potential determination can be easily done through this transformation more clearly. The spatial and temporal information will provide the real time data strategy in eagle's eye. The advantage over the conventional time-frequency analysis is that it can decompose any signal of time-frequency into multi resolution functions.

$\psi(t) \in L^2(R)$ satisfies certain admissibility conditions as

$$C_\psi = \int_R \frac{|\hat{\Psi}(\omega)|^2}{|\omega|} d\omega < \infty \qquad (1)$$

$\Psi(t)$ is called wavelet; $\hat{\Psi}(\omega)$ is fourier transform of $\Psi(t)$. The Continuous Wavelet Transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function,

$$\Psi_{a,b}(t) = |a|^{-\frac{1}{2}} \Psi\left(\frac{t-b}{a}\right) \qquad (2)$$

$$W_f(a,b) = f(t), \Psi_{a,b}(t) = |a|^{-\frac{1}{2}} \int_R f(t)\Psi\left(\frac{t-b}{a}\right) dt \qquad (3)$$

Wavelet coefficients of locations Anna Nagar, Adyar, T.Nagar and Kilpauk shown in figures 3, 4, 5 & 6 respectively.

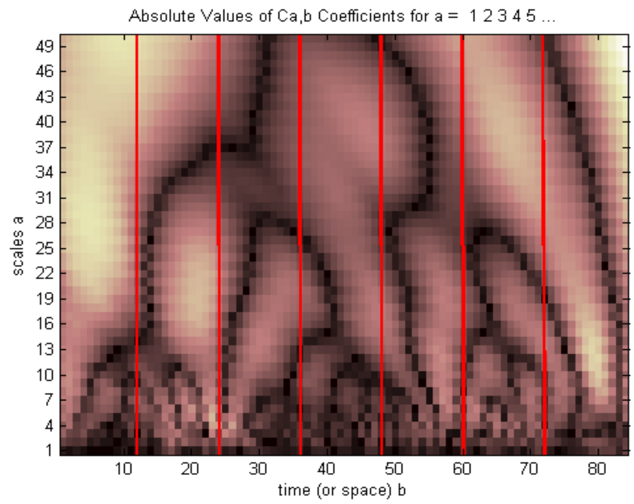


Fig. 3. Wavelet coefficients of Anna Nagar region

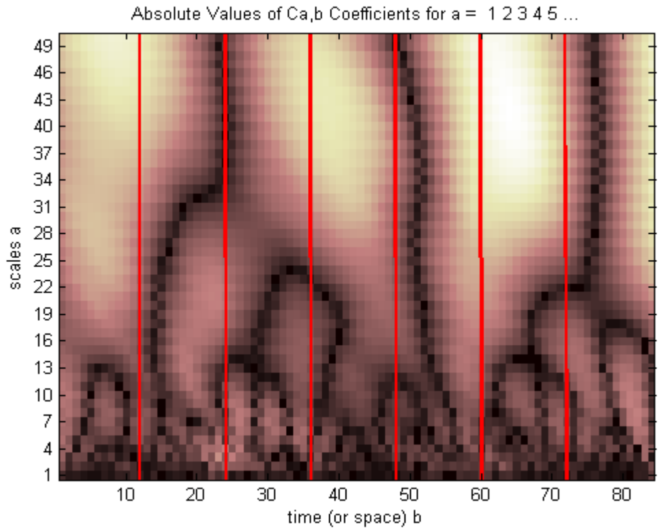


Fig. 4. Wavelet coefficients of Adyar region

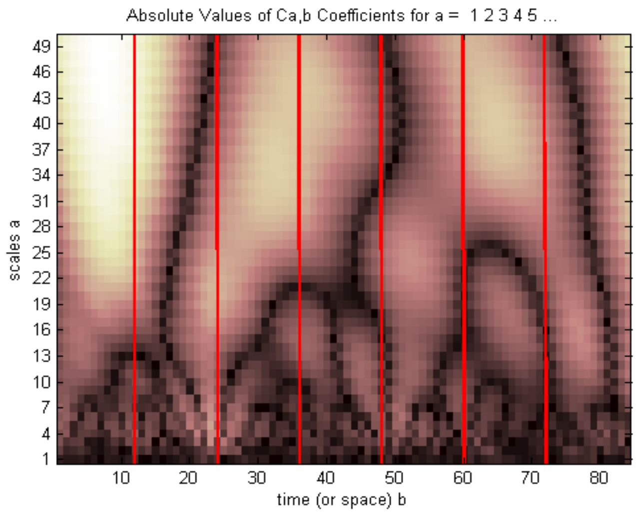


Fig. 5. Wavelet coefficients of T.Nagar

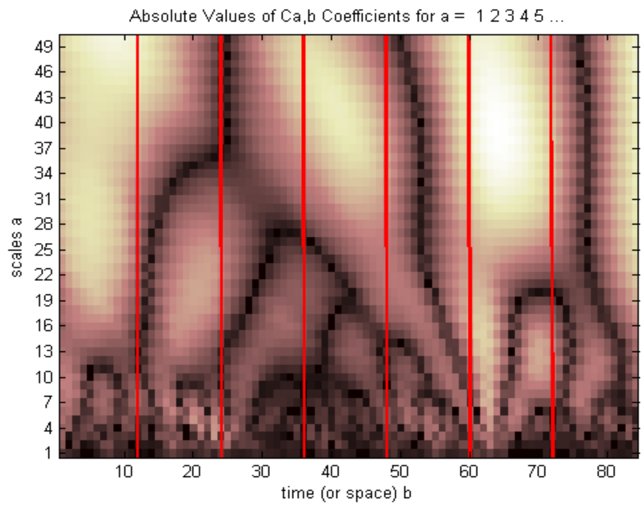


Fig. 6. Wavelet coefficients of Kilpauk region

The lower variations of wavelet coefficients reveal that the higher the level of wavelet resolution for years 2007 to 2013 (7*12 = 84 months). Red lines in each figures represents the yearly variations in wavelet coefficients. Moreover based on the wavelet coefficients, Multi Resolution Analysis (MRA) has been done and the results proclaim the clear picture of pollution level increase in the study area. CWT uses discrete sampling of data in order to obtain the finer details depends on the scaling parameter of the wavelet. Finer resolution will be obtained from increased computational time and more memory required calculating the coefficients. Multi Resolution analysis (MRA) is formed on the basis of orthonormal supported wavelet. Its applications is developing rapidly in various fields of science since the representation of particular information gives more clear picture than other transformation algorithms like Fourier and Short Term Fourier Transform (STFT). The concept was introduced by Meyer (1993) & Mallat (1989) which provides the excellent platform in understanding wavelet bases.

Figures 7, 8, 9 & 10 reveal the energy spectrogram of Anna Nagar, Adyar, T. Nagar and Kilpauk region, respectively.

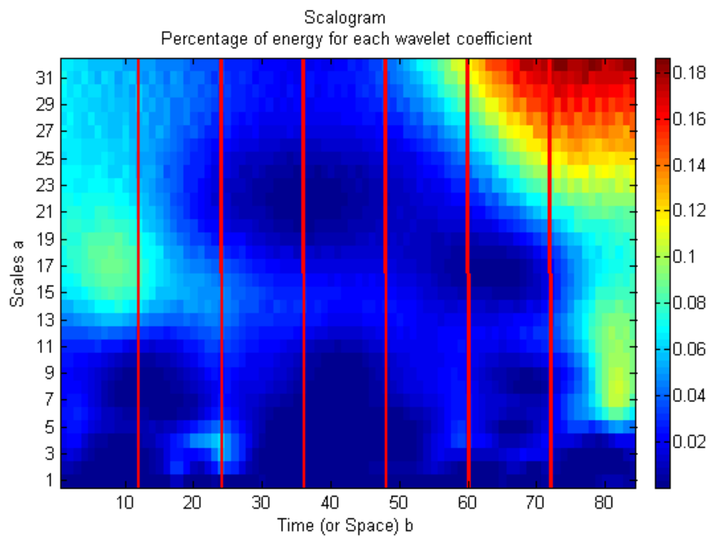


Fig. 7. Distribution energy spectrogram of Anna Nagar Region

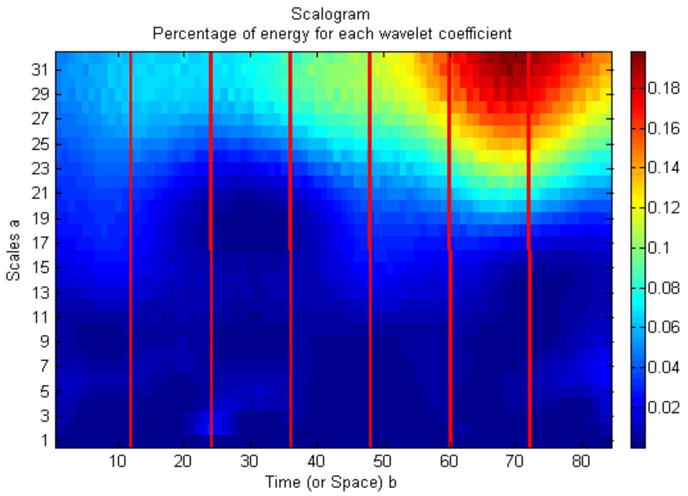


Fig. 8. Distribution energy spectrogram of Adyar Region

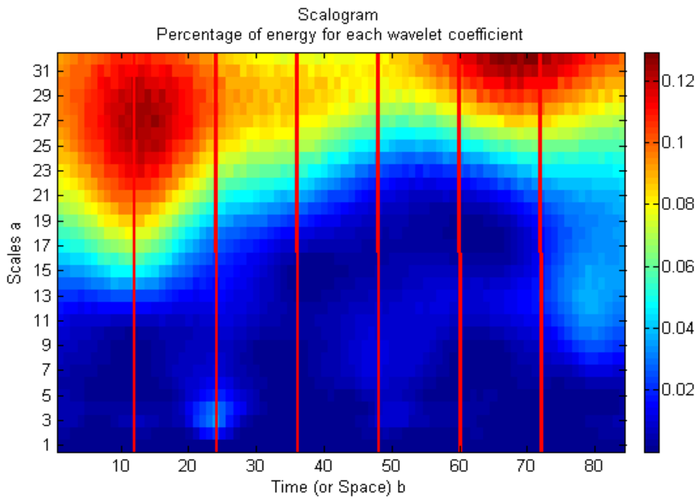


Fig. 9. Distribution energy spectrogram of T. Nagar Region

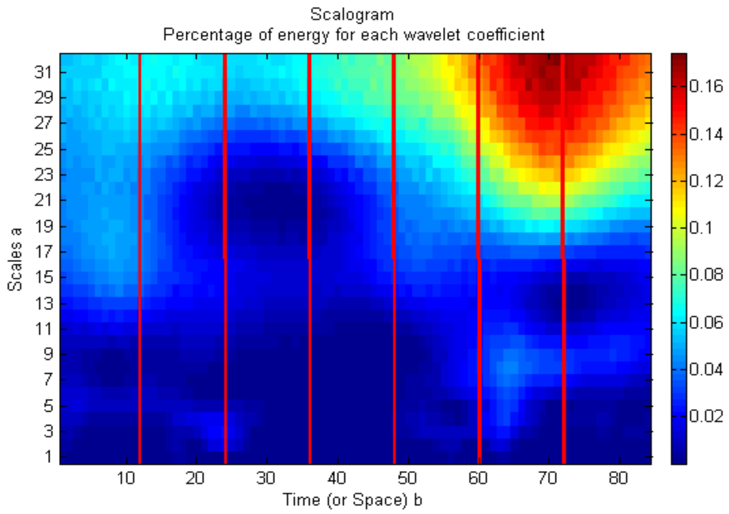
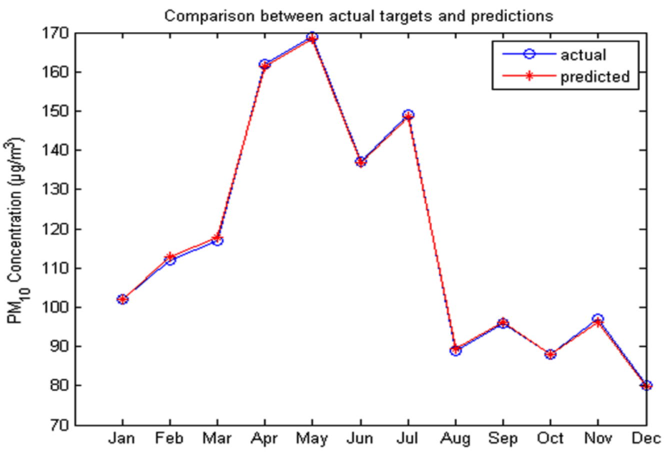


Fig. 10. Distribution energy spectrogram of Kilpauk Region

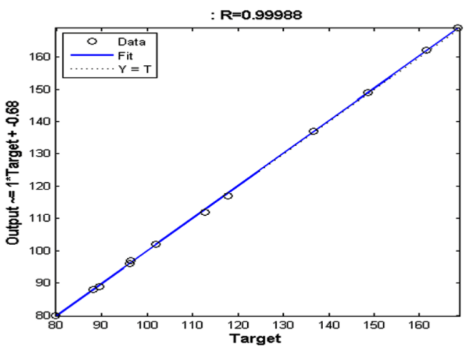
Feed forward back propagation (FFBP) algorithm is the technique used here for studying the field data by means of training function which updates weights with the specified learning function. Thus the network is trained with six years data (2007-2012) PM10 pollution data. Training large number of data will provide us good results of the problem and make the hidden units to train the data more effectively.

The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data (Yegnanarayana 2005). The function approximation interpretation of a single layer feedforward neural network enables us to view different hidden layers of the network performing different functions. FFBP algorithm is used here to forecast the 2013 data. Backpropagation learning technique will be the most efficient technique for obtaining good results (Papert & Minsky, 1969).

Best training performance can be achieved after the iterations has been successfully completed the goal using the number of epochs for the synthetic data. The training stops whenever the goal has been achieved in a particular number of epochs. The test using trained data indicates that the ANN system can converge to the target rapidly and accurately. The results of interpretation shows the oscillatory behavior by means of this ANN technique is not satisfactory as this PM10 pollution level depends on various parameters including rainfall, fog and humidity of the atmosphere.Figs.11 , 12, 13 & 14 represents the ANN forecasting levels for 2013 in Anna Nagar, Adyar, T. Nagar and Kilpauk respectively.

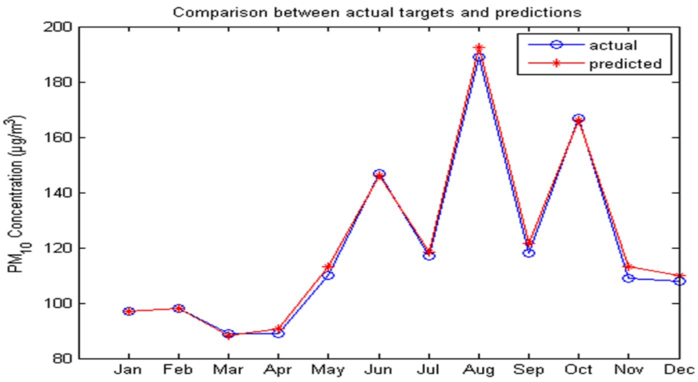


(a)

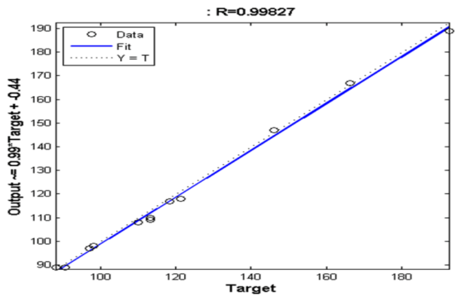


(b)

Fig. 11. Neural Networks forecasting on PM10 pollution in 2013 with observed values of Anna Nagar with regression plot.

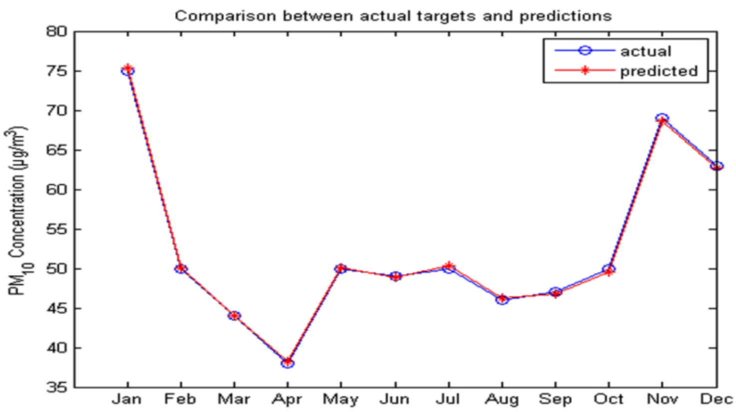


(a)

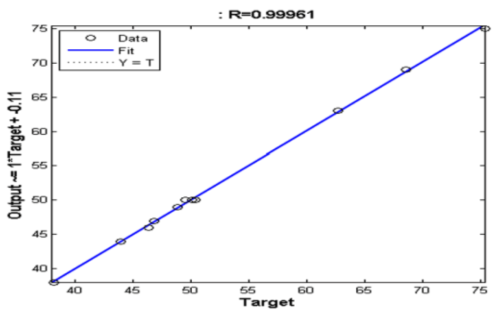


(b)

Fig. 12. Neural Networks forecasting on PM10 pollution in 2013 with observed values of Adyar with regression plot.



(a)



(b)

Fig. 13. Neural Networks forecasting on PM10 pollution in 2013 with observed values of T.Nagar with regression plot.

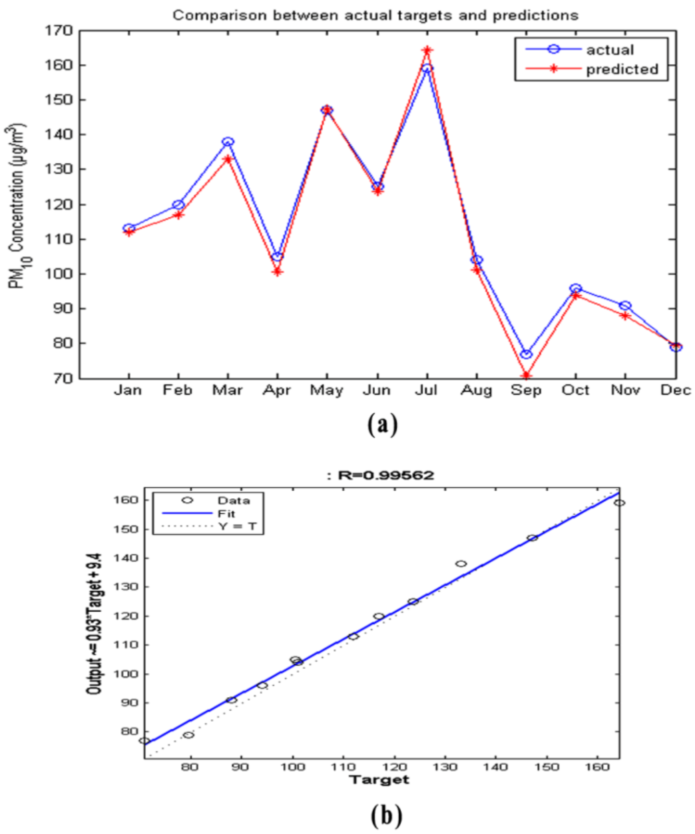


Fig. 14. Neural Networks forecasting on PM10 pollution in 2013 with observed values of Kilpauk with regression plot.

Box Jenkins methodology is a set of algorithm for identifying and estimating the time series models with Auto Regressive Integrated Moving Average (ARIMA) models. This can be applied to both seasonal and non-seasonal data

The auto regressive model of order (p) AR(p) is represented as

$$y_t = \delta + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots\dots\dots \varphi_p y_{t-p} + \epsilon_t \qquad (4)$$

i.e., y_t depends on its p-previous values

The Moving average model of order q is represented as MA (q) as

$$y_t = \delta + \epsilon_t - \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots\dots\dots \theta_q \epsilon_{t-q} \qquad (5)$$

i.e., y_t depends on its q-previous random error terms

Autoregressive moving average model is represented as ARMA (p,q);

$$y_t = \delta + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots\dots\dots \varphi_p y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots\dots\dots \theta_q \epsilon_{t-q} \qquad (6)$$

ϵ_t is the random disturbance term which is typically assumed to be 'white noise' i.e., it is identically and independently distributed with mean 0 and common variance σ^2 across all observations (Box & Jenkins, 1970; Zhang, 2003)

$$\epsilon_t \sim \left(0, \sigma^2\right)$$

Five steps iterative procedure of ARIMA model:

1. Stationary checking and differencing
2. Model Identification
3. Parameter Estimation
4. Diagnostic Checking
5. Forecasting

The h-period ahead of forecast based on ARMA (p,q) is given by,

$$\hat{y}_{t+h} = \hat{\delta} + \hat{\varphi}_1 y_{t+h-1} + \hat{\varphi}_p y_{t+h-p} + e_{t+h} - \hat{\theta}_1 e_{t+h-1} - \dots\dots\dots\dots \hat{\theta}_q e_{t+h-q} \qquad (7)$$

where elements on the right hand side of equations may be replaced by their estimates when the actual values are not available.Figures 15, 16, 17 & 18 shows the ARIMA forecasting models for Anna Nagar, Adyar, T.Nagar and Kilpauk regions respectively. It correlates with the ANN models. Trend analysis result gives the clear picture on increase in pollution levels of each zone. Figure19, 20, 21 and 22 corresponds to Anna Nagar, Adyar, T.Nagar and Kilpauk respectively.

Feed forward back propagation (FFBP) algorithm is the technique used here for studying the field data by means of training function which updates weights with the specified learning function. Thus the network is trained with six years (2007-2012) PM_{10} pollution data. Training large number of data will provide us good results of the problem and make the hidden units to train the data more effectively.

The backpropagation algorithm updates neuronal activations in the network for the input layer as

$$\delta\left(x_i^k\right)=x_i^k,\ i=1,\ldots\ldots,\ n \tag{8}$$

$$\delta\left(x_0^k\right)=x_0^k=1 \tag{9}$$

where x_i^k is the i^{th} component of the input vector presented in the network, and $\delta(x_0^k)$ is the input layer bias neuron signal that is independent of iteration index.

And for the hidden layer the network activation will be

$$z_h^k=\sum\nolimits_{i=0}^{n}w_{ih}^k\delta\left(x_i^k\right)=\sum\nolimits_{i=0}^{n}w_{ih}^k x_i^k,\quad h=1,\ldots\ldots,q \tag{10}$$

$$\delta\left(z_h^k\right)=1\Big/\left(1+e^{-z_h^k}\right),\ h=1,\ldots\ldots,q \qquad \delta\left(z_0^k\right)=1 \tag{11}$$

where w_{oh}^k are the biases of the hidden neurons, and δ (z_0^k) is the hidden layer bias neuron signal which is independent of the iteration index (Satish kumar 2007).

The output layer neuronal activations for the backpropagation will be

$$y_j^k=\sum_{h=0}^{q}w_{hj}^k\,\delta\left(z_h^k\right),\ j=1\ldots\ldots,\ p \tag{12}$$

$$\delta\left(y_j^k\right)=1\Big/\left(1+e^{-y_j^k}\right),\ j=1,\ldots..,p \tag{13}$$

where $w_{oj}^k$are the biases of the output neurons (Satish kumar, 2007),

The learning rate η in the Backpropagation algorithm has to be kept small in order to maintain a smooth trajectory in weight space, because large learning rate can lead to oscillations during learning.

$$\Delta w_{hj}^k=\eta\sum_{t=1}^{k}\alpha^{k-t}\delta_j^t s_h^t=-\eta\sum_{t=1}^{k}\alpha^{k-t}\frac{\partial\varepsilon_t}{\partial w_{hj}^t} \tag{14}$$

The above equation generalizes the weight change at the k thiteration in terms of the weight gradient at each of the previous iterations (Satish kumar, 2007).

The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data (Yegnanarayana 2005). The function approximation interpretation of a single layer feedforward neural network enables us to view different hidden layers of the network performing different functions. FFBP algorithm is used here to forecast the 2013 year data. Training Neural Networks with 2007-2012 data will be effectively forecast the 2013 data. Thus 2013 is a tested data applied in this algorithm to evaluate the performance of the algorithm. Backpropagation learning technique will be the most efficient technique for obtaining good results (Papert & Minsky, 1969).

Best training performance can be achieved after the iterations have been successfully completed for the synthetic data. The training stops whenever the goal has been achieved in a particular number of epochs. The test using trained data indicates that the NN system can converge to the target rapidly and accurately. The results of interpretation shows the oscillatory behavior by means of this NN technique is not satisfactory as this PM_{10} pollution level depends on various parameters including rainfall, fog and humidity of the atmosphere.

CONCLUSION

Figure 7 reveals the wavelet spectrogram of particulate matter $PM_{10}$of Anna Nagar from 2007 to 2013. Figure 8 reveals the pollution PM_{10} increased during the last few years of 2010 to 2012. It reveals the impact of air pollution in the year 2007 and gradually drops after 2011. But after 2011 it is started rising and shows peak value during the last few months of 2013. Figure 9 reveals the energy spectrogram of pollution level in T. Nagar. Last two years of study (2012 &2013) expose the high level of pollution concentration of T. Nagar. As it is one of the commercial hubs of Chennai, it got new bridges and ventures to extend its avenues. Due to which there is a raise in pollution level. Figure 10 shows the energy spectrogram of Kilpauk. Neural Networks forecast model correlates with actual and predicted model as shown in Figure 11 with maximum regression coefficient. Chennai is considered as one of the cleanliest city in view of air pollution during 1990 but the air quality got depreciate after 1990 (Arunan et al., 2009). But after 2013 it started decreasing. Neural networks model matches with the actual and predicted values. Figs. 11, 12, 13 & 14 represents the NN forecasting levels for 2013th year in Anna Nagar, Adyar, T.Nagar and Kilpauk respectively.

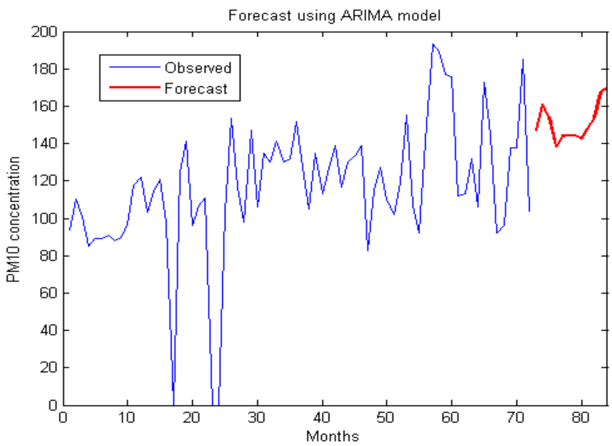


Fig. 15. ARIMA models for PM10 pollution in 2013- Anna Nagar region

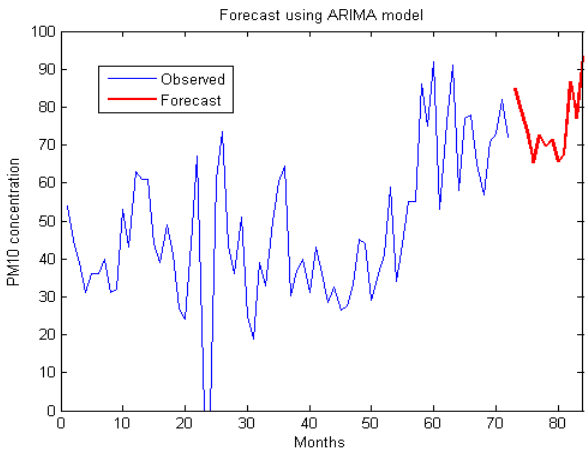


Fig. 16. ARIMA forecasting for PM10 pollution in 2013- Adyar region

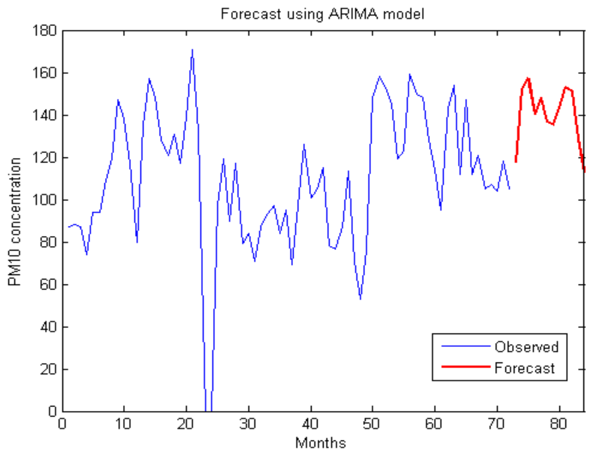


Fig. 17. ARIMA forecasting models for PM10 pollution in 2013- T.Nagar region

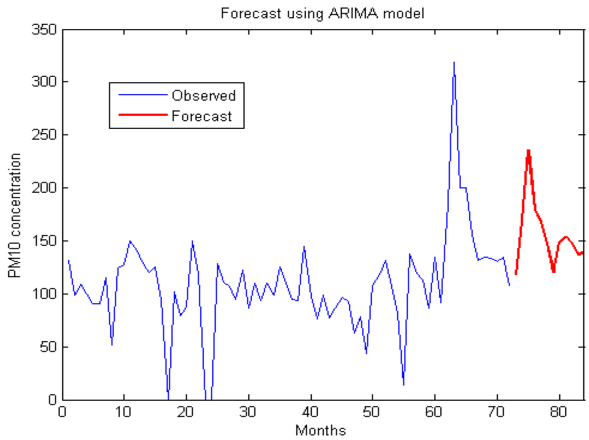


Fig. 18. ARIMA statistical forecasting of PM10 pollution in 2013- Kilpauk region

Figure 15 shows the ARIMA model prediction with observed and forecasted values. Figure 16 shows the increasing pollution levels of PM_{10} in ARIMA model. The forecasted values increased in last few months and sudden dips and drops to low value. Figure 17 estimates the neural network model prediction. Figure 18 shows the neural networks forecasted model.

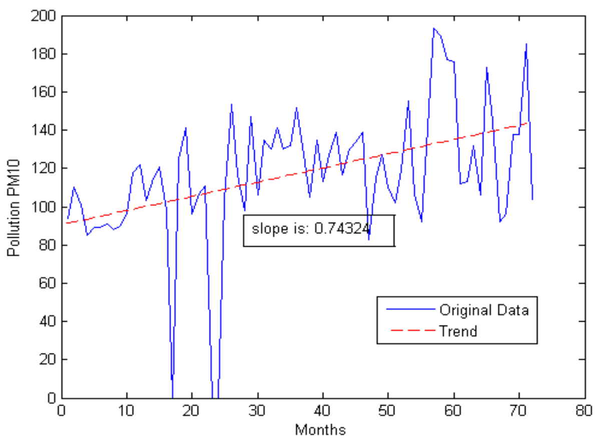


Fig. 19. Trend analysis on PM10 pollution of Anna Nagar region

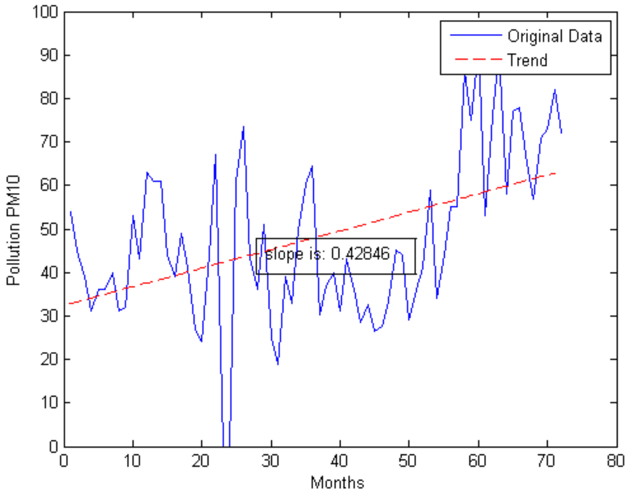


Fig. 20. Trend analysis on PM10 pollution of Adyar region

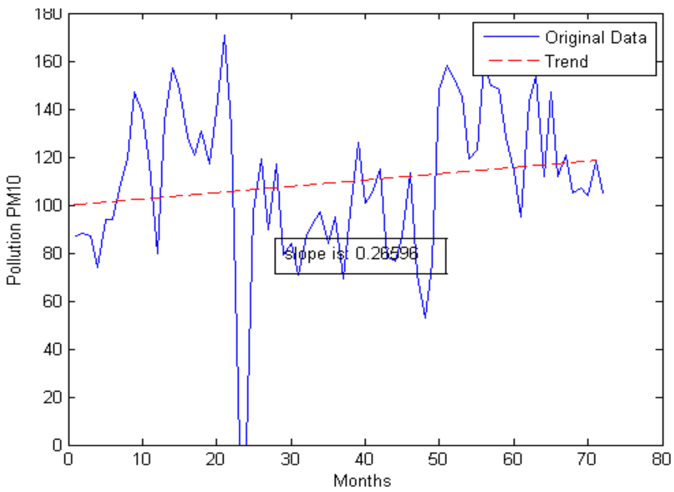


Fig. 21. Trend analysis on PM10 pollution of T.Nagar region

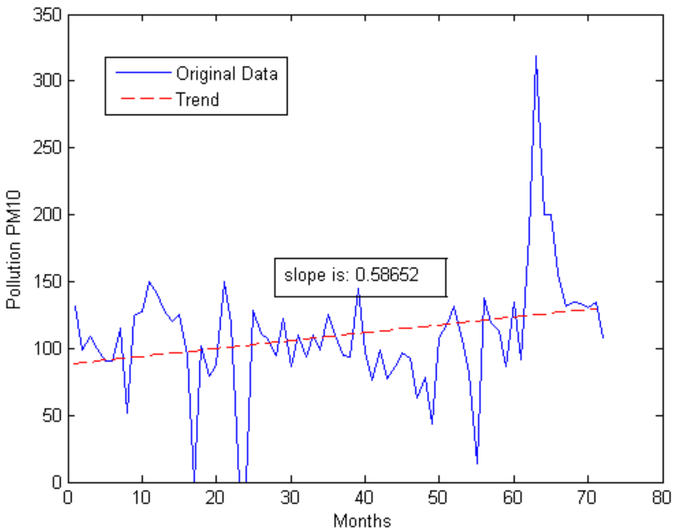


Fig. 22. Trend analyses on PM10 pollution of Kilpauk region

It indicates the concentration is not steady in this region and Figure 19 trend line reveals a steady increase with a slope of 0.26 steep. The trend analysis of four regions which has been taken under study shows significant increase in pollution levels. The sensitivity and rate of increase in three zones is very high (Adyar, Kilpauk and T.Nagar). Adyar located in Chennai district with one of the prominent river called Adyarriver flowing from Chembarambakkam tank, a natural reservoir. Adyarriver got polluted due to emissions from vehicles (Brook et al., 2004). Adyar river flows across the city are highly polluted due to industrial and organic wastes which act as a major source for generation of green house gases. Figure 20 reveals the trend line with increasing slope value (0.4284). It exhibits the behaviour of pollution pattern for the past few years. Figure 21 shows the much increased slope value of 0.743 depicts the threatening pollution levels of T. Nagar.Figure 22 shows the slope variations. The slope value 0.586 reveals that the area is widening and started polluting the environment. While considering Anna Nagar the rate of increase is gradual. Adyar, Kilpauk and T.Nagarare showing the linear slope of 0.42846, 0.58652 and 0.74324 respectively. Tables 1, 2 and 3 represent the mean, standard deviation and year wise percentage of the PM_{10} concentrations.

Table 1. Mean Value of PM_{10} concentration of respective regions with years under study

Years	Anna Nagar	Percentage from normal	Adyar	Percentage from normal	T.Nagar	Percentage from normal	Kilpauk	Percentage from normal
2007	102.8333	71.3888	41.9167	-30.1388	97.8333	63.0555	110.9167	84.8612
2008	114.9167	91.5278	38.0833	-36.5278	84.7500	41.2500	83.6667	39.4445
2009	92.7500	54.5833	46.3167	-22.8055	128.6500	114.4167	108.0750	80.1250
2010	91.0000	51.6667	34.2917	-42.8472	121.8917	103.1528	91.8250	53.0417
2011	135.0833	125.1388	54.1667	-9.7222	140.6667	134.4445	99.5000	65.8333
2012	118.5833	97.6388	71.0833	18.4722	127.8333	113.0555	160.4167	167.3612
2013	112.8333	88.0555	52.5833	-12.3612	119.8333	99.7222	116.5000	94.1667

Table 2. Standard deviation of PM_{10} Concentration of respective regions with years under study

Years	Anna Nagar	Adyar	T.Nagar	Kilpauk
2007	23.1942	10.1932	12.3938	26.7189
2008	55.7339	21.9647	52.5532	53.9955
2009	14.1255	16.7123	18.9800	12.9205
2010	22.1034	6.0640	16.5052	20.1163
2011	24.2392	20.5684	36.2349	37.7588
2012	19.1238	11.1229	29.6029	60.3888
2013	26.0413	10.7911	31.6395	30.5034

Table 3. Year-wise percent change of PM_{10} Concentration of respective regions under study

Years	Anna Nagar	Adyar	T.Nagar	Kilpauk
2007-2008	11.7504	-9.1451	-13.3731	-24.5680
2008-2009	-19.2893	21.6193	51.7994	29.173
2009-2010	-1.8868	-25.9626	-5.2533	-15.035
2010-2011	48.4432	57.9587	15.4030	8.35
2011-2012	-12.2147	31.2308	-9.1232	61.2228
2012-2013	-4.8489	-26.0258	-6.2581	-27.3766

Specifically, T.Nagar shows the high increase in rate as it is one of the prime localities of shopping centres and malls whereas Anna Nagar is residential area with minimum slope value. More hospital zones were seen in the Kilpauk regions shows gradual increase. This research work creates awareness to the Chennai residents who were residing in the nearby localities. Moreover ANN and ARIMA model which is taken under consideration for forecasting yet seems to be unsatisfactory. Since the pollution PM_{10} forecasting shows more oscillatory behaviour in both models and it need more additional parameter to stabilize the result. Environmental conditions available in the local domain also play a key role in PM_{10} pollution. If ANN trained with more number of supporting parameters then the forecasting efficiency will increase.

Theresearch paper concludes the variation of particulate matter PM_{10} in Anna nagar and how it varies in the year 2007 -2013. The Neural Networks forecast model shows and correlates the energy spectrogram of T.Nagar and Kilapauk with the actual and predicted values. Neural networks model matches with the actual and predicted values of the air pollution in Chennai after 1990.The ARIMA model gives the increase in pollution level by PM_{10}.The ARIMA model and Neural network forecasted model of these four region Anna Nagar, Adyar, T.Nagar and Kilpauk explains that there is a significant variation in pollution levels. The above research work gives a detailed report on the sensitivity and rate of increase is very high in Adyar, Kilpauk and T.Nagar. It creates awareness to the Chennai residents who are residing in the nearby localities. Moreover ANN and ARIMA model which is taken under consideration for forecasting needs more additional parameter to stabilise the result. Environmental conditions also play a key role in PM_{10} pollution. If ANN trained with more number of supporting parameters then the forecasting efficiency will increase.

LIMITATIONS

- Neural Networks have basic issue with intractability. The processing inside the hidden neurons is forbidden and it is a black box for the user to train the data.
- It is convicted that the Neural Networks training and testing methods can be modelled with hybrid algorithm so that the inherent latency of training time can be overlooked.
- Training data is more important and it requires a bulk amount of data to get good performance.
- Wavelet can analyse the data using multiresolution analysis but it depends on some other algorithm to interpret it.

RECOMMENDATIONS

- Increasing more number of monitoring station will be helpful in collecting data and analysing it.
- The sensitivity of neural networks depends completely on the amount of data trained. Thus increasing the amount of data or relying on hybrid methodology will be nifty for predicting exact results.
- Future works on this topic can be carried out using hybrid methodologies like wavelet fuzzy integration , Fuzzy based dynamic models, Fuzzy based expert system model etc.,

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CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING:

No life science threat was practiced in this research.

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