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An Integrated Model using Artificial Neural Network (ANN) and Kriging for Forecasting Air Pollutants using Meteorological Data

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Abstract: Forecasting of air pollutants is an important area of research in view of the current concerns regarding environment. In particular, air quality is deteriorating due to emissions increasing, particularly in urban locations. . In view of the health hazards posed by increasing air pollution, it will be useful to have a model that can predict the level of atmospheric pollutants and a geospatial interpolation approach to forecast the air pollutants over the whole domain. This paper presents an integrated model using Artificial Neural Networks and Kriging to predict the level of air pollutants at various locations in Mumbai and Navi Mumbai using past data available from meteorological department and Pollution Control Board. The proposed model is implemented and tested using MATLAB for ANN an R for Kriging and the results are presented.

Keywords: Artificial Neural Networks, Kriging, Air Pollution, Meteorological data.

I. INTRODUCTION

Rapid industrialisation over the last five decades has significantly contributed to the rise in air pollutants. Several researchers and policy makers have expressed concerns over declining quality of atmosphere, particularly at urban locations where population density is very high and emissions from vehicles and industry is constantly increasing. In particular, cities like Mumbai and Navi Mumbai that attract an influx of people and industries are vulnerable to rise in pollution arising out of increased aspirations and energy consumption. Rapid growth also causes unplanned urban and industrial development of city contributing to air pollution. As a fallout of economic growth in urban areas, high concentration of industries and thermal power plants and vehicular contribute to air pollutants in urban locations. The World Health Organization estimates that about two million people die prematurely every year as a result of air pollution, while many more suffer from breathing ailments, heart disease, lung infections and even cancer. In view of the health hazards posed by increasing air pollution, it will be useful to have a model that can predict the level of atmospheric pollutants and a geospatial interpolation approach to forecast the air pollutants over the whole domain. [28]

Artificial intelligence based methodologies such as artificial neural networks can help to forecast the pollutants in complicated non-linear contexts. The predictive accuracy obtained by artificial neural networks (ANNs) is often higher than that of other methods or human experts. [4] The ANN model can be used to predict the air pollutants in the areas where the monitoring stations are set up. The air quality has to be generalized for the whole area where there are no monitoring stations. Interpolation can be applied to the measured data and can be used to obtain the air quality at unmonitored locations. Kriging is a geo statistical interpolation method which is flexible in terms of input and output data and takes the location into consideration while predicting the values of the desired parameters. Kriging predicts the values of the parameters along with the prediction errors and probabilities. The success of kriging is indicated by the prediction errors and cross validation. This paper proposes an integrated model combining the techniques of ANN based forecasting and Kriging model and examines the results obtained by using the hybrid model to predict the levels of air pollutants in Mumbai and Navi Mumbai using data from the meteorological departments and pollution control boards.

II. LITERATURE REVIEW

Between 1951 and 1991, the urban population has tripled, from 62.4 million to 217.6 million, and its proportion has increased from 17.3% to 25.7%. Nearly two-thirds of the urban population is concentrated in 317 class I cities (population of over 100 000), half of which lives in 23 metropolitan areas with populations exceeding 1 million. The number of urban cities with populations of over a million has increased from 5 in 1951 to 9 in 1971 and 23 in 1991 [20].The number of motor vehicles has increased from 0.3 million in 1951 to 37.2 million in 1997 .32% of these are concentrated in 23 metropolitan cities.[6][7][8][9][19].

Nastos et al. (2013) estimated the possibility of forecasting the maximum daily precipitation for the next coming year using ANN [21]. Fernando et.al (2012) used ANN to predict the particulate matter concentration at a regulatory monitoring site in Phoenix, Arizona and found that it better predicted the PM 10 concentrations than continuous monitoring.[11] Viotti et al.(2002) used ANN to forecast short and middle long-term concentration levels for some

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of the well-known pollutants. They found that the perceptron with back-propagation algorithm model used exhibited a good performance.[20] Wang et al. (2006) forecasted the Air Pollution Index (API), a referential parameter describing air pollution levels using autoregressive moving average (ARMA) method.[29] Martin et al. (2008) used ANN as a predictive tool for high levels of ambient carbon monoxide (CO).[17] Heo(2005)[14] developed a fuzzy expert and neural network systems to forecast air pollutants and meteorological variables. The neural network model was improved continuously through verification and augmentation.

Nikovb et. al. (2005) presented a web-based tool for air pollution prediction and control in Istanbul. The model relates the local meteorological data and air pollution indicators concentrations like SO2, PM10 and CO by using ANN [3]. Yike Guo et al. (2006) monitored the air pollution pattern in London using the distributed *K*-means algorithm [24] . Huang et.al (2013) studied the spatial distribution and source contribution of SO2 and NO2 pollution in Ulaanbaatar, Mongolia using multiple regression models [30]. Chen et.al. (2007) present a Decision-Making Framework (DMF) for reducing ozone pollution in the metropolitan using mining and meta modelling tools [1]. Vincent Ng et al. (2001) developed an agent framework to study the effect of meteorological data on the air pollutants [27]. Athanasiadis et. Al (2013) used the classification technique of data mining for supporting the decision making process of environmental management to monitor the ambient air quality and trigger alerts in case of emergency. Spatial Data mining provides an excellent tool for solving air pollution management problems. It uses sophisticated statistical analysis and modelling techniques to uncover predictive and descriptive patterns by using the toolbox of statistical methods based on Generalised Additive Models (GAMs) to analyze local air quality problems in Europe[12][16]

Kriging is a geostatistical technique [15] using the spatial parameters estimated by the experimental variogram. Kriging is a set of linear regressions that determine the best combination of weights to interpolate the data as in the inverse weight distance method by minimizing the variance as derived from the spatial covariance in the data. The spatial difference of air pollutants is structured but complex and is spatially autocorelated [5]. The spatial autocorrelation can be expressed in terms of a semi variogram. The variogram expresses the degree of similarity between two observations separated by a given distance. An empirical variogram can then be computed from sampled data. Kriging is a widely used technique for air quality data, since data is spatially continuous [23]. Ordinary kriging is the most commonly used techniques use to predict the value Y(S). The general concept is that the prediction of at any s location as the weighted average of the neighbouring [5]. The optimal weights are estimated and kriging results are evaluated statistically. E. Sertel et. Al integrated the use of geostatistical methods and spatial analysis to obtain valuable information to identify, visualize and explore the relationship between transportation, land-use and air quality. The integrated approach solved the complex task of decision makers and lead to more reliable decisions where common approach suggest that there is no relationship amongst the various types of data [25]. Vikas et.al. proposed a model to estimate the ozone and PM10 concentrations at unmonitored sites using kriging. The methodology provides a cost-effective and fast technique over a domain not having sufficient measurement stations. [26] This paper proposes to integrate the two techniques of ANN and Kriging to help the decision makers as a support tool to related the multi-source data collection system and inform decision making for regular pollution. The Kriging scheme is also known as the best linear unbiased estimator, and its estimates are based on the variogram model and the values and location of the measured points.

III. CASE STUDY

In 1984, the Central Pollution Control Board initiated National Ambient Air Quality Monitoring (NAAQM) programme with 7 stations at Agra and Anpwara. Subsequently the programme was renamed as National Air Monitoring Programme (N.A.M.P.). The number of monitoring stations under N.A.M.P. has increased steadily over the years covering all 25 States and Union Territories of the country. The objectives of the N.A.M.P. are to (a) determine status and trends of ambient air quality, (b) ascertain violations in prescribed ambient air quality standards, (c) to identify cities where violations occur, (d) obtain the knowledge and understanding necessary for developing preventive and corrective measures, and (e) understand the natural cleansing process undergoing in the environment through pollution dilution, dispersion, wind based movement, dry deposition, precipitation and chemical transformation of pollutants generated.

Under N.A.M.P., four air pollutants viz., Sulphur Dioxide (SO2), Oxides of Nitrogen such as NO2 and Suspended Particulate Matter (SPM) and Respirable Suspended Particulate Matter (RSPM/PM10), have been identified for regular monitoring at all the locations. Besides this, additional parameters such as Respirable Lead and other toxic trace metals. The monitoring of meteorological parameters such as wind speed and direction, relative humidity and temperature was also integrated with the monitoring of air quality. According to WHO, [28] Mumbai is next to Kolkata and Delhi as one of the top ten most polluted cities in the world. Mumbai is one of the most populated cities in the world. The increase in the population has led to the increase in the number of vehicles and industrial activities. This in turn has increased the air pollution levels. The main sources of air pollution are emissions from various chemical processes and fuel. Major air pollution sources include a number of chemical complexes; two oil refineries and a thermal power plant.With this increasing air pollution there is a serious danger of health hazards to the people of Mumbai and Navi Mumbai (World Bank).

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Increase in the construction activities like concreted and non-concreted road dust constitutes 38% of the emission load of particulate matter (PM) in Mumbai. Power plants are the second major offenders accounting for 21% of air pollution, followed by burning at 11%. In the vehicular category, heavy duty diesel (HDDV) vehicles contribute to 3.4% of emissions.

The Municipal Corporation of Greater Mumbai (MCGB) monitors the air quality within the city limits; MCGB measure the ambient air quality frequently at 22 monitoring stations in Mumbai for over 15 years. These monitoring stations measure the air pollutant levels according to who prescribed guidelines and methods. The pollutants measured are sulphur dioxide (SO_2), Suspended Particulate Matter (SPM/TSP), Oxides of Nitrogen (NO_x) and Ammonia (NH_3). Ambient air quality is also occasionally measured at selected traffic junctions in Mumbai for SO_2, NO_x, Carbon Monoxide (CO), and other pollutants. [6][7][8][9]

In order to be able to predict air pollution conditions, it is necessary to handle historical data sets of the parameters considered. Considering data available and the required degree of relationships and distinguish patterns for efficient and useful knowledge extraction, there is a need for utilizing techniques such as data mining. The necessity assumes more of convenience when it is known that data sets are available for free of charge in MPCB data repositories and meteorological centre. Once an efficient tool is built for abstracting these large quantities of data sets and deriving useful knowledge from the same, it will enable planners to utilize the same for effective air pollution mitigation and management. We now describe an ANN and Kriging based model to predict the various pollutants in the atmosphere at the monitored and unmonitored sites of Mumbai and Navi Mumbai.

IV. PROPOSED ANN MODEL FOR POLLUTANT PREDICTION

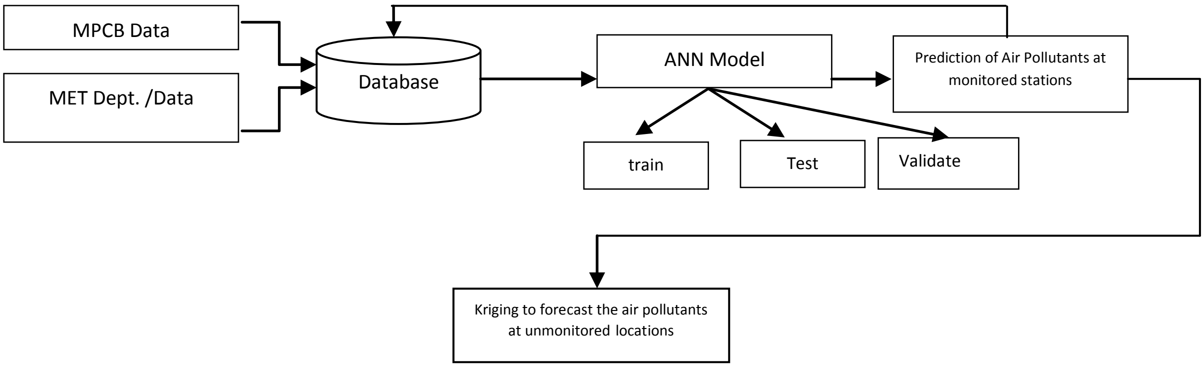

Figure. 1. Framework for forecasting air pollutants

Data from Maharashtra Pollution Control Board (MPCB) and Meteorological departments (MET) are fed into a database from which it is taken as input to the ANN model. The ANN model is then run to train using selected test data and validation of the parameters carried out. The variables are predicted and the values are sent back to GIS as a feedback. The predicted values of the air pollutants are then feed into the Kriging model which interpolates the values of the air pollutants are the unmonitored locations in Mumbai. Figure . 1. Shows the proposed integrated model for prediction of pollutants in the atmosphere**.**

Artificial neural networks (ANN) are mathematical models that are motivated from biological nervous systems. Initial interest in neural networks emerged after the introduction of simplified neurons by McCulloch and Pitts (1943). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In the simplest ANN model, the effects of the synapses are represented by weightages that capture the effect of various input signals and learning occurs by adjusting the weights according to the learning algorithm.A typical ANN model uses a multi-layered configuration as in Figure 2. The output of a stage can be used to feedback and adjust the weights.

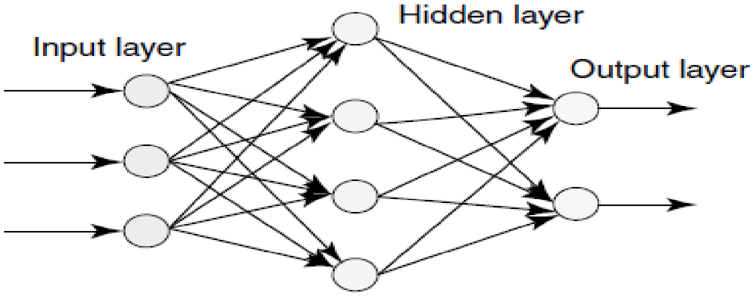

Figure. 2. A multi-layered ANN (Source: Abraham, 2005)

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V. ANN AND KRIGING MODEL FOR AIR QUALITY PREDICTION

A feed-forward back propagation neural network has been applied in this study. A 3-layer perception model was used to develop the artificial neural network. The first input layer contains the input variables is meteorological variables of the network. Here, there were fifteen neurons in the input layer including three pollutants which is NOx, SOx and RSPM and one hidden layer. The last layer is the output layer, which consists of the target of the prediction model which predicts the values of the air pollutants for the next three days. The variables NOx, SOx and RSPM were used as the output. The database was divided into randomly into three sections for training the networks, validating and testing the networks. The function optimization technique used is the Levenberg-Marquardt algorithm. The mean square error (MSE) was chosen as the statistical criteria for measuring of the network performance.
This research work includes nine input parameters namely the month, relative humidity, rainfall, Wind Speed and the wind Direction, cloud octa, temperatures(maximum and minimum), and the pressure in the areas of Mumbai and Navi Mumbai. The latitude and the longitude are also considered in order to include the spatial parameters of the monitoring stations. Figure 3 represents the input output RBFNN model for the prediction for the air pollutants.

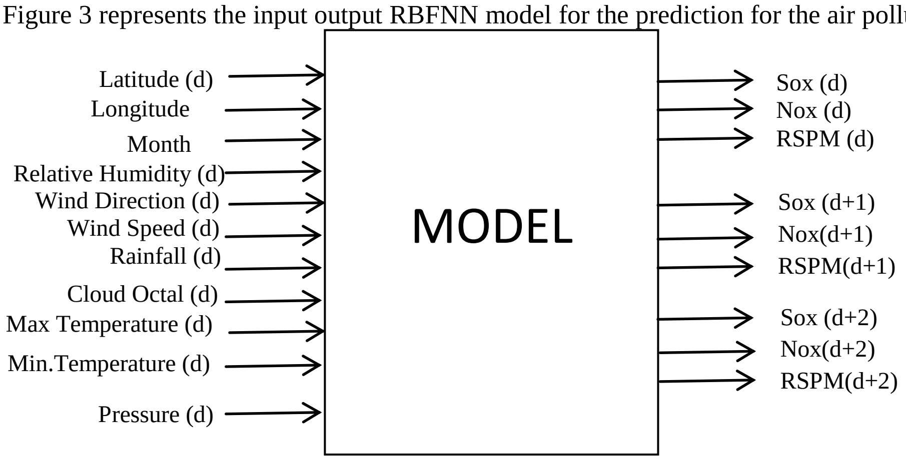

Figure 3: Inputs and outputs of RBFNN model for prediction of Air Pollutants Sox, Nox and RSPM

The next step of Kriging consisted of two stages: Firstly, semivariogram and covariance functions estimation of the statistical dependence values, because both measures the strength of statistical correlation as a function of distance and secondly, prediction using generalized linear regression techniques (kriging) of unknown values. Thus, geostatistics uses the observed spatial data twice: first to estimate the spatial autocorrelation and second to make the predictions based on the weighted average approach. The output of the ANN model which is the air pollutant values namely is NOx, SOx and RSPM at the monitored sites is input to the kriging model. A simple kriging is applied in the study and the distances between all input points (n) are determined and semi-variogram value is estimated for these distances. the weights λ_I are determined for local interpolation. The Kriging interpolation weights are chosen using the modelled variogram so that the estimate is unbiased and the estimation variance is less than any other linear combination of the observed values.

VI. PROPOSED ALGORITHM

Step 1. Initialize the network using random numbers with weights to be small random numbers between –1 and +1
Step 2. Apply the input pattern
Step 3. Predict the output i.e Target Apply it to the validation Set.
Step 4. Calculate the error ErrorB = OutputB (1-OutputB)(TargetB – OutputB)
Step 5. Change the weight. Let W+AB be the new (trained) weight and WAB be the initial weight.
i. W+AB = WAB + (ErrorB x OutputA)
Step 6. Calculate the Errors for the hidden layer neurons ErrorA = Output A (1 - Output A)(ErrorB WAB + ErrorC WAC)
Step 7. Repeating this method until the network is trained
Step 8. Forecast the output parameters for input parameters and create a matrix of forecasted values for the next three days
Step 9. For each day
a. Get the forecasted output parameters.
b. Find the valid input points
c. Determine the distances between all valid input points (n) and find the semi-variogram value for these distances
d. For each of the output pixel
i. Determine the distances towards all input points, and find the semi-variogram value for these distances
ii. Calculate the weight factors (vector w):
iii. Calculate the estimated or predicted values for this output pixel
iv. calculate the error variance and standard error for this output pixel

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VII. DATA SETS

The data used in this study are daily ambient minimum and maximum air temperature, relative humidity, wind speed, wind direction, atmospheric pressure at station level and mean sea level and daily concentration of NOx, SOx and RSPM at 3 locations in Mumbai and five locations in Navi Mumbai for a period of 3 years from 2009 – 2011. This data was provided by regional centre of Meteorology Department and the Maharashtra Pollution Control Board. Further, the month and date information was also provided as input. In some subtle way, the information about seasons gets conveyed to the model through the month and date information. The data was divided into two sets which become the learning set for ANN training and testing set to verify the efficiency and correctness of the developed model. The Matlab© Neural Network Toolbox was used for development of the air quality prediction model, due to its ease and flexibility. The model gives as output the predictions for the desired number of days.

VIII. RESULTS AND DISCUSSIONS

Feed-forward back propagation neural network have been applied in this study. During the training, the weights are adjusted to minimize the MSE error value which decreases after several iterations of training. Regression analysis was performed to check the correlation between the actual and predicted results. As shown in Figure. 4, a very good fit between the observed and predicted results was obtained as indicated by R values between 0.7 – 0.9 for the 8 monitored locations in Mumbai and Navi Mumbai . Figure 5 shows the reduction in MSE values with increase in epoch. Table 1 gives the predictions for coming 3 days for three pollutants. The Predicted values for the three air Pollutants using the Artificial Neural Networks is as in Table 1

Table 1: Forecasted values of the three pollutants at monitored locations for the next three days

Sr. No	Location	Sox (µg/m3)			Nox (µg/m3)			RSPM (µg/m3)		
		Day 1	Day 2	Day 3	Day 1	Day 2	Day 3	Day 1	Day 2	Day 3
1	Bandra	19.69	17.94	17.02	55.10	42.25	41.24	197.88	151.64	126.36
2	Sion	25.19	21.05	25.58	150.17	135.86	152.67	262.52	293.52	341.69
3	Mulund	52.22	52.17	50.01	38.84	38.87	39.02	189.72	188.21	159.1
4	Vashi	27.22	27.84	22.63	65.55	66.67	51.66	144.18	171.55	156.51
5	Nerul	13.50	14.37	13.90	42.53	39.98	40.33	122.4	155.39	123.91
6	Airoli	24.59	33.09	21.84	109.34	117.87	118.44	135.93	204.75	156.76
7	Rabale	20.24	17.69	22.49	48.73	47.58	48.62	147.39	99.811	171.17
8	Mahape	23.28	24.35	16.63	40.49	43.63	40.96	182.33	129.03	59.814

The Regression (R) values for all the locations of Mumbai and Navi Mumbai are as shown in the Table 2
Table 2: Regression (R) values obtained using the ANN model

Location	Bandra	Sion	Mulund	Vashi	Nerul	Airoli	Rabale	Mahape
R-Value using	0.89	0.9	0.96	0.79	0.79	0.85	0.72	0.86

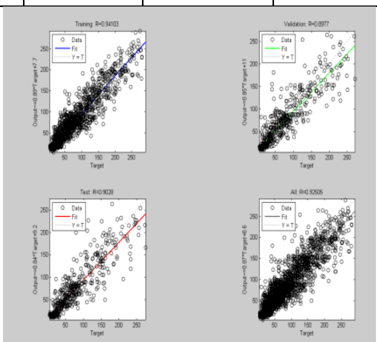

Figure 4 . R values for regression analysis of training, validation, testing and all data

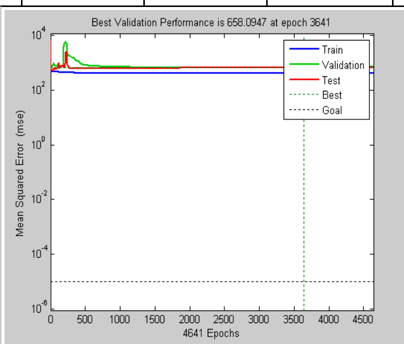

Figure. 5 MSE **for** training, validation, testing

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The R values indicate the unmonitored points were selected separately in Mumbai and Navi Mumbai areas. The observed locations are used to set up a prediction grid. The ordinary kriging function using the model with constant mean and global neighbourhood was used to produce the kriging predictions at 10 locations in Mumbai and 5 locations in Navi Mumbai which were selected separately in Mumbai and Navi Mumbai. The kriging model was deployed using R for selected locations in Mumbai and Navi Mumbai obtaining the values at the above said locations for the next three days and the results obtained are tabulated in Table 3

Table 3: Predicted values using Kriging at the unmonitored locations for the next three days

Sr. No	Location	Lat	Long	Sox (μg/m3)			Nox (μg/m3)			RSPM (μg/m3)		
				Day 1	Day 2	Day 3	Day 1	Day 2	Day 3	Day 1	Day 2	Day 3
1	Borivali	19.2300	72.8600	41.80	41.57	39.05	30.822	27.21	24.61	183.40	158.14	120.23
2	Malad	19.1861	72.8486	37.97	37.44	35.27	36.36	31.10	29.01	186.81	158.86	124.16
3	Andheri	19.1190	72.8470	30.47	29.24	28.01	51.44	42.80	42.48	196.34	166.16	140.92
4	Sakinaka	19.0881	72.8907	32.58	30.45	31.27	87.05	77.87	84.24	220.55	219.38	221.67
5	Dadar	19.0180	72.8448	23.04	19.56	22.54	123.17	109.05	120.73	244.11	252.16	279.32
6	Girgaon	18.9530	72.8130	22.81	19.54	22.07	115.23	101.32	111.54	238.73	240.73	261.81
7	Colaba	18.9750	72.8258	22.88	19.54	22.21	117.62	103.64	114.30	240.34	244.15	267.06
8	Chembur	19.0587	72.8997	31.35	28.37	30.89	116.33	105.61	117.09	240.21	257.77	281.92
9	Ghansoli	19.7000	72.5900	23.73	30.67	21.88	101.60	108.28	107.80	132.19	195.88	165.04
10	Mumbra	19.1767	73.0222	24.11	31.78	20.88	100.13	108.12	109.12	142.80	193.79	140.94
11	Kopar Khairane	19.1031	73.0106	25.61	27.04	20.11	59.26	62.00	53.54	160.16	156.64	115.39

IX. CONCLUSIONS

Prediction of atmospheric pollutants is a very relevant problem in modern times. This paper shows an integrated approach how Artificial Neural Networks and Kriging can be used to predict the values of atmospheric pollutants at monitored and unmonitored locations. The high R values show that the desired value of fit is obtained between predicted and observed values. Artificial Neural Networks gave better R value and forecast as compared to simple regression models. Kriging was able to predict pollutant values for unknown locations thus making it possible to estimate the values of the air pollutants at unmonitored locations. This prediction of air pollutants at monitored and unmonitored locations can be used to develop a Support System. The Support System thus built will be of great use to the policy makers and Urban Development Authorities to take necessary actions.

X. ABOUT THE AUTHORS

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REFERENCES

1. A C. P. Chen, Zehua Yang, Victor, , Michael E. Chang, Terrence E. Murphy And Julia C. C. Tsai "Mining and modeling for a metropolitan Atlanta ozone pollution decision-making framework", IIE Transactions (2007) 39, 607–615
2. Air Quality Assessment, Emissions Inventory and Source Apportionment Studies Mumbai, (2010) Central Pollution Control Board, New Delhi and , National Environmental Engineering Research Institute
3. Alexander Nikovb, Ferhat Karacaa, Omar Alaghaa, Atakan Kurtc and Hüseyin Hakkoymazc, "AirPolTool: A Web-Based Tool For Istanbul Air Pollution Forecastig And Control", Proceedings of the Third International Symposium own Air Quality Management at Urban, Regional and Global Scales. 26-30 September 2005, Istanbul – Turkey
4. Artificial Neural Networks, Ajith Abraham, Handbook of Measuring System Design, edited by Peter H. Sydenham and Richard Thorn.2005 John Wiley & Sons, Ltd. ISBN: 0-470-02143-8. For figure and ANN
5. Bailey, T.C., Gatrell, A.C., 1995, Interactive Spatial Data Analysis, Longman, Colchester
6. CPCB (1995) 'Air pollution and its control'. Parivesh Newsletter 2(1), June 1995. Delhi: Central Pollution Control Board. 20 pp.
7. CPCB (1998) Annual report (1997-98). Delhi: Central Pollution Control Board
8. CPCB (2002: c): 'National Ambient Air Quality Standards', Central Pollution Control Board, Ministry of Forests and Environment, NAAQMS/22/2001-02, Delhi.
9. CPCB (2005): Air Quality Data, Central Pollution Control Board, www.cpcb.nic.in
10. Davor Z. Antanasijević, Viktor V. Pocajt, Dragan S. Povrenović ,Mirjana Đ. Ristić Aleksandra A. Perić-Grujić , " PM10 emission forecasting using artificial neural networks and genetic algorithm input variable optimization", Science of The Total Environment, Volume 443, 15 January 2013, Pages 511–519
11. H.J.S. Fernando, M.C. Mammarella, G. Grandoni, P. Fedele, R. Di Marco, R. Dimitrova, P. Hyde "Forecasting PM10 in metropolitan areas: Efficacy of neural networks", Environmental Pollution 163 (2012) 62e67.
12. Ioannis N. Athanasiadis and Pericles A. Mitkas, "An agent-based intelligent environmental monitoring system" , In Management of Environmental Quality, An International Journal vol.15, no.3, pp.238-249, 2004. Emerald Publishers.
13. Jef Hooyberghsa,_, Clemens Mensinka, Gerwin Dumontb, Frans Fierensb, Olivier Brasseur, " A neural network forecast for dailyaverage PM10 concentrations in Belgium", Atmospheric Environment 39 (2005) 3279–32
14. Jeong-Sook Heo, Dong-Sool Kim, " A new method of ozone forecasting using fuzzy expert and neural network systems" Science of The Total Environment Volume 325, Issues 1–3, 5 June 2004, Pages 221–237
15. Journel, A. G., Huijbregts, C. J. (1978), *Mining Geostatistics*. Academic Press, London
16. Keith McCabe, Paul J Taylor, Alex Bywaters , Joanna White, Dr David Carslaw, Paul J Taylor , "Managing air quality by 'Data Mining' Exploratory statistical analysis to determine causal factors affecting pollutant concentrations close to a motorway", 2007, www.atkinsglobal.com/media
17. M.L. Martin , I.J. Turias, F.J. Gonzalez, P.L. Galindo, F.J. Trujillo , C.G. Puntonet, J.M. Gorriz ," Prediction of CO maximum ground level concentrations in the Bay of Algeciras, Spain using artificial neural networks" , Chemosphere 70 (2008) 1190–1195
18. McCulloch, W.S. and Pitts, W.H. (1943) A Logical Calculus of the Ideas Immanent in Nervous Activity. Bulletin of Mathematical Biophysics, 5, 115–133.
19. MoST (2000) Handbook on transport statistics in India (1999). New Delhi: Transport research wing, Ministry of Surface Transport

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ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
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20. P. Viotti ,G. Liuti , P. Di Genova, " Atmospheric Urban Pollution: Applications of an Artificial Neural Network (ANN) to the City of Perugia", Ecological Modelling 148 (2002) 27–46
21. P.T. Nastos ,A.G. Paliatsos, K.V. Koukouletsos, I.K. Larissi, K.P. Moustris , "Artificial neural networks modeling for forecasting the maximum daily total precipitation at Athens, Greece", www.elsevier.com, Atmospheric Research xxx (2013) xxx–xxx, Article in Press
22. Pachauri, R.K.; Sridharan, P.V. (1998) Looking Back to Think Ahead: growth with resource enhancement of environment and nature. New Delhi: Tata Energy Research Institute. 346 pp.
23. Potoglou, D., Kanaroglou, P.S., 2005. Carbon monoxide emissions from passenger vehicles: predictive mapping with an application to Hamilton, Canada, Transportation Research Part D 10, pp. 97-109
24. Prof Yike Guo, Researchers , Dr Yajie Ma, Dr Moustafa Ghanem, Mr. Xiangchuan Tian, "Mobile Environmental Sensing System Across Grid Environments", www.commsp.ee.ic.ac.uk
25. Sertel, E., H. Demirel, S. Kaya and I. Demir, "Spatial Prediction of Transport Related Urban Air Quality, The International Archives of the Photogrammetry," Remote Sensing and Spatial Information Science, Vol. XXXVII, Part B2, 805-809, Beijing, 2008.
26. Vikas Singh, Claudio Carnevale, Giovanna Finzi, Enrico Pisoni , Marialuisa Volta,"A cokriging based approach to reconstruct air pollution maps, processing measurement station concentrations and deterministic model simulations", Environmental Modelling & Software 26 (2011) 778e786
27. Vincent Ng, Stephen C F Chan, Sandra Au, "Web Agents for Spatial Mining on Air Pollution Meteorology", Computer Supported Cooperative Work in Design, The Sixth International Conference, London , 2001
28. WHO/UNEP (1992) Urban air pollution in megacities of the World. Oxford: Basil Blackwell, World Health Organisation United Nations Environment
29. Xie-Kang Wang, Wei-Zhen Lu, " Seasonal variation of air pollution index: Hong Kong case study", Chemosphere 63 (2006) 1261–1272 Yu-Kai Huang, Munkh-Erdene Luvsan, Enkhjargal Gombojav, Chimedsuren Ochir, Jargal Bulgan, Chang-Chuan Chan, " Land use patterns and SO2 and NO2 pollution in Ulaanbaatar, Mongolia.", Environ. Res. 2013.

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