Review Paper on Modeling And Simulation of Ambient Air Pollutants Through Artificial Neural Network

Priyanka yadav[1], Dr. J.K. Srivastava[2]
[1]Dept of Chemical Engineering
[2]Principal, Dept of Chemical Engineering
[1, 2] Ujjain Engineering College Ujjain, Madhya Pradesh, India.

Abstract- *Air Quality assessment and foreseeing are the requirements today and they captivating many researchers. Environmental organizations consistently monitor and predict the air contaminants to make the public acknowledgement, provide a better environment, and suitable for human health. Physical factors like climate changes, Westernization, Fires and Urbanization are some of the factors which straightly affect and bring down the air quality. All these data are time-series and real-time data. Slight attentiveness is given to applying the artificial neural network (ANN) modeling technique to understand site–specific air pollution dispersion mechanisms in order to know the importance of meteorological variables in determining concentrations as well as the important time scales that influence emission patterns. Modeling a system that initiates a future value from earlier observations is considered as time series forecasting system. Artificial neural network is a machine learning method that is widely used in the prediction of future values. In this paper, we propose a methodology for gathering the key information from daily–available meteorological parameters and the emission pattern of sources present throughout the year (e.g. Industrial emissions, traffic emissions, residential emissions) to build a reliable and bodily based ANN air pollution forecasting tool. The proposed approach illustrates how the ANN modeling technique can be used to identify the key meteorological variables required to adequately seize the temporal flexibility in air pollution concentrations for a specific scenario.*

Keywords- Artificial neural Network, Air Quality Index, Particulate Matter, Respirable Suspended Particulate Matter, Air Quality Model.

I. INTRODUCTION

Air pollution is a serious environmental problem in metro cities of India. Air pollution is nothing but changes of quality of air. Activities of humans are the major goal for the mortification of air quality (1-3). Air is said to be polluted when it is diluted by a mix of particulate matter like particulate matter 2.5 (PM2.5) (particles that have size less than 250nm), particulate matter 10 (PM10) (particles that have size less than 1000nm) and other gases like sulphur oxides (SO_X), nitrogen oxides (NOx), ozone (O3), carbon monoxide (CO) and RSPM. Each pollutant has allowable range in ppm(3-7). In case of high or low level of concentration it is dangerous to human who inhale it (7-12). Therefore, proper prediction and counter measures are necessary. The prediction may be done by the following ways.

- Simulating the weather conditions and predict the air quality (13-14).
- Using Wireless Sensor Networks (WSN), to acquire "the real-time" data by gaseous instruments and performing the forecasting (14-16).
- Meteorological Elements can be collected from the government official sites, and can be used as historical data and apply different algorithms can be used for current estimation and further prediction (17)

These pollutants exert a wide range of impacts on biological, physical, and economic systems, especially, effects on plant and human health are of particular concern (18). The problem of air pollution has significant health impacts on human and the environment (19). Air pollutants are under escalated toxicological and epidemiological examinations (19) and has been considered in affecting human health (20), namely by causing diseases such as respiratory illness (21) and cardiovascular diseases (22). Air pollutants also leave its footprints on climatic system by bringing about changes in the pattern of weather and temperature, which ultimately leads to loss in the crops (23). This subsequently leads to a market equilibrium shift in the food supply chain (24).Atmospheric air pollutants concentrations have attracted increasing worldwide attention during the past years due to its effect on human health and the environment (25). Controlling the air pollution is a challenging task in many developing countries. Governments in international, national and regional levels work along with the research institutions to develop and implement an efficient policy for identifying the hot-spots and controlling of air pollution, because it creates a harmful consequence to the public health and the eco-system (26).

The meteorological factors and gaseous pollutants are ambient temperatures, relative humidity, wind speed, wind direction, rainfall amount, sulphur oxides (SO_X), carbon monoxide (CO) and nitrogen oxides (NO_X), RSPM and SPM. Meteorological factors have a powerful influence on ambient air quality through the different mechanisms in the atmosphere, both directly and indirectly (27). Wind speed and wind direction are accountable for some mechanisms of particle emission in the atmosphere, such as re-suspension of particles and diffusion, as well as the dissipation of particles (28). The increase of wind speed results in low pollutant concentration, as it adulterated the pollutant. Rain removes particulates in the atmosphere through a “scavenging” process, and it is able to liquefy other gaseous pollutants. The persistent high rainfall amount generally results in better air quality. Precipitation provides the information on the removing process of pollutants in the atmosphere through wet deposition. Measuring ambient temperature strengthens air quality accomplish, air quality modeling and anticipated forecasting model. Recorded daily maximum temperatures are linked with low wind speed, little precipitation and high daily maximum mixing height (29).

There is a growing interest in recent years on the use of artificial neural networks (ANNs) in predicting and forecasting ambient air pollution and have been successfully implemented in many short- and long-term forecasting applications (30-35). Many recent studies have shown that ANN–based air pollution models perform better than other statistical techniques (36-39) and ANN–based air pollution forecasting models are being implemented in some cities (40-43). Several scholars have focused on improving ANN model performance using different input data classification techniques (44-48). Deep learning can take huge amount of data within one single realm and learn to predict or decide at superhuman accuracy (49-51).

The artificial neural network approaches are frequently used for the relationship of pollutants and metrological condition (52-54). Regression modelling is most popular statistical approach has been used to develop air quality predictive models in number of studies (b).Furthermore, more practitioners resort to data-driven approaches such as ANNs as stand in to conventional deterministic or physics-based approaches, e.g. the Urban Airshed Model (UAM) (55), Weather Research and Forecasting Model with Chemistry (WRF/Chem) (56) and Community Multiscale Air Quality model (CMAQ) (57).

Artificial Intelligence (AI) has been a buzzword but it is not some magical dust that can miraculously solve problems rather, it is a powerful tool created by humans, to gauge and solve the problems of the humanity. In general, AI techniques allow machines to mimic human behavior while utilizing the deep involved techniques such as Machine learning, deep learning, neural networks and synthetic data. Moreover, AI technologies possess the potential to transform everyday processes and industries in a way that can lead us to greater self-sufficiency and productivity (58).

Many fields of research are attempt in some way to use this beneficial tool, to solve problems that previously seemed very complicated or even impossible including medical science, computational engineering, speech recognition and movement, photography, agriculture, advertisement, social media recommendations and the list goes on and on. Hence, we see great possibilities for this technology in the field of Sustainable Development as well by WHO (2018, 2019)

The objective of this study is to design an ANN pollutant predictor model of air contaminants (SOx, NOx, RSPM and SPM) utilizing historical data from the year 2018–2020. Thus, a separate ANN model was developed for each pollutant of SOx, NOx, RSPM and SPM. Besides, a comparative analysis between a linear (MLR) and a non-linear method (ANN) of pollutant modelling to ascertain the better air quality forecasting tool would be performed. Accurate prediction of air quality is essential for efficient planning of various sectors related to economic performances (61-62) and strategic management of air quality as well.

Artificial neural network is a machine learning approach that furnishes the compelling performance in the field of time-series forecasting and prediction. ANN can incorporate complex non-linear relationships between the concentration of air pollutants and metrological variables (5). Various ANN structures have been developed to predict air pollution over different study areas, such as neuro-fuzzy neural network (NFNN) (63).

The commonly used structure of the neural network is the “feed forward” where the data goes from input to output units is precisely feed forward and are able to discover and identify complex patterns in datasets which may not be well clarified by a simple mathematical formula or a set of known processes(64).

Several attempts have been made to better predict accuracy of time-series forecasting problems using ANN models. In order to obtain advantages of several recurrent neural network models, a combination of different models can be applied (65).

Due to a non-linear relationship between air pollutant concentration and meteorological parameters, advanced statistical approaches based on machine learning algorithms are needed such as ensemble learning algorithms (66).

The artificial neural network approaches are frequently used for the relationship of pollutants and metrological condition (67-69).

Neural networks have been shown to give acceptable results for atmospheric pollution forecasting of pollutants such as; SOx, NOx, RSPM and SPM and it allows for non-linear relationships between variables (70-76).

These soft computing programs have own individual structure; possess the ability to learn non-linear relationships with confined prior knowledge about the process anatomy. Since ANNs showed their ability to model non-linear functions in a wide range of applications, ANN-based models would be assessed in this work for short-term concentrations. A multi-layer perceptron neural network (MLP) trained with back- propagation algorithm, a radial basis function (RBF) neural network, and generalized regression neural network (GRNN) would be used in the study to evaluate the best-suited model for the pollutants concentration prediction(77-83).

II. APPLICATION OF ARTIFICIAL NEURAL NETWORK

An ANN tool was widely used to simulate and identify the pollutants amount in the research area. Various ANN structures have been developed to predict air pollution over different study areas, such as neuro-fuzzy neural network (NFNN) (84-86), there are several types of ANNs based on their architecture, such as Multilayer Perceptron (MLP), Elman Recurrent Network, and the Radial Basis Function Network. Multilayer perceptron feed-forward network is the most commonly used network for prediction modelling where the flow of information is in one direction from input through output (87)

The development of ANN was inspired by the human nervous system and mathematical operators are used to simulating this system by using predictors and predict and, which act as inputs and output, respectively (88). There are input, output, and hidden layers where the neurons are located; the interconnection of neurons can form networks (89).

As ANN's have the capability to map the complex nonlinear functions with the desired accuracy, found to be very flexible and is used in various research study to perform seasonal predictions.

Artificial neural networks (ANNs), are networks of simple processing elements (called 'neurons') working on their confined data and communicating with other elements. ANNs learns from training data to find patterns and relationships between the input and the output. There are many types of ANNs but the proposition is similar, each ANN consists of an input layer, one or more hidden layers of neurons and a final layer of output neurons. The input layer passes the facts to the next layer. Each neuron in an individual layer is bind with all neurons in the succeeding layer. The connection between the ith and jth neuron is characterized by the weight coefficient wij and the ith neuron by the threshold coefficient ϑi. The weight coefficient is the grade of importance of the connection in the neural network. In the hidden layer, all the processing and calculation are done. ANNs are fashioned from several neurons, depending on the model. Each neuron is connected with a coefficient (weight). They are also known as processing elements as they process information (90-91). Each neuron has also a transfer function (1,2) (92) and one output. The inputs of each neuron are multiplied by the connection weights, then combined and passed through a transfer function (3) (93) to make the output of the neuron. There are many transfer functions in the composition. The output value (activity) of the ith neuron xi is set on by the equations below (94-95). Organizing data or pre-processing for the neural network is an imperative and crucial stage that has a massive influence on the success as well as the performance of the ANN results(96). As suggested by (97-98), very large or very small values of input variables cause network overflow, so all model inputs had to be scaled before entering the network. Forecast conventional neural networks provide 24-h forecasts based on a history of 24-h observations (of the previous day). The back propagation algorithm and gradient- based amend technique are widely used for training of such networks (99). Deep networks (with more computation layers) with large initial weights usually lead to poor local minima. Those with small initial weights, however, assemble shallow gradients in the later layers, which degrade the applicability of training networks with numerous hidden layers (100). To settle this issue, (101) used a greedy layer-wise learning technique to train deep networks efficiently. As the training strategy for this technique, the first layer learned the simpler concepts, and then the next layer learned more hypothetical features using the feature representation provided by the previous layer. Hence, the aim was to train the deep network layer by- layer and use the back propagation algorithm to fine tune all of the network parameters (102-103).

III. CONCLUSION

This research paper snooped the relationship between AQI and supplementary factors affecting AQI. Our final goal is to develop unique and more efficient models to predict AQI with excellent efficiency in minimum computational time. Many current air quality forecasting methods use only linear techniques which would miss nonlinear relationship in the data. After implementation, the result manifested that Artificial Neural Networks can express the non-linear relationship between the contributory variables and AQI even though the accuracy to predict was less favorable.

This study has demonstrated the potential of using nonlinear machine learning methods to improve air quality forecasts. In the future, aggregation of model selection and time series analysis can be considered for better efficiency of the model and to provide results with higher accuracy in less computational time.

As discussed here, the deep learning approach has been widely used in the air quality classification and forecasting problems. For Indian context also, researchers have employed various conventional machine learning and deep learning methods for predicting the air pollutants and results show that meteorological factors play most vital role in the prediction of pollutant concentration, whereas all factors, including meteorological, traffic, and emission characteristics, are significant in governing the prediction of pollutants & Similarly, both the meteorological data and traffic data are most important variables in predictions. The results we saw in different papers prove that ANN and its model are well suited for prediction of air pollutant concentrations.

The study also demonstrated that the predictions of the ANN model were generally more accurate (higher IOA and r values with a lower mean bias) for the prediction of air pollutants.

The ANN model not only predicts real-time pollutant concentration with favorable figures but also generates the result within less than a minute of initiating the model. For instance, a proper number of input variables (predictors) should be used with a sufficiently large amount of training data. However, if an important predictor of pollutant concentration is missing (e.g., cloud fraction and solar radiation), it will influence the sensitivity of the model to the other input variables, which may lead to ‘‘misprediction.’’

The proposed approach in this paper can be applied to and yield a high prediction accuracy for pollutants in other metropolitan areas. In addition, the deep learning approach can potentially be used for a multiple day forecast of air pollution or air quality index. Fast and accurate air quality prediction using the ANN model could be used to reduce the adverse health effects of urban air pollution. Given the computational efficiency of the ANN algorithm, deep learning could supplement deterministic models to more rapidly and accurately forecast air pollution concentrations. We expect that this paper will not only provide a more comprehensive understanding of ANNs but also facilitate future research activities and applications within the field of atmospheric sciences.

REFERENCES

[1] Dimitriou, Konstantinos, A. K. Paschalidou,and P. A. Kassomenos. "Assessing airquality with regards to its effect on humanhealth in the European Union through airquality indices." *Ecological Indicators* 27 (2013): 108-115.

[2] Gardner, M. W., and S. R. Dorling. "Neuralnetwork modelling and prediction of hourlyNOx and NO2 concentrations in urban airin London." *Atmospheric Environment* 33.5(1999): 709-719.

[3] Hosamane, Sateesh N., and G. P. Desai."Air pollution Modelling frommeteorological parameters using artificialneural network." *Computational Visionand Bio Inspired Computing*. Springer,Cham, 2018. 466-475.

[4] Sejnowski, Terrence J., and Charles R.Rosenberg. "Parallel networks that learn toPronounce English text." *Complexsystems* 1.1 (1987): 145-168.

[5] Kandasamy, S., Baret, F., Verger, A.,Neveux, P., Weiss, M.: A comparison ofmethods .For smoothing and gap fillintime series of remote sensing observationsapplication to MODIS LAI products.Biogeosciences 10(6), 4055–4071 (2013)

[6] Surakhi, Ola, Sami Serhan, and Imad Salah."On the ensemble of recurrent neuralnetwork for air pollution forecasting:Issues and challenges." *Adv. Sci. Technol.Eng. Syst. J* 5 (2020): 512-526.

[7] Lelieveld, Jos, et al. "The contribution ofoutdoor air pollution sources to prematuremortaliy on aglobal scale." *Nature* 525.7569(2015): 367-371.

[8] Satya Sai, K. V. R., S. Krishnaiah, and A.Manjunath. "Statistical Downscaling ofRainfall Under Climate Change in KrishnaRiver Sub-basin of Andhra Pradesh, IndiaUsing Artificial Neural Network(ANN)." *Nature Environment & PollutionTechnology* 20.2 (2021).

[9] Cannon, Alex J., and Edward R. Lord."Forecasting summertime surface-levelozone concentrations in the Lower FraserValley of British Columbia: An ensembleneural network approach." *Journal of theAir & Waste Management Association* 50.3(2000): 322-339.

[10] Mishra, Dhirendra, and Pramila Goyal."Neuro-fuzzy approach to forecast NO_2Pollutants addressed to air qualitydispersion model over Delhi,India." *Aerosol and air qualityresearch* 16.1 (2016): 166-174.

[11] Amuthadevi, C., D. S. Vijayan, andVaratharajan Ramachandran. "Developmentof air quality monitoring (AQM) modelsusing different machine learningapproaches." *Journal of AmbientIntelligence and HumanizedComputing* (2021): 1-13.

[12] Gardner, M. W., and S. R. Dorling. "Neuralnetwork modelling and prediction of hourlyNOx and NO2 concentrations in urban air inLondon." *Atmospheric Environment* 33.5(1999): 709-719.

[13] Chelani, Asha B., et al. "Prediction ofsulphur dioxide concentration using artificialneural networks." *Environmental Modelling& Software* 17.2 (2002): 159-166.

[14] Grivas, G., and A. Chaloulakou. "Artificialneural network models for prediction ofPM10 hourly concentrations, in the GreaterArea of Athens, Greece." *Atmosphericenvironment* 40.7 (2006): 1216-1229.

[15] Singh, Kunwar P., et al. "Linear andnonlinear modeling approaches for urban airquality prediction." *Science of the TotalEnvironment* 426 (2012): 244-255.

[16] Jiang, Dahe, et al. "Progress in developingan ANN model for air pollution indexforecast." *Atmospheric Environment* 38.40(2004): 7055-7064.

[17] Kurt, Atakan, and Ayşe Betül Oktay."Forecasting air pollutant indicator levelswith geographic models 3 days in advanceusing neural networks." *Expert Systems withApplications* 37.12 (2010): 7986-7992.

[18] Perez, Patricio. "Combined model for PM10forecasting in a large city." *Atmosphericenvironment* 60 (2012): 271-276.

[19] Dimitriou, Konstantinos, A. K. Paschalidou,and P. A. Kassomenos. "Assessing airquality with regards to its effect on humanhealth in the European Union through airquality indices." *Ecological Indicators* 27(2013): 108-115.

[20] Han, Xianglu, and Luke P. Naeher. "Areview of traffic-related air pollutionexposure assessment studies in thedeveloping world." *Environmentinternational* 32.1 (2006): 106-120.

[21] Rai, Prabhat. *Biomagnetic monitoring ofparticulate matter: in the Indo-Burmahotspot region*. Elsevier, 2015.

[22] Utell, Mark J., and Mark W. Frampton."Acute health effects of ambient airpollution: the ultrafine particlehypothesis." *Journal of aerosolmedicine* 13.4 (2000): 355-359.

[23] Perez, Laura, et al. "Coarse particles fromSaharan dust and dailymortality." *Epidemiology* (2008): 800-807.

[24] Ravina, Marco, Deborah Panepinto, andMaria Chiara Zanetti. "DIDEM-Anintegrated model for comparative healthdamage costs calculation of airpollution." *Atmospheric Environment* 173(2018): 81-95.

[25] Sun, Wei, et al. "Prediction of 24-hour-average PM2. 5 concentrations using ahidden Markov model with differentemission distributions in NorthernCalifornia." *Science of the totalenvironment* 443 (2013): 93-103.

[26] Satya Sai, K. V. R., S. Krishnaiah, and A.Manjunath. "Statistical Downscaling ofRainfall Under Climate Change in KrishnaRiver Sub-basin of Andhra Pradesh,VIndiaUsing Artificial Neural Network(ANN)." *Nature Environment & PollutionTechnology* 20.2 (2021).

[27] Chofreh, Abdoulmohammad Gholamzadeh,et al. "Value chain mapping of the waterand sewage treatment to contribute tosustainability." *Journal of environmentalmanagement* 239 (2019): 38-47.

[28] Cannon, Alex J., and Edward R. Lord."Forecasting summertime surface-levelozone concentrations in the Lower FraserValley of British Columbia: An ensembleneural network approach." *Journal of theAir & Waste ManagementAssociation* 50.3 (2000): 322-339.

[29] Abdullah, Samsuri, et al. "Forecastingparticulate matter concentration usinglinear and non-linear approaches for airquality decisionsupport." *Atmosphere* 10.11 (2019): 667.

[30] Biancofiore, Fabio, et al. "Recursive neuralnetwork model for analysis and forecast ofPM10 and PM2. 5." *Atmospheric PollutionResearch* 8.4 (2017): 652-659.

[31] Cabaneros, Sheen Mclean S., John KaiserS. Calautit, and Ben Richard Hughes."Hybrid artificial neural network models foreffective prediction and mitigation of urbanroadside NO2 pollution." *EnergyProcedia* 142 (2017): 3524-3530.

[32] Coman, Adriana, Anda Ionescu, and YvesCandau. "Hourly ozone prediction for a24-h horizon using neuralnetworks." *Environmental Modelling &Software* 23.12 (2008): 1407-1421.

[33] Ibarra-Berastegi, Gabriel, et al. "Fromdiagnosis to prognosis for forecasting airpollution using neural networks: Airpollution monitoring inBilbao." *Environmental Modelling &Software* 23.5 (2008): 622-637.

[34] Lightstone, Samuel D., Fred Moshary, andBarry Gross. "Comparing CMAQ forecastswith a neural network forecast model forPM2. 5 in New York." *Atmosphere* 8.9(2017): 161.

[35] Rahimi, Akbar. "Short-term prediction ofNO 2 and NO x concentrations usingmultilayer perceptron neural

network: acase study of Tabriz, Iran." *EcologicalProcesses* 6.1 (2017): 1-9.

[36] Gardner, M. W., and S. R. Dorling."Neural network modelling and predictionof hourly NOx and NO2 concentrations inurban air in London." *AtmosphericEnvironment* 33.5 (1999): 709-719.

[37] Hrust, Lovro, et al. "Neural networkforecasting of air pollutants hourlyconcentrations using optimised temporalaverages of meteorological variables andpollutant concentrations." *AtmosphericEnvironment* 43.35 (2009): 5588-5596.

[38] Chelani, Asha B., et al. "Prediction of sulphur dioxide concentration usingartificial neural networks." *EnvironmentalModelling & Software* 17.2 (2002): 159-166.

[39] Grivas, G., and A. Chaloulakou. "Artificialneural network models for prediction ofPM10 hourly concentrations, in theGreater Area of Athens,Greece." *Atmospheric environment* 40.7(2006): 1216-1229.

[40] Singh, Kunwar P., et al. "Linear andnonlinear modeling approaches for urbanair quality prediction." *Science of the TotalEnvironment* 426 (2012): 244-255.

[41] Jiang, Dahe, et al. "Progress in developingan ANN model for air pollution indexforecast." *Atmospheric Environment* 38.40(2004): 7055-7064.

[42] Kurt, Atakan, and Ayşe Betül Oktay."Forecasting air pollutant indicator levelswith geographic models 3 days in advanceusing neural networks." *Expert Systemswith Applications* 37.12 (2010): 7986-7992.

[43] Perez, Patricio. "Combined model forPM10 forecasting in a largecity." *Atmospheric environment* 60 (2012):271-276.

[44] Nagendra, SM Shiva, and Mukesh Khare."Artificial neural network approach formodelling nitrogen dioxide dispersionfrom vehicular exhaustemissions." *Ecological Modelling* 190.1-(2006): 99-115.

[45] Hrust, Lovro, et al. "Neural networkforecasting of air pollutants hourlyconcentrations using optimised temporalaverages of meteorological variables andpollutant concentrations." *AtmosphericEnvironment* 43.35 (2009): 5588-5596.

[46] Yang, C., et al. "Big Earth data analytics: asurvey. Big Earth Data 3: 83–107." (2019).

[47] Faghmous, James H., and Vipin Kumar."A big data guide to understandingclimate change: The case for theory-guided data science." *Big data* 2.3 (2014):155-163.

[48] Jeltsch, Florian, et al. "Integratingmovement ecology with biodiversityresearch-exploring new avenues toaddress spatiotemporal biodiversitydynamics." *Movement Ecology* 1.1(2013): 1-13.

[49] Boznar, Marija, Martin Lesjak, and Primoz Mlakar. "A neural network-based methodfor short-term predictions of ambient SO2concentrations in highly pollutedindustrial areas of complexterrain." *Atmospheric Environment. PartB. Urban Atmosphere* 27.2 (1993): 221-230.

[50] Ruiz-Suarez, J. C., et al. "Short-term ozoneforecasting by artificial neuralnetworks." *Advances in EngineeringSoftware* 23.3 (1995): 143-149.

[51] Elkamel, A., et al. "Measurement andprediction of ozone levels around a heavilyindustrialized area: a neural networkapproach." *Advances in environmentalresearch* 5.1 (2001): 47-59.

[52] Chang, Michael E., and Carlos Cardelino."Application of the urban airshed model toforecasting next-day peak ozoneconcentrations in Atlanta,Georgia." *Journal of the Air & WasteManagement Association* 50.11 (2000):2010-2024.

[53] Chuang, Ming-Tung, Yang Zhang, andDaiwen Kang. "Application ofWRF/Chem-MADRID for real-time airquality forecasting over the SoutheasternUnited States." *Atmosphericenvironment* 45.34 (2011): 6241-6250.

[54] Mueller, Stephen F., and Jonathan W.Mallard. "Contributions of naturalemissions to ozone and PM2. 5 assimulated by the community multiscale airquality (CMAQ) model." *Environmentalscience & technology* 45.11 (2011): 4817-4823.

[55] Chauhan, Ritu, Harleen Kaur, and Bhavya Alankar. "Air quality forecast usingconvolutional neural network forsustainable development in urbanenvironments." *Sustainable Cities andSociety* 75 (2021): 103239.

[56] Lelieveld, Jos, et al. "The contribution ofoutdoor air pollution sources to prematuremortality on a globalscale." *Nature* 525.7569 (2015): 367-371.

[57] Mishra, Dhirendra, and Pramila Goyal."Neuro-fuzzy approach to forecast NO2pollutants addressed to air qualitydispersion model over Delhi,India." *Aerosol and air qualityresearch* 16.1 (2016): 166-174.

[58] Surakhi, Ola, Sami Serhan, and ImadSalah. "On the ensemble of recurrentneural network for air pollutionforecasting: Issues and challenges." *Adv.Sci. Technol. Eng. Syst. J* 5 (2020): 512-526.

[59] Cannon, Alex J., and Edward R. Lord."Forecasting summertime surface-levelozone concentrations in the Lower FraserValley of British Columbia: An ensembleneural network approach." *Journal of theAir & Waste ManagementAssociation* 50.3 (2000): 322-339.

[60] Chauhan, Ritu, Harleen Kaur, and BhavyaAlankar. "Air quality forecast usingconvolutional neural network forsustainable development in

urbanenvironments." *Sustainable Cities andSociety* 75 (2021): 103239.

[61] Abd Rahman, Nur Haizum, et al."Forecasting of air pollution index withartificial neural network." *JurnalTeknologi* 63.2 (2013).

[62] Lelieveld, Jos, et al. "The contribution ofoutdoor air pollution sources to prematuremortality on a global scale." *Nature* 525.7569 (2015): 367-371.

[63] Mishra, Dhirendra, and Pramila Goyal."Neuro-fuzzy approach to forecast NO2pollutants addressed to air qualitydispersion model over Delhi,India." *Aerosol and air qualityresearch* 16.1 (2016): 166-174.

[64] Sejnowski, Terrence J., and Charles R.Rosenberg. "Parallel networks that learn topronounce English text." *Complexsystems* 1.1 (1987): 145-168.

[65] Surakhi, Ola, Sami Serhan, and ImadSalah. "On the ensemble of recurrent neuralnetwork for air pollution forecasting: Issuesand challenges." *Adv. Sci. Technol. Eng.Syst. J* 5 (2020): 512-526.

[66] Cannon, Alex J., and Edward R. Lord."Forecasting summertime surface-levelozone concentrations in the Lower FraserValley of British Columbia: An ensembleneural network approach." *Journal of theAir & Waste ManagementAssociation* 50.3 (2000): 322-339.

[67] Boznar, Marija, Martin Lesjak, and PrimozMlakar. "A neural network-based methodfor short-term predictions of ambient SO2concentrations in highly polluted industrialareas of complex terrain." *AtmosphericEnvironment. Part B. UrbanAtmosphere* 27.2 (1993): 221-230.

[68] Ruiz-Suarez, J. C., et al. "Short-term ozoneforecasting by artificial neuralnetworks." *Advances in EngineeringSoftware* 23.3 (1995): 143-149.

[69] Babadjouni, Robin M., et al. "Clinicaleffects of air pollution on the centralnervous system; a review." *Journal ofClinical Neuroscience* 43 (2017): 16-24.

[70] Ravina, Marco, Deborah Panepinto, andMaria Chiara Zanetti. "DIDEM-Anintegrated model for comparative healthdamage costs calculation of airpollution." *Atmospheric Environment* 173(2018): 81-95.

[71] Sun, Wei, et al. "Prediction of 24-hour-average PM2. 5 concentrations using ahidden Markov model with differentemission distributions in NorthernCalifornia." *Science of the totalenvironment* 443 (2013): 93-103.

[72] Abd Rahman, Nur Haizum, et al."Forecasting of air pollution index withartificial neural network." *JurnalTeknologi* 63.2 (2013).

[73] Boznar, Marija, Martin Lesjak, and PrimozMlakar. "A neural network-based methodfor short-term predictions of ambient SO2concentrations in highly polluted industrialareas of complex terrain." *AtmosphericEnvironment. Part B. UrbanAtmosphere* 27.2 (1993): 221-230.

[74] Ruiz-Suarez, J. C., et al. "Short-term ozoneforecasting by artificial neuralnetworks." *Advances in EngineeringSoftware* 23.3 (1995): 143-149.

[75] Elkamel, A., et al. "Measurement andprediction of ozone levels around a heavilyindustrialized area: a neural networkapproach." *Advances in environmentalresearch* 5.1 (2001): 47-59.

[76] Chauhan, Ritu, Harleen Kaur, and BhavyaAlankar. "Air quality forecast usingconvolutional neural network forsustainable development in urbanenvironments." *Sustainable Cities andSociety* 75 (2021): 103239.

[77] Yang, C., et al. "Big Earth data analytics: asurvey. Big Earth Data 3: 83–107." (2019).

[78] Faghmous, James H., and Vipin Kumar. "Abig data guide to understanding climatechange: The case for theory-guided datascience." *Big data* 2.3 (2014): 155-163.

[79] Jeltsch, Florian, et al. "Integratingmovement ecology with biodiversityresearch-exploring new avenues to addressspatiotemporal biodiversitydynamics." *Movement Ecology* 1.1 (2013):1-13.

[80] Amann, Markus. *Health risks of ozonefrom long-range transboundary airpollution*. WHO Regional Office Europe,2008.

[81] Gatari, Michael J. "First WHO globalconference on air pollution and health: abrief report." *Clean Air Journal* 29.1(2019): 7-7.

[82] World Health Organization. "Ambient airpollution: A global assessment of exposureand burden of disease." (2016).

[83] Araújo, Teresa, et al. "Classification ofbreast cancer histology images usingconvolutional neural networks." *PloSone* 12.6 (2017): e0177544.

[84] Kankaria, Ankita, Baridalyne Nongkynrih,and Sanjeev Kumar Gupta. "Indoor airpollution in India: Implications on healthand its control." *Indian journal ofcommunity medicine: official publicationof Indian Association of Preventive &Social Medicine* 39.4 (2014): 203.

[85] Saud, T., et al. "Emission estimates oforganic and elemental carbon fromhousehold biomass fuel used over theIndo-Gangetic Plain (IGP)India." *Atmospheric environment* 61(2012): 212-220.

[86] Mishra, Dhirendra, and Pramila Goyal."Neuro-fuzzy approach to forecast NO2pollutants addressed to air qualitydispersion model over Delhi,India." *Aerosol and air quality research* 16.1 (2016): 166-174.

[87] Shakerkhatibi, Mohammad, et al. "Using ANN and EPR models to predict carbonmonoxide concentrations in urban area ofTabriz." *Environmental Health Engineering and Management Journal* 2.3 (2015): 117-122.

[88] Cakir, Sedef, Mikdat Kadioglu, and NihatCubukcu. "Multischeme ensembleforecasting of surface temperature usingneural network over Turkey." *Theoretical and applied climatology* 111.3 (2013): 703-711.

[89] Unnikrishnan, Reshma, and G. Madhu."Comparative study on the effects ofmeteorological and pollutant parameterson ANN modelling for prediction ofSO2." *SN Applied Sciences* 1.11 (2019): 1-12.

[90] Li, Hao, Zhien Zhang, and Zhijian Liu."Application of artificial neural networksfor catalysis: a review." *Catalysts* 7.10(2017): 306.

[91] Schmidhuber, Jürgen. "Deep learning inneural networks: An overview." *Neuralnetworks* 61 (2015): 85-117.

[92] Srivastava, Nitish, et al. "Dropout: a simpleway to prevent neural networks fromoverfitting." *The journal of machinelearning research* 15.1 (2014): 1929-1958.

[93] Wilamowski, Bogdan M., and Hao Yu."Improved computation for Levenberg–Marquardt training." *IEEE transactions onneural networks* 21.6 (2010): 930-937.

[94] Gardner, Matt W., and S. R. Dorling."Artificial neural networks (the multilayerperceptron)—a review of applications inthe atmospheric sciences." *Atmosphericenvironment* 32.14-15 (1998): 2627-2636.

[95] Hecht-Nielsen R (1988) Theory of thebackpropagation neural network. NeuralNetw 1:445–448

[96] Yu, Jianming, et al. "A unified mixed-model method for association mappingthat accounts for multiple levels ofrelatedness." *Nature genetics* 38.2 (2006):203-208.

[97] Shakerkhatibi, M., Dianat, I., AsghariJafarabadi, M., Azak, R., & Kousha, A.(2015). Air pollution and hospitaladmissions for cardiorespiratory diseases inIran: artificial neural network versusconditional logisticregression. *International journal ofenvironmental science andtechnology*, *12*(11), 3433-3442.

[98] Gardner, M. W., & Dorling, S. R. (1998).Artificial neural networks (the multilayerperceptron)—a review of applications inthe atmospheric sciences. *Atmosphericenvironment*, *32*(14-15), 2627-2636.

[99] Vemuri, V., & Hecht-Nielson, R. (1988).Neurocomputing: Picking the HumanBrain. *Artificial Neural Networks:Theoretical Concepts, IEEE ComputerSociety Press, Washington, DC*, 13-18.

[100] .Hinton GE, Salakhutdinov RR (2006)Reducing the dimensionality of data withneural networks. Science 313:504–507

[101] Bengio Y, Lamblin P, Popovici D,Larochelle H (2007) Greedy layer-wisetraining of deep networks.Adv NeuralInform Process Syst 19:153–160

[102] Wang D, Wei S, Luo H, Yue C, Grunde(2017) A novel hybrid model for airquality index forecasting based on two-phase decomposition technique andmodified extreme learning machine.*Sci Total Environ* 580:719–733

[103] Olah, Christopher. "UnderstandingLSTM Networks. Aug. 2015." *URLhttps://colah.github.io/posts/2015-08-Understanding-LSTMs* (2017).