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Original Article

Estimation of Ambient Air $PM_{2.5}$ Concentration Using MLP and RBF

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Abstract
Background: Exposure to air pollutants, such as $PM_{2.5}$ is recognized as a significant health risk, contributing to the development of various diseases, and increased risk of premature mortality.
Methods: Multilayer perceptron (MLP) and radial basis function (RBF) neural networks, were used to predict the hourly concentration of $PM_{2.5}$ in Isfahan, Iran. The MLP model was designed with five input variables, including $PM_{2.5}$ concentration and weather characteristics, ten hidden layers, and a single output layer. The dataset was divided into three subsets: 70% for training, 15% for testing, and 15% for validation.
Results: The results showed that the average concentration of $PM_{2.5}$ was 26.5 μg/m^3. The root mean square error (RMSE) was estimated as 6.49 μg/m^3. Increasing the input data resulted in a slight reduction in network error, with the RBF model, utilizing 1450 inputs and an RMSE of 6.47, achieving the same accuracy as the MLP model with 10 inputs.
Conclusion: Given that the $PM_{2.5}$ concentration estimates from the RBF and MLP models deviated by less than 23 and 25%, respectively, compared to the observed concentrations, both MLP and RBF can be regarded as reliable tools for predicting $PM_{2.5}$ levels.
Keywords: Artificial neural network, RBF, MLP, Particulate matter, Isfahan

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Introduction
Industrialization and urbanization led to health risks caused by exposure to air pollutants, including gases and particles released from stationary and mobile sources, which are of the serious environmental challenges.[1,2] Particulate matter (PM) is one of the most important air pollutants due to its proven health consequences, including cancer.[3,4] However, the intensity of PM impact depends on various factors, including size.[5,6] PM with a diameter of 2.5 micrometers and less ($PM_{2.5}$) have more severe effects due to higher penetration into the respiratory system.[7-9] Air quality monitoring as well as pollutant emission modeling are significantly important in managing cities so that people receive health recommendations and warnings in real time based on pollution levels. Also, governments and policymakers use this strategy to control pollutants based on the recommended standards of the World Health Organization (WHO).[10]

Accurate prediction of air pollution concentrations is a critical step in managing and mitigating pollutants, as it provides essential information about $PM_{2.5}$ levels.[11] However, predicting $PM_{2.5}$ concentrations is challenging due to the complex interplay of human activities and natural, unpredictable atmospheric changes. While some of these activities exhibit repetitive or periodic patterns,[12] recent years have seen a growing preference for neural networks over traditional statistical methods in air pollutant modeling. Neural networks have become widely adopted as effective tools for estimating $PM_{2.5}$ concentrations.[13,14] Multilayer perceptron (MLP) and radial basis function (RBF) neural networks are among the most common neural networks for predicting $PM_{2.5}$ concentration.[15-18] In a study by MLP in Tehran, it was found that there was a correlation between the observed and predicted concentrations of $PM_{2.5}$.[19] An investigation into the relationship between the concentrations of air pollutants, including CO, SO_2, O_3, and NO_2, and $PM_{2.5}$ levels using a MLP model in China revealed that these pollutants play a significantly more critical role in determining $PM_{2.5}$ concentrations compared to meteorological conditions.[20] One-hour prediction of $PM_{2.5}$ concentration by MLP showed that this network can predict pollutant concentration at 4.45 μg/m^3.[21] In a study conducted in eight cities of Brazil and Finland, it was found that trainable hybrid methods such as MLP performed better in predicting $PM_{2.5}$ concentration.[22]

Climate factors such as relative humidity, wind speed, temperature, and inversion have an important effect on the dispersion of pollutants in the air.[17-23] These factors and estimated emission from different sources such as vehicles and industries can be considered in the definition of prediction systems such as MLP and RBF. The aim of this study was to predict the hourly $PM_{2.5}$ concentration using concentration information as well as meteorological data by MLP and RBF. This model was developed and tested using one-year hourly data of Isfahan, Iran.

Material and Methods

Study Area

This study was conducted in Isfahan, Iran. The city covers an area of 551 km^2 and is situated in central Iran at an altitude of 1571 m above sea level. Its geographical coordinates are 32°38′30″N latitude and 51°39′40″E longitude. Isfahan experiences a semi-arid climate, with an average annual rainfall of 127 mm, an average annual temperature of 16.5 °C, and an annual relative humidity of 38.7%. The city has a population exceeding 2 million and faces persistent issues with high $PM_{2.5}$ concentrations due to its proximity to large steel industries, oil refineries, and petrochemical facilities, as well as high traffic levels, recurring droughts, and its location near desert regions.

Neural Networks

MLP was used as a neural network in this study. The MLP is composed of input layers, hidden layer, and output layer with different neurons.[24] The topology of this artificial neural network is determined by the number of layers, the number of neurons in each layer, the learning algorithm, and the transfer function in the network.[25] In this study, neurons were placed in the input layer according to the number of dimensions of each input pattern. The number of hidden layer neurons was chosen in such a way that the output of the network provides an accurate answer.[26,27] The overall output of MLP was defined according to equation 1.[28]

$$s = \sum_{j\ 1}^{n} w_{ji} X_j^p + b_i \tag{1}$$

Where *s, n, w*, and *b* are the parameters transferred through a scalar to the activation function, the number of samples or input neurons, the weights connecting neurons across different layers, and the bias error, respectively. In this study, sigmoid and hyperbolic tangent functions were used as transfer functions. These functions, like biological cells, keep the output of neurons within a certain range. The first range is between (0)-(1) and the second range is between (-1)-(1) (Equations 2 and 3:[23,29])

$$\log\sin\left(x\right) = \frac{1}{1+e^{-x}} \tag{2}$$

$$\tan sig\left(x\right) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

RBF were also used. In this network, the transfer function in the intermediate layer is the Gaussian function, and in the output layer is the RB linear function.[30] An RBF network can be considered as a three-layer network in which the hidden layer performs a fixed nonlinear transformation without changing its weights and parameters. This layer (hidden layer) contains a number of neurons and a parameter vector called "Center", which can be considered as the weight vector of the hidden layer.[31] To use RBF, functions in the hidden layers, the number of adaptive neurons, and the training algorithm to find the network parameters were defined. The input of the network was modeled as a vector of real numbers and the output of this network was calculated as a scalar function of the input vector according to equation 4[32,33]:

$$\varphi(X) = \sum_{i=1}^{N} a_i \rho(\| X - C_i \|) \tag{4}$$

N is the number of hidden layer neurons, C_i is the center vector of neuron i, and a_i is the weight of neuron i in the linear output neuron.

To determine the efficiency of MTB and BBT, the root mean square error (RMSE) was used. RMSE is a measure of the absolute error between the simulation variable and the observation that varies from zero to infinity.[34] The lower value indicates the better simulation. RMSE value close to zero indicates the lowest error rate, which is calculated by equation 5.[35,36]

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^{N} [P_i - O_i]^2 \right)^{1/2} \tag{5}$$

where O_i, P_i, and N are the observed value, the predicted value and the number of observations, respectively.

Also, correlation coefficient according to equation 6 was used to determine the conformity of model output results with real values.[37, 38]

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(P_i - \bar{O}\right)^2}{\sum_{i=1}^{N} \left(O_i - \bar{O}\right)^2} \tag{6}$$

where O_i, P_i, and N are the observed value, the predicted value and the number of observations, respectively.

Data Collection and Preparation

The hourly concentration of $PM_{2.5}$ for one year (March 2018-March 2019) was obtained from Isfahan Environmental Protection Organization. Also, other weather characteristics such as temperature, relative humidity, wind speed, and wind direction were also received from Isfahan Meteorological Center. Considering that entering data in raw form reduces the speed and accuracy of the network. In order to avoid this error and also to equalization of the data, the normalization was done according to equation 7.[39, 40]

$$N = \left[\frac{2*(x_r - x_{min}}{X_{max} - X_{min}} \right] - 1 \tag{7}$$

where X_r, X_{min}, X_{max}, and N are real data, minimum data, maximum data, and corrected data respectively. Due to the use of hourly data, a total of 8760 data were prepared for each of the variables, and after data processing, a total of 8644 input data were obtained for each component.

Results and Discussion

The results of the analysis have been presented in Table 1. The results showed that the average annual concentration of $PM_{2.5}$ in Isfahan was higher than the recommended standards by the World Health Organization. In addition, as shown in Figure 1, the direction of pollution transfer in the ambient air was in accordance with the direction of wind-rose towards the west. Output values of R for training, validation, test, and total are shown in Figure 2. The results showed that the value of R in training, testing, validation, and all was equal to 0.8992, 0.9055, 0.9080, 0.9012 respectively. As shown in Figure 3, the mean squared error (MSE) in the neural network was 42.26. Therefore, R2 and RMSE were calculated as 0.81 and 6.49 µg/m³, respectively.

RBF was also used to investigate the relationship between meteorological parameters and the $PM_{2.5}$ concentration. As shown in Figure 3, initially, RBF was designed with zero neurons. As a result, the MSE and RBF were calculated by 243.56 and 15.61, respectively. Then, by adding 50 neurons RMSE and RBF were reduced. As the number of neurons increased, the error rate decreased, with the network achieving a MSE of 35.33 and a RMSE of 5.94 at 1700 neurons. The network's output results indicate that increasing the number of neurons reduces the error, which continued until the neuron count reached 1650. Beyond this point, specifically at 1700 neurons, the RMSE increased, suggesting that the RBF network exhibited optimal performance with 1650 neurons.

Table 1. Data Analysis for Study Area

Parameter	Value
PM_2 concentration	26.5 µg/m³
Temperature	15.9 °C
Relative humidity	37.83 %
Wind speed	2.79 m/s
Wind angle	170.55 °
Estimated concentration by MLP	20.01-32.99 µg/m³
Estimated concentration by RBF	20.56-32.44 µg/m³
RMSE value	6.49 µg/m³

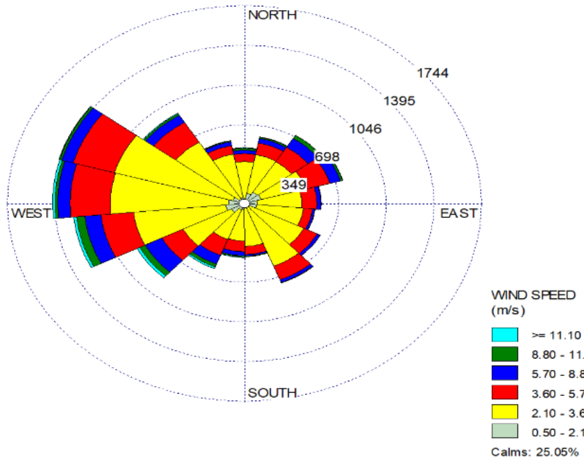

Figure 1. Wind-Rose of Studied City

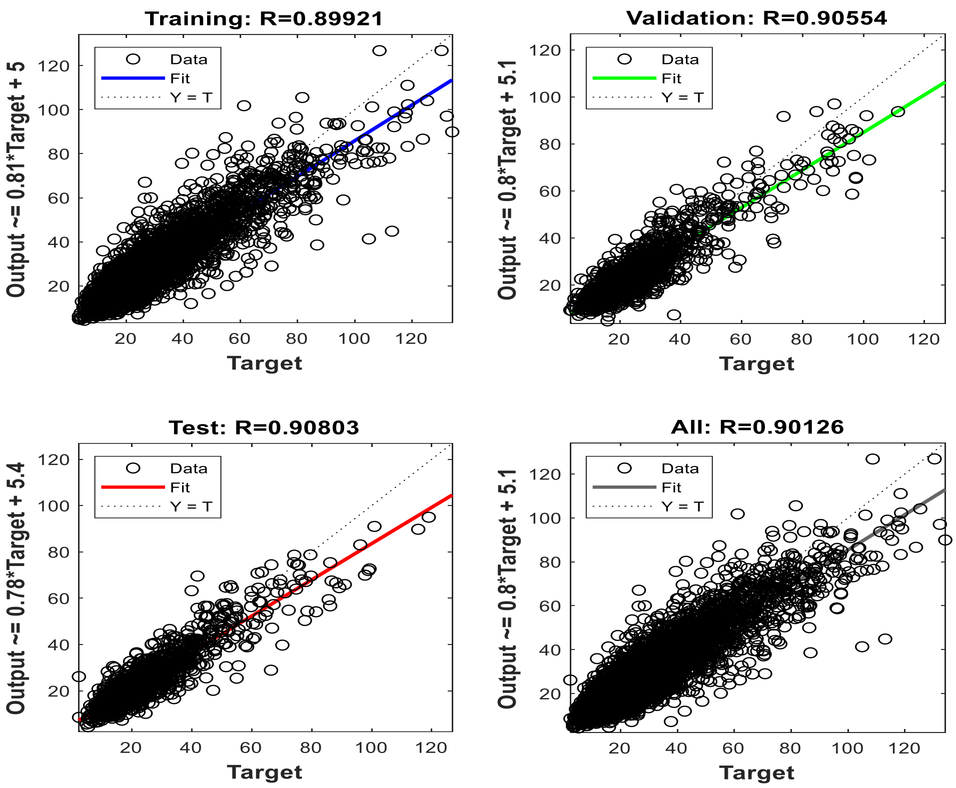

Figure 2. Correlation Value (R)

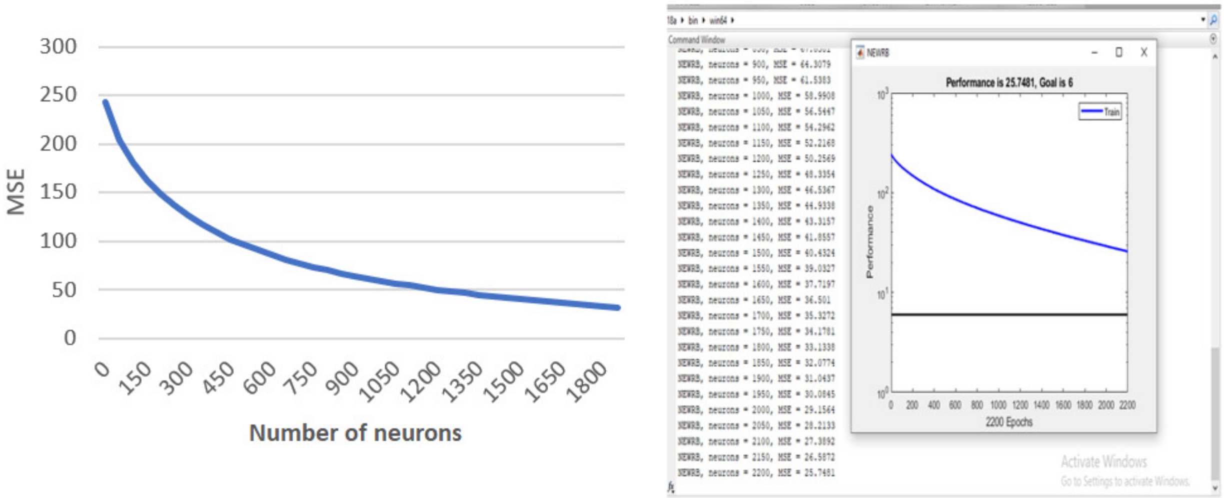

Figure 3. MSE Error Reduction in the RBF by Increase in the Number of Neurons

Furthermore, the RBF network with 1500 neurons demonstrated comparable accuracy to the MLP network with 10 neurons.

The results indicated strong agreement between the predicted values and the recorded data. This consistency can be attributed to the inclusion of all relevant factors influencing $PM_{2.5}$ concentrations as system inputs. Recent studies highlight the significant role of relative humidity in determining $PM_{2.5}$ concentrations in ambient air.[41] Changes in air humidity, which are often associated with an increase in rainfall due to the settling of PM, have a significant effect on the concentration of these particles in the atmosphere, and the inclusion of this parameter in the structure of the neural network had a positive effect on the accuracy of prediction.[41] Also, wind speed had a positive effect on reducing atmospheric $PM_{2.5}$ concentration because many studies have proven the correlation between wind speed and $PM_{2.5}$ concentration.[42] Considering the density of various industries around Isfahan, the wind direction was one of the most important factors affecting the concentration of pollutants. Therefore, the wind direction was considered as one of the important components to predict the concentration of $PM_{2.5}$ in the design of the artificial neural network. Also, temperature changes in different regions, especially big cities, cause atmospheric phenomena such as inversion.[43] This phenomenon strongly affects the increase in the concentration of suspended particles, especially $PM_{2.5}$.[44] Therefore, temperature changes were used as one of the important atmospheric parameters to be used in the structure of artificial neural networks.

Although the official data on $PM_{2.5}$ concentrations in Isfahan and the predicted values exceeded the standard limits, the concentrations were generally higher than the standard in most cities across Iran.[45] Previous studies have reported $PM_{2.5}$ concentrations in ambient air across various cities within the range of 8 to 73 μg/m³.[45] In this situation, exposure to this pollutant can lead to an increase in health risk caused by air pollution. The health risk caused by $PM_{2.5}$ depends on its chemical composition in addition to its physical characteristics. For example, in various studies, the chemical composition of $PM_{2.5}$ reported to contain elements such as aluminum, lead, iron, and other heavy metals.[46] In addition to heavy metals, compounds such as polycyclic aromatic hydrocarbons have also been reported in the chemical composition of $PM_{2.5}$.[47] Therefore, the health risk attributed to $PM_{2.5}$ depends on its origins.[45] Traffic, industries, and dry land around the city were the main origins of $PM_{2.5}$ in Isfahan.[45] Therefore, investigating the chemical composition of $PM_{2.5}$ in the studied city can provide complementary data.

Therefore, policies and planning efforts to control air pollution, including $PM_{2.5}$, should be intensified due to their significant role in mitigating various pollutants and associated health consequences. For instance, traffic control programs implemented in Tehran in previous years resulted in a 17.2% reduction in PM concentrations.[48] Enhanced attention to industrial pollution control and the regulation of dust activity centers could further strengthen the management of PM in the ambient air of Isfahan.

Conclusion

The concentration of $PM_{2.5}$ in the ambient air of Isfahan was analyzed over a one-year period. Using two neural network models—MLP and RBF—the concentration of this pollutant was predicted based on meteorological variables. The results indicated that the annual average $PM_{2.5}$ concentration was 26 μg/m³. The predicted values ranged from 20.01 to 32.99 μg/m³ by the MLP model and from 20.56 to 32.44 μg/m³ by the RBF model. The alignment between the predicted concentrations and the officially recorded values can be attributed to the incorporation of all relevant factors influencing pollutant concentrations, such as temperature, relative humidity, wind speed, and wind direction. While both the MLP and RBF models demonstrated strong performance in predicting $PM_{2.5}$ concentrations, the development and implementation of effective pollutant control programs remain essential to achieve the air quality standards set by the WHO.

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Authors' Contribution

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Project administration: Tayebeh Tabatabaie .
Resources: Nematollah Jaafarzadeh.
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Validation: Nematollah Jaafarzadeh.
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Writing–review & editing: Ali Mohammadi Bardshahi, Nematollah Jaafarzadeh, Tayebeh Tabatabaie, Fazel Amiri.

Competing Interests

The author declares no conflict of interest.

Ethical Approval

There were no ethical considerations to be considered in this research.

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References

1. Zeng J, Liu T, Feiock R, Li F. The impacts of China's provincial energy policies on major air pollutants: a spatial econometric analysis. Energy Policy. 2019;132:392-403. doi: 10.1016/j.enpol.2019.05.052.
2. Li P, Lin Z, Du H, Feng T, Zuo J. Do environmental taxes reduce air pollution? Evidence from fossil-fuel power plants in China. J Environ Manage. 2021;295:113112. doi: 10.1016/j.jenvman.2021.113112.
3. Hopke PK, Croft DP, Zhang W, Lin S, Masiol M, Squizzato S, et al. Changes in the hospitalization and ED visit rates for respiratory diseases associated with source-specific $PM_{2.5}$ in New York State from 2005 to 2016. Environ Res. 2020;181:108912. doi: 10.1016/j.envres.2019.108912.
4. Wang W, Sun X, Zhang M. Does the central environmental inspection effectively improve air pollution?-An empirical study of 290 prefecture-level cities in China. J Environ Manage. 2021;286:112274. doi: 10.1016/j.jenvman.2021.112274.
5. Chen B, Song Z, Pan F, Huang Y. Obtaining vertical distribution of PM2.5 from CALIOP data and machine learning algorithms. Sci Total Environ. 2022;805:150338. doi: 10.1016/j.scitotenv.2021.150338.
6. Hajizadeh Y, Jafari N, Fanaei F, Ghanbari R, Mohammadi A, Behnami A, et al. Spatial patterns and temporal variations of traffic-related air pollutants and estimating its health effects in Isfahan city, Iran. J Environ Health Sci Eng. 2021;19(1):781-91. doi: 10.1007/s40201-021-00645-6.
7. Mainka A, Fantke P. Preschool children health impacts from indoor exposure to PM2.5 and metals. Environ Int. 2022;160:107062. doi: 10.1016/j.envint.2021.107062.
8. Herman DA, Wingen LM, Johnson RM, Keebaugh AJ, Renusch SR, Hasen I, et al. Seasonal effects of ambient PM2.5 on the cardiovascular system of hyperlipidemic mice. J Air Waste Manag Assoc. 2020;70(3):307-23. doi: 10.1080/10962247.2020.1717674.
9. Olaniyan T, Pinault L, Li C, van Donkelaar A, Meng J, Martin RV, et al. Ambient air pollution and the risk of acute myocardial infarction and stroke: a national cohort study. Environ Res. 2022;204(Pt A):111975. doi: 10.1016/j.envres.2021.111975.
10. Samal KK, Babu KS, Das SK. Multi-directional temporal convolutional artificial neural network for PM2.5 forecasting with missing values: a deep learning approach. Urban Clim. 2021;36:100800. doi: 10.1016/j.uclim.2021.100800.
11. Liu H, Dong S. A novel hybrid ensemble model for hourly PM2.5 forecasting using multiple neural networks: a case study in China. Air Qual Atmos Health. 2020;13(12):1411-20. doi: 10.1007/s11869-020-00895-7.
12. Yin PY, Yen AY, Chao SE, Day RF, Bhanu B. A machine learning-based ensemble framework for forecasting PM2.5 concentrations in Puli, Taiwan. Appl Sci. 2022;12(5):2484. doi: 10.3390/app12052484.
13. Chen YC, Li DC. Selection of key features for PM2.5 prediction using a wavelet model and RBF-LSTM. Appl Intell (Dordr). 2021;51(4):2534-55. doi: 10.1007/s10489-020-02031-5.
14. Menares C, Perez P, Parraguez S, Fleming ZL. Forecasting PM2.5 levels in Santiago de Chile using deep learning neural networks. Urban Clim. 2021;38:100906. doi: 10.1016/j.uclim.2021.100906.
15. Bai Y, Zeng B, Li C, Zhang J. An ensemble long short-term memory neural network for hourly PM2.5 concentration forecasting. Chemosphere. 2019;222:286-94. doi: 10.1016/j.chemosphere.2019.01.121.
16. Champati BB, Padhiari BM, Ray A, Jena S, Sahoo A, Mohanty S, et al. Implementation of multilayer perceptron (MLP) and radial basis function (RBF) neural networks for predicting shatavarin IV content in *Asparagus racemosus* accessions. Ind Crops Prod. 2023;191:115968. doi: 10.1016/j.indcrop.2022.115968.
17. Alimissis A, Philippopoulos K, Tzanis CG, Deligiorgi D. Spatial estimation of urban air pollution with the use of artificial neural network models. Atmos Environ. 2018;191:205-13. doi: 10.1016/j.atmosenv.2018.07.058.
18. Ismail A, Kumar N. AI in global health: the view from the front lines. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. New York, NY: Association for Computing Machinery; 2021. p. 1-21. doi: 10.1145/3411764.3445130.
19. Khoshand A, Shahbazi Sehrani M, Kamalan H, Bodaghpour S. Prediction of ground-level air pollution using artificial neural network in Tehran. Anthropog Pollut. 2017;1(1):61-7.
20. Feng R, Gao H, Luo K, Fan JR. Analysis and accurate prediction of ambient PM2.5 in China using multi-layer perceptron. Atmos Environ. 2020;232:117534. doi: 10.1016/j.atmosenv.2020.117534.
21. Wang H, Wang P, Zhang Y. PM2.5 prediction based on feature extraction with LASSO and multilayer perceptron. In: Second International Conference on Sensors and Information Technology (ICSI 2022). Vol 12248. SPIE; 2022. p. 166-74. doi: 10.1117/12.2637473.
22. de Mattos Neto PS, Firmino PR, Siqueira H, de Souza Tadano Y, Alves TA, de Oliveira JF, et al. Neural-based ensembles for particulate matter forecasting. IEEE Access. 2021;9:14470-90. doi: 10.1109/access.2021.3050437.
23. Asadollahfardi G, Madinejad M, Homayoun Aria SH, Motamadi V. Predicting particulate matter (PM2.5) concentrations in the air of Shahr-e Ray city, Iran, by using an artificial neural network. Environ Qual Manag. 2016;25(4):71-83. doi: 10.1002/tqem.21464.
24. Pham BT, Nguyen MD, Bui K-TT, Prakash I, Chapi K, Bui DT. A novel artificial intelligence approach based on multi-

layer perceptron neural network and biogeography-based optimization for predicting coefficient of consolidation of soil. Catena (Amst). 2019;173:302-11. doi: 10.1016/j.catena.2018.10.004.
25. Ismailov VE. On the approximation by neural networks with bounded number of neurons in hidden layers. J Math Anal Appl. 2014;417(2):963-9. doi: 10.1016/j.jmaa.2014.03.092.
26. Amanollahi J, Ausati S. PM2.5 concentration forecasting using ANFIS, EEMD-GRNN, MLP, and MLR models: a case study of Tehran, Iran. Air Qual Atmos Health. 2020;13(2):161-71. doi: 10.1007/s11869-019-00779-5.
27. Phaisangittisagul E. An analysis of the regularization between L2 and dropout in single hidden layer neural network. In: 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS). Bangkok, Thailand: IEEE; 2016. p. 174-9. doi: 10.1109/isms.2016.14.
28. Rodríguez-Rajo FJ, Astray G, Ferreiro-Lage JA, Aira MJ, Jato-Rodriguez MV, Mejuto JC. Evaluation of atmospheric Poaceae pollen concentration using a neural network applied to a coastal Atlantic climate region. Neural Netw. 2010;23(3):419-25. doi: 10.1016/j.neunet.2009.06.006.
29. Rezaei F, Jafari S, Hemmati-Sarapardeh A, Mohammadi AH. Modeling of gas viscosity at high pressure-high temperature conditions: integrating radial basis function neural network with evolutionary algorithms. J Pet Sci Eng. 2022;208(Pt A):109328. doi: 10.1016/j.petrol.2021.109328.
30. Hashemi Fath A, Madanifar F, Abbasi M. Implementation of multilayer perceptron (MLP) and radial basis function (RBF) neural networks to predict solution gas-oil ratio of crude oil systems. Petroleum. 2020;6(1):80-91. doi: 10.1016/j.petlm.2018.12.002.
31. Haiming Z, Xiaoxiao S. Study on prediction of atmospheric PM2.5 based on RBF neural network. In: 2013 Fourth International Conference on Digital Manufacturing & Automation. Shinan, China: IEEE; 2013. p. 1287-9. doi: 10.1109/icdma.2013.306.
32. Sudheer KP, Jain SK. Radial basis function neural network for modeling rating curves. J Hydrol Eng. 2003;8(3):161-4. doi: 10.1061/(asce)1084-0699(2003)8:3(161).
33. Madhiarasan M. Accurate prediction of different forecast horizons wind speed using a recursive radial basis function neural network. Prot Control Mod Power Syst. 2020;5(3):1-9. doi: 10.1186/s41601-020-00166-8.
34. Bai Y, Li Y, Zeng B, Li C, Zhang J. Hourly PM2.5 concentration forecast using stacked autoencoder model with emphasis on seasonality. J Clean Prod. 2019;224:739-50. doi: 10.1016/j.jclepro.2019.03.253.
35. Zhou G, Liu R, Zhang Z, Yang C, Ding H. Optimization of diesel engine dual-variable geometry turbocharger regulated two-stage turbocharging system based on radial basis function neural network-quantum genetic algorithm. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. 2025;47(1):1910-26. doi: 10.1080/15567036.2020.1837299.
36. Vafaei A, Ghaedi AM, Avazzadeh Z, Kiarostami V, Agarwal S, Gupta VK. Removal of hydrochlorothiazide from molecular liquids using carbon nanotubes: radial basis function neural network modeling and culture algorithm optimization. J Mol Liq. 2021;324:114766. doi: 10.1016/j.molliq.2020.114766.
37. Vakili M, Sabbagh-Yazdi SR, Kalhor K, Khosrojerdi S. Using artificial neural networks for prediction of global solar radiation in Tehran considering particulate matter air pollution. Energy Procedia. 2015;74:1205-12. doi: 10.1016/j.egypro.2015.07.764.
38. Park S, Kim M, Kim M, Namgung HG, Kim KT, Cho KH, et al. Predicting PM10 concentration in Seoul metropolitan subway stations using artificial neural network (ANN). J Hazard Mater. 2018;341:75-82. doi: 10.1016/j.jhazmat.2017.07.050.
39. Ren M, Sun W, Chen S. Combining machine learning models through multiple data division methods for PM2.5 forecasting in Northern Xinjiang, China. Environ Monit Assess. 2021;193(8):476. doi: 10.1007/s10661-021-09233-5.
40. Shanmugaprakash M, Sivakumar V. Development of experimental design approach and ANN-based models for determination of Cr(VI) ions uptake rate from aqueous solution onto the solid biodiesel waste residue. Bioresour Technol. 2013;148:550-9. doi: 10.1016/j.biortech.2013.08.149.
41. Cheng Y, He KB, Du ZY, Zheng M, Duan FK, Ma YL. Humidity plays an important role in the PM2.5 pollution in Beijing. Environ Pollut. 2015;197:68-75. doi: 10.1016/j.envpol.2014.11.028.
42. Kleine Deters J, Zalakeviciute R, Gonzalez M, Rybarczyk Y. Modeling PM2.5 urban pollution using machine learning and selected meteorological parameters. J Electr Comput Eng. 2017;2017(1):5106045. doi: 10.1155/2017/5106045.
43. Trinh TT, Trinh TT, Le TT, Nguyen TDH, Tu BM. Temperature inversion and air pollution relationship, and its effects on human health in Hanoi city, Vietnam. Environ Geochem Health. 2019;41(2):929-37. doi: 10.1007/s10653-018-0190-0.
44. Shao M, Xu X, Lu Y, Dai Q. Spatio-temporally differentiated impacts of temperature inversion on surface PM2.5 in eastern China. Sci Total Environ. 2023;855:158785. doi: 10.1016/j.scitotenv.2022.158785.
45. Torkashvand J, Jonidi Jafari A, Hopke PK, Shahsavani A, Hadei M, Kermani M. Airborne particulate matter in Tehran's ambient air. J Environ Health Sci Eng. 2021;19(1):1179-91. doi: 10.1007/s40201-020-00573-x.
46. Li F, Yan J, Wei Y, Zeng J, Wang X, Chen X, et al. PM2.5-bound heavy metals from the major cities in China: Spatiotemporal distribution, fuzzy exposure assessment and health risk management. J Clean Prod. 2021;286:124967. doi: 10.1016/j.jclepro.2020.124967.
47. Bandowe BA, Meusel H, Huang RJ, Ho K, Cao J, Hoffmann T, et al. PM2.5-bound oxygenated PAHs, nitro-PAHs and parent-PAHs from the atmosphere of a Chinese megacity: seasonal variation, sources and cancer risk assessment. Sci Total Environ. 2014;473-474:77-87. doi: 10.1016/j.scitotenv.2013.11.108.
48. Shahbazi H, Hassani A, Hosseini V. Evaluation of Tehran clean air action plan using emission inventory approach. Urban Clim. 2019;27:446-56. doi: 10.1016/j.uclim.2019.01.002.