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COOT Bird-Inspired Algorithm for Daily Fine Particulate Matter Concentration Prediction Statistical Study

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Abstract. **Fine particulate matter (PM2.5) poses significant risks to public health and the natural environment. Accurate prediction of PM2.5 concentration is crucial for effective environmental management. In this study, we present a novel hybrid model, the COOT bird-inspired natural life model combined with Artificial Neural Network (COOT-ANN), for predicting daily PM2.5 concentration in hydier abad and Delhi from 2014 to 2022. The performance of the COOT-ANN model is compared with standalone ANN and Dragonfly-ANN (DA-ANN) hybrid models. Using the Taylor diagram, we demonstrate that the COOT-ANN model exhibits the closest proximity to the observation point, resulting in a 13.94 % and 11.42 % reduction in prediction errors compared to the ANN model in Hyderabad and Delhi, respectively. Furthermore, the box-plot of the COOT-ANN model closely resembles the actual data distribution. Consequently, the COOT-ANN model outperforms both the ANN and DA-ANN models at both monitoring stations. This innovative approach to air quality prediction can significantly enhance the accuracy of environmental protection programs.**

Keywords: **COOT bird-inspired natural life model, Dragonfly algorithm, fine particulate matter, prediction.**

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Introduction

The global economy's rapid growth over the past two decades, coupled with increased fossil fuel usage, industrialization, and urbanization, has resulted in a significant decline in air quality and the release of high levels of pollutants and haze (Akesson M., Singh P., Wrede F. & Hellander). Fine particulate matter (PM2.5) is a major component of haze and serves as a critical indicator of air quality (Zhang Z., Hua B. S., Yeung S. K. (2019). PM2.5 is considered the most significant air pollutant in urban areas. It consists of a complex and heterogeneous mixture of solid particles and small liquid droplets with a diameter smaller than 2.5 microns. PM2.5 exhibits long-lasting characteristics and high mobility in the atmosphere, and it is a primary

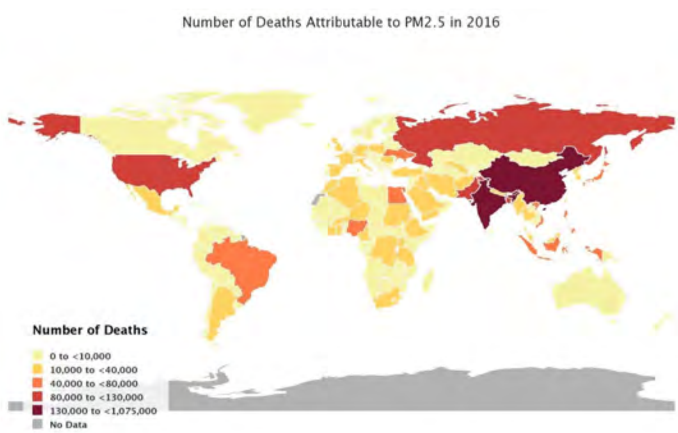

Fig. 1. The number of deaths related to PM 2.5 in 2016

contributor to reduced visibility in cities. Furthermore, fine particulate matter has detrimental environmental effects and plays a significant role in climate change. Increased PM2.5 emissions lead to reduced soil nutrient levels, increased acidity in surface water, altered nutrient balance in coastal water and river basins, damage to crops and forests, decreased ecosystem diversity, and the deterioration of various materials (Ruospo A. et. al. (2023).

Despite the efforts of civil societies, countries, and international and national organizations, PM2.5 remains a global health and environmental concern (Lee H., & Song J., 2019).

In 2019, the health damage caused by the release of PM2.5 in the world was equivalent to 3.3 % of global GDP (2.9 trillion per year). The emission of PM2.5 is known as the tenth risk factor for increasing mortality in the world. Figure 1 presents the number of deaths attributable to PM2.5 in 2019. Annually 6.67 million deaths were reported due to the release of PM2.5 worldwide, which China and India having the highest ranking with 1.38 and 1 million deaths, respectively (World Health Organization, 2020). In 2016, these two countries accounted for 58 % of deaths attributed to PM2.5 pollution worldwide. Each 1 percent increase in average PM2.5 concentration has led to 2.5 percent increase in mortality rate in China (Liu X., He C., Zhang Q., Liao M. (2019).

Adverse environment, economic, and health effects of PM2.5 increased the attention of the researchers to this issue. Modeling and prediction of the PM2.5 is one of the strong tools to make accurate policies in reducing PM2.5 concentration. Generally, the models that are used to predict air pollutants categorized in data-driven statistical models and mechanism-based models. The CMAQ (Yamaji et. al., 2008), and WRF/Chem (Zhang et. al., 2016) are two models of mechanism-based models. However, in the mechanism-based models, observing the chemical and physical processes is easy, they could not be implemented for modeling and prediction of PM2.5 concentration. Because the propagation process of PM2.5 is intricate, and in various regions and time periods, propagation condition and formation of PM2.5 is different. In the absence of sufficient previous information, there is a limitation in using this model in prediction air pollutants. Hence, the novelity of the present paper is developing and evaluating the capabilityof the COOT-ANN hybrid model in predicting PM2.5 concentration and to compare its ability with the ANN and Dragonfly-ANN (DF-ANN) hybrid model in hydirabad and Delhi. Although the DF-ANN algorithm was developed earlier than the COOT-ANN algorithm, it was a new optimization method with satisfactory performance in different sciences.

Methods and Material

In the present study, to evaluate the non-linear dynamics of the PM2.5 concentration, we select the hyderabad, China and Delhi, India. Because China and India rank first and second in suspended mortality due to particulate matter emissions, respectively. hyderabad with area of 16411 km² is the capital of People's Republic China. hyderabad is located in north of China, and with 21 million residents is the most populous capital of the country in the world. hyderabad is a global city and is so important city in terms of culture, tourism, diplomacy, research, finance, economics, education, sport, transportation, technology and science. Delhi is the second most populous metropolis of India and New Delhi, the capital of India, is also part of this metropolis. Delhi is considered to be the oldest inhabited area in the world and has always been inhabited. Delhi with 18.98 million is the second populous city. Delhi is located in the north of India with area of 1484 km².

Data

The daily time series span 1. January 2014 to 1 May 2022 for hayderabad and Delhi, including 3051 observations. Figure (3a) presents the daily time series of the PM2.5 concentration in Beijing, China. When the PM2.5 concentration is up than 35.5 (mg/m^3), the air quality is unhealthy for human, which for hyderabad this value often was more than 50 (mg/m^3). Because of the pollution control programs in China, such as replacing coal with gas in industrial and residential sectors and a decrease in industrial emissions, the concentration of the PM2.5 is declined by 34 % compared to last decade. But, yet the concentration of particular matter in China is higher than the standards and it is needing to continue such policies. Figure (3b) shows the daily time series of the PM2.5 concentration in Delhi, India. Similar to the Beijing, the air quality was unhealthy and almost the PM2.5 was upper than 50 (mg/m^3). The concentration of PM2.5 did not control in Delhi, and yet there were peak values for it. The attributed death related to PM2.5 in India has increased by 2.5 times in last two decades. Centre for

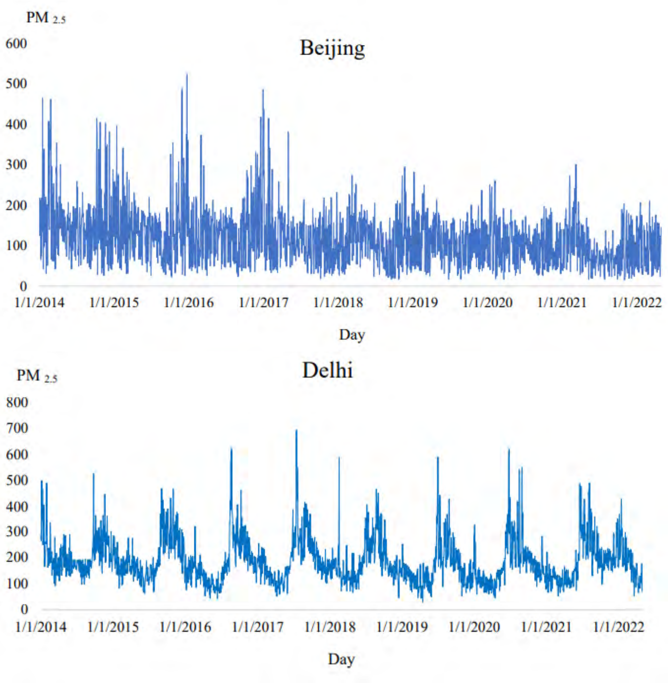

Fig. 2. Daily PM 2.5 concentration during 2014–2021: a) in hyderabad, China, and b) Delhi, India

Research on Energy and Clean Air (CREA), which closely monitors China and India's pollution control policies, said that although China has set targets for reducing particulate matter emissions from many of its cities by 2019, India still has not provided such a plan.

Artificial Neural Network (ANN)

Is a subfield of artificial intelligence (AI) that falls under the category of supervised machine learning models. It was initially conceptualized by Warren McCulloch and Walter Pitts in 1940 when they developed a logic model for simulation, which laid the foundation for ANN (Shabani et al., 2021). ANN draws inspiration from the functioning of the human brain to solve computational problems in various scientific fields, including computer science, environmental science, economics, finance, and more.

Similar to biological neuronal networks, ANN receives, processes, and generates information. It consists of three main layers: the input layer, hidden layer(s), and output layer. Neurons within each layer are interconnected with neurons in other layers. There are different types of ANNs, such as Radial Basis Function (RBF) and Multilayer Perceptron (MLP). Various algorithms, including Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), Gradient Descent with Momentum Bayesian Regularization (BR), and Adaptive Learning Rate (GDX), can be used in ANN. Prior to training an ANN, it is necessary to scale the data within a given interval to obtain an optimal cost function topology (Nourani, 2017). In an ANN, the relationship between inputs and outputs can be represented as follows:

$$Y = f\,(W_1X_1 + W_2X_2 + \ldots + W_nX_n + b). \qquad (1)$$

Here, f denotes the activation function, Y represents the output, X refers to the inputs, Wi represents the weight of the connection, and b represents the bias

Performance evaluation statistics

The performance of the ANN, DA-ANN, and COOT-ANN models is evaluated using three performance criteria: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and correlation coefficient (R). These metrics are presented in Table 1, along with their respective equations and ranges.

Evaluation metrics of the models

Metric Definition Equation Range

RMSE Root-mean Square Error $RMSE = \sqrt{(1/N)\,\Sigma\left((oi) - p(i)^2\right)}$

$0 < RMSE < \infty$

MAE Mean Absolute Error $MAE = (1/n)\,\Sigma\left|oi - p(i)\right|)$

$0 < MAE < \infty$

R^2 Coefficient of Determination $R\hat{}2 = \left(\Sigma(oi - \bar{o})(p(i) - \bar{p})\right) / \sqrt{\left(\Sigma(o(i) - \bar{o})\hat{}2\right)}\sqrt{\left(\Sigma(p(i) - \bar{p})\hat{}2\right)})\hat{}2$

$0 < R\hat{}2 < 1$

Where *o(i)* and *p(i)* are the observed and predicted PM2.5 values, N is the number of observations, and $\bar{o}$ and $\bar{p}$ indicate the average of the observed and predicted PM2.5 values.

results

In the results section, there are four subsections. The first subsection discusses the average mutual information (AMI) findings for the data collected from hyderabad and Delhi. The second and third subsections present the performance of the ANN, DA-ANN, and COOT-ANN models for hyderabad and Delhi, respectively. The results are analyzed in the fourth subsection.

Average Mutual Information (AMI)

In the AMI analysis, the optimal time delay values of the PM2.5 input variable are determined using the average mutual information method. Figure 7 shows the results of the AMI technique for hyderabad and Delhi. It is found that up to 4 (T, T-1,

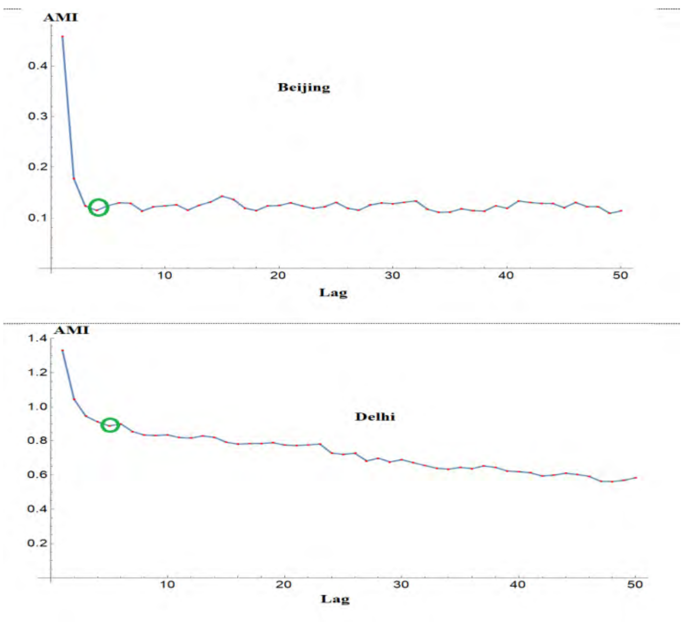

Fig. 3. AMI results for selecting optimal time lags in hyderabad and Delhi

T-2, T-3, T-4) and 5 (T, T-1, T-2, T-3, T-4, T-5) time delays can be used as the optimal time delays for the daily PM2.5 variable in hydeabad and Delhi, respectively.

Models' performance

The performance of the developed models was evaluated by statistical metrics including R, RMSE, and MAE, as well as the Taylor diagram, box-plot, and scatter diagram. The performance of the ANN, DA-ANN, and COOT-ANN models in the training and testing phases in hyderabad and Delhi are presented in Table 2. As the testing phase is crucial in the prediction studies, we continue our evaluation with the testing phase results. For Beijing, the correlation coefficient in testing phase is 0.626, 0.642, and 0.725 for the ANN, DA-ANN, and COOTANN models, respectively. The RMSE for the ANN, DA-ANN, and COOT-ANN is 40.873, 38.828, and 35.174, respectively. The DA-ANN, and COOT-ANN hybrid models could decrease the RMSE of the ANN model by 5 % and 13.94 %, respectively for Delhi, the correlation coefficient in testing phase is 0.838, 0.854, and 0.879 for the ANN, DA-ANN, and COOT-ANN models, respectively. The RMSE for the ANN, DA-ANN, and COOT-ANN is 45.289, 42.315, and 40.114, respectively. In the other word, where the DAANN model could deacrese the RMSE of the ANN model by 6.56 %, the COOT-ANN model could deacrese it by 11.42 %. According to the table 5, the DA-ANN and COOT-ANN hybrid models have superior performance than the stand-alone ANN model, and the COOT-ANN model has better performance than the DA-ANN model. Furthuermore, the COOT-ANN model is the most precise model in predicting the PM2.5 concentration in Delhi, too.

Region	Model	Training R^2	Training RMSE	Training MPAE	Testing R^2	Testing RMSE	Testing MPAE
HY- ABAD	ANN	0.708	44.391	35.135	0.721	43.873	38.112
	DA-ANN	0.637	39.945	41.681	0.742	40.784	36.224
	COOT-ANN	0.710	39.027	34.258	0.635	36.174	29.016
Dalhi	ANN	0.835	45.762	30.924	0.838	45.289	30.076
	DA-ANN	0.843	43.7	40.361	0.854	42.315	28.210
	COOT-ANN	0.861	44.734	31.196	0.811	41.124	25.120

For accurate comparing the performance of the ANN, DA-ANN, and COOT-ANN models in predicting the PM2.5 concentration in hyderabad and Delhi, we utilized the Taylor diagram. The Taylor diagram determines a corresponding point in space for each model used for prediction based on three criteria, including R 2, standard deviation, and RMSE. Hence, it could be an excellent and comprehensive measure for comparing the performance of the models, especially when the number of models is more or the creteria are in opposite of each other. Based on the Taylor diagram, the model which has the lawest distance from the observation point is selected as the most accurate model for prediction (Shabani et. al., 2021). The Taylor diagram of the ANN, DA-ANN, and COOT-ANN models for precting the PM2.5 concentration in hyderabad and Delhi is presented. For hyderabad the distance of the ANN, DA-ANN, and COOT-ANN models from observation point is

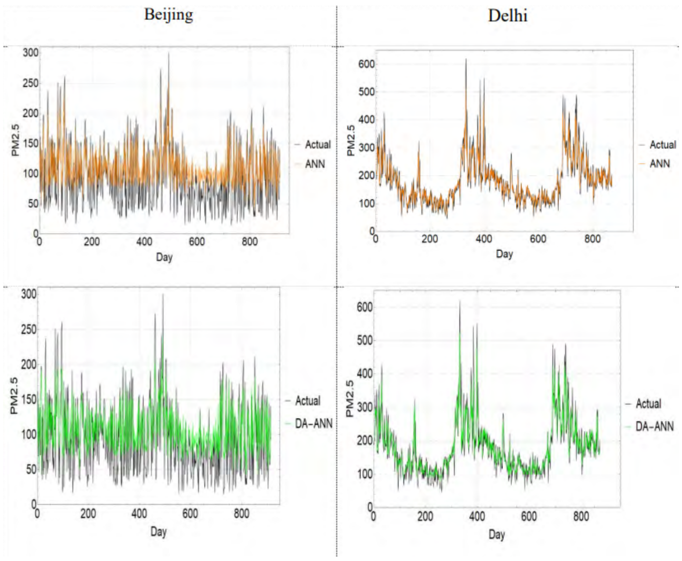

Fig. 4. Time series of the actual and predicted values of the PM2.5 with the ANN, DAANN, and COOT-ANN models for a) Beijing, and b) Delhi

44.067, 42.562, and 39.002, respectively. For Delhi, the distance between the ANN, DA-ANN, and COOT-ANN models with the observation point is 46.15, 42.277, and 43.575, respectively. Hence, for both regions, the performance of the hybrid models is better than the stand-alone ANN, and the COOT-ANN model with the lowest distance from observation point is the most accurate model in predicting the PM2.5 concentration in hyderabad and Delhi.

For visual comparison of the temporal variation of the PM2.5 concentration in hyderabad and Delhi, the time series analysis was utilized. The time series of the actual values and the predicted values of the PM2.5 concentration with the ANN, DA-ANN, and COOT-ANN in hyderabad and Delhi is presented in Figure 10a, and Figure 10b, respectively. Based on the figure, two results can be said: i) all three models have a law ability in predicting small amounts of PM2.5 concentration compared to their high amounts in both regions (e.g. the errors in modeling the low amonts of the PM2.5 concentration is bigger than the errors in modeling the high amonts of it); and ii) the predicted values with the COOT-ANN model is more closer to the actual values compared to the ANN and DA-ANN models. Hence, based on the time-series analysis, the COOT-ANN model has the superior performance than the ANN and DA-ANN models.

As an precise prediction of the PM 2.5 concentration is crucial in terms of precise heaith and environmental policies, it is needed to choose an accurate model for predicting. According to the performance metrics (R2, RMSE, MAE) and diagnostic graphs (Taylor diagram, scatter plot, and time series analysis), the COOT-ANN model has high ability in predicting the PM2.5 concentration in Beijing.

Conclusion

In the present paper, we developed a novel optimization algorithm, namely COOT-ANN model which hybridized the coot life algorithm with the ANN, and evaluated its capability in prediction of the daily PM2.5 concentration in hyderabad and Delhi. The perfoemance of the COOT-ANN was compared with the ANN and DA-ANN hybrid model in terms of correlation coefficient (R), RMSE, MAE, and the Taylor diagram, scatter and box plot. Based on the results, the DA-ANN model and COOT-ANN model was more efficient and accurate than the ANN model in predicting daily PM2.5 concentration, and the COOT-ANN model had surerior performance than ANN, and DA-ANN models. Hence, the COOT algorithm could be a strong optimization way to improve the capability of the ANNs. It is suggested that the COOT-ANN model used in predicting other air pollutant in other cites of the world. Also, the COOT algorithm could be hybrized with other AI models and used in prediction various scientific fields.

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Алгоритм COOT Bird для ежедневного прогнозирования концентрации мелкодисперсных твердых частиц. Статистическое исследование

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Аннотация. **Мелкодисперсные твердые частицы (PM2,5) представляют значительный риск для здоровья населения и окружающей среды. Точное прогнозирование концентрации PM2,5 имеет решающее значение для эффективного управления окружающей средой. В этом исследовании мы представляем новую гибридную модель, модель естественной жизни COOT, вдохновленную птицами, в сочетании с искусственной нейросетью (COOT-ANN) для прогнозирования ежедневной концентрации PM2,5 в Хайдарабаде и Дели с 2014 по 2022 год. Производительность модели COOT-ANN сравнивается с моделью ANN и гибридной моделью Dragonfly-ANN (DA-ANN). Используя диаграмму Тейлора, мы видим, что модель COOT-ANN демонстрирует наибольшую близость к точке наблюдения, что приводит к снижению ошибок прогнозирования на 13,94 % и 11,42 % по сравнению с моделью ANN в Хайдарабаде и в Дели соответственно. Более того, усиковая диаграмма модели COOT-ANN очень похожа на фактическое распределение данных. Следовательно, модель COOT-ANN превосходит модели ANN и DA-ANN на обеих станциях мониторинга. Этот инновационный подход к прогнозированию качества воздуха может значительно повысить точность программ защиты окружающей среды.**

Ключевые слова: **модель естественной жизни COOT, алгоритм DragonFly, мелкодисперсные твердые частицы, прогнозирование.**

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