ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2024, 9 (1): 46-56 doi: 10.28978/nesciences.1489228

Prediction of Air Pollution Utilizing an Adaptive Network Fuzzy Inference System with the Aid of Genetic Algorithm

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Abstract

With the growth of modern lifestyles and the growing urbanization and reliance on fossil fuels, the need for tracking and monitoring air pollution has become more significant. This research used existing information on significant pollutants to forecast their future condition using time-series modeling. Most studies have used Autoregressive Integrated Moving Average (ARIMA) and Logistic Regression (LR) methods to analyze time-series data. Still, employing an Adaptive Neuro Fuzzy Inference System (ANFIS) for this purpose has been infrequent. Conventional time-series prediction approaches use the assumption that there is a linear connection among variables. However, in air pollution modeling, there are non-linear and intricate factors. This paper used an Adaptive Network Fuzzy Inference System with the help of Improved Genetic Algorithm (ANFIS-IGA) to predict air pollution. This work aimed to address this constraint by enhancing the precision of everyday air pollutant prediction via the analysis of time-series data using ANFIS modeling. Air pollution data, including Fine Particulate Matter (FPM), CO, SO2, O3, and NO2, is gathered from the Air Quality Open Data Platform. This research examines the surveillance and prediction of air pollution concentration in indoor and outdoor situations using the ANFIS-IGA model. The model's effectiveness was enhanced and

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optimized for using IGA. The results indicate that the proposed ANFIS-IGA framework achieved superior performance compared to other models, as shown by the Root Mean Square Error (RMSE) value of 0.052658.

Keywords:

Air pollution, prediction, genetic algorithm, adaptive network fuzzy inference system, anfis tree, root mean square error.

Article history:

Received: 24/02/2024, Revised: 02/04/2024, Accepted: 23/04/2024, Available online: 30/05/2024

Introduction to Air Pollution

The escalating environmental issues significantly threaten the natural world and human well-being. The issue of air pollution is now a significant concern. Air, the fundamental essence of existence, is essential for the sustenance of humans and all living organisms. Hence, air pollution is a worldwide menace that substantially affects both human well-being and ecosystems. Air pollution may arise from natural phenomena, such as wildfires, volcanic eruptions, tremors, and wetlands, as well as human activity, including industry, heating, transport, and energy generation. Furthermore, air pollution is influenced by population expansion, growing cities, industry, dryness, geographical circumstances, inversion, and climatic aspects (Fuller et al., 2022; Knezevic & Knezevic, 2019).

The World Health Organization (WHO) reports that roughly 7 million fatalities occur annually due to external and internal air pollution. Air pollution is a substantial environmental hazard to human health. Decreasing air pollution decreases the occurrence of early deaths and the prevalence of illnesses such as stroke, heart disorders, lung cancer, persistent and severe respiratory illnesses, and bronchitis. These untimely deaths and illnesses are caused by the inhalation of Particulate Matter (PM2.5), which consists of particles that are 2.5 microns or smaller in size. PM2.5 is recognized as one of the most detrimental elements of air pollution (Afghan et al., 2022).

The emergence of the COVID-19 viral pandemic in late 2019 has highlighted the significant connection between community wellness and the surroundings. Research suggests that those who are consistently subjected to prolonged air pollution are at an increased chance of getting and experiencing negative effects from viruses like COVID-19 as a result of developing chronic illnesses. Given the recent advancements, air quality management has become a progressively significant concern for individuals and policymakers all over the globe (Barthwal & Acharya, 2022).

ANFIS is well recognized as an extremely prevalent neuro-fuzzy system. The combined Artificial Intelligence (AI) approach is a fusion of fuzzy logic and Artificial Neural Networks (ANN). ANFIS does not explain the physical components of the information being examined during the design stage (Arora, 2024; Asadov, 2018; Gomathi et al., 2022; Prasad Babu & Vasumathi, 2023).

However, it effectively identifies the connection between the input and output of the method. Therefore, it has been extensively used to address many issues related to predicting air pollution (Abdullah, 2020; Culpa et al., 2021; Yilmaz et al., 2022). Furthermore, fuzzy modeling may be used as an evolutionary strategy to address the imprecision and unpredictability of real-life problems by using fuzzy 'If-Then' rules. A rule set is created to govern the potential relationships between the input and output components via fuzzification. Fuzzy programming is a reliable technique for addressing intricate engineering issues that are hard to tackle using conventional mathematical models. These modeling techniques capture the imprecision of language characteristics and the terminology used to describe qualitative aspects (Sovannarith et al., 2023).

Although ANFIS offers many benefits, finding the most suitable configuration and settings for the platform remains difficult. The GA, a powerful optimization approach based on natural selection and genetics, is used in this context (Albadr et al., 2020). GAs effectively address intricate optimization issues that include extensive search spaces. The integration of GA with ANFIS allows the hybrid approach to efficiently explore the best combination of fuzzy rules and membership functions, resulting in improved forecasting accuracy. Integrating GA with ANFIS for air pollution forecasting has several advantages (Harandizadeh & Armaghani, 2021). Firstly, it enables the algorithm to adjust to changing external circumstances by consistently upgrading its variables via the processes of evolution.

Furthermore, the hybrid framework can accurately represent the complex and non-linear relationships between different contaminants and climatic conditions, a feature often disregarded by traditional approaches. Furthermore, incorporating IGA guarantees that the ANFIS model is not confined to local maxima, enhancing its ability to generalize across various databases and contexts.

Survey on Related Works

This literature overview examines a range of research that has used ANFIS and GA, either alone or in conjunction with other techniques, to forecast levels of air pollution. The study examines various models' approaches, implementations, and performance results, offering insights into their benefits and constraints.

Kaloop and colleagues (2021) utilize adaptive swarm intelligence methodologies with an ANFIS to forecast photovoltaic (PV) power. More precisely, the authors combine Particle Swarm Optimization (PSO) with ANFIS to improve the accuracy of predictions. The hybrid model is applied and validated using historical data on photovoltaic power production (Kaloop et al., 2021). The PSO technique is used to adjust the parameters of the ANFIS model to obtain optimal performance. The hybrid PSO-ANFIS model exhibited enhanced predictive accuracy and decreased error rates compared to conventional approaches. The findings demonstrate a significant decrease in the mean absolute percentage error (MAPE) and RMSE.

The study "(Yonar & Yonar, 2023)" combines the ANFIS with other metaheuristic algorithms, such as GA and PSO, to create a model for predicting air pollution levels. The integrated model is used for air quality data, whereby metaheuristic algorithms optimize the parameters of the fuzzy inference system (Yonar & Yonar, 2023). The hybrid models exhibit exceptional performance in forecasting air pollution levels, with dramatically decreased prediction errors compared to solo ANFIS models. Utilizing metaheuristic algorithms improves optimization, resulting in more precise and dependable forecasts. Nevertheless, like other hybrid models, the heightened computing load and intricacy might provide difficulties, especially when dealing with extensive datasets.

Okoji et al., (2023) researched to assess the effectiveness of an ANFIS-GA hybrid model in forecasting and optimizing NOx emissions from cement manufacturing plants (Okoji et al., 2023). The ANFIS model is trained using past NOx emission data from cement kilns, and the system parameters are optimized using GA. The hybrid ANFIS-GA model demonstrates superior prediction accuracy, resulting in substantial decreases in prediction error metrics compared to conventional techniques.

Saini et al. (2022a): The purpose of this research is to provide an Adaptive Dynamic Fuzzy Inference System Tree (ADFIST) that can be used to predict indoor PM2.5 levels (Saini et al., 2022) accurately. The ADFIST model utilizes data collected from sensor networks based on the Internet of Things (IoT) technology. The ADFIST model processes real-time sensor data, adaptively modifying its structure in response to incoming input. The model exhibits a high degree of accuracy in forecasting PM2.5 levels, surpassing the performance of static models.

Saini et al., (2022b) have improved the ADFIST technique by integrating an optimal knowledge base, resulting in increased flexibility and accuracy of the model. The model is evaluated using comprehensive datasets on indoor air quality, with optimizations implemented using heuristic approaches. The improved ADFIST model, surpassing earlier models, demonstrates greater predictive accuracy and resilience. Nevertheless, the intricacy of improving the knowledge base might augment the installation and upkeep endeavors (Saini et al., 2022). Purnomo & Anugerah, (2020) conducted a study using ANFIS to forecast air pollution levels in Yogyakarta. The objective of this research is to assist in the implementation of sustainable environmental management (Purnomo & Anugerah, 2020). The ANFIS model is trained using past air quality data from Yogyakarta, specifically emphasizing important contaminants. The model offers precise forecasts of pollution levels, assisting in efficient environmental monitoring and policy formulation.

Zeinalnezhad et al., (2020) conducted research that used a semi-experimental regression model in combination with ANFIS to forecast levels of air pollution (Zeinalnezhad et al., 2020). The hybrid model analyzes air quality data, where the regression component deals with linear features, and ANFIS is employed to handle non-linear correlations. The hybrid model demonstrates enhanced prediction accuracy compared to individual regression or ANFIS models. Saini et al., (2022c) provide a new approach in their research, using a fuzzy inference system optimized using PSO and GA to forecast PM10 levels. The PM10 data is used to evaluate the model, and the parameters of the fuzzy inference system are optimized using PSO and GA to improve its performance (Saini et al., 2022).

Saini et al., (2021) provide a novel approach to anticipate PM10 levels using a fuzzy inference system tree tuned using PSO and GA. The model is used for PM10 data, where the optimization algorithms adjust the system parameters to improve performance (Saini et al., 2021). The model achieves superior prediction accuracy, exhibiting reduced errors compared to traditional forecasting approaches. Using both PSO and GA guarantees comprehensive optimization, leading to the development of an exact forecasting model.

The combination of ANFIS and GA has shown considerable potential in forecasting air pollution, providing exceptional precision and flexibility. The studies examined in this study show that the hybrid ANFIS-GA model reflects the intricate and non-linear connections present in air quality data well. This combination improves the model's ability to make accurate predictions compared to conventional techniques.

Prediction of Air Pollution Utilizing ANFIS with the Aid of IGA

Data Sources

This work aimed to create a model for the air pollutant PM2.5, which is the primary indicator of air pollution in Istanbul. The dataset includes daily atmospheric measurements, including SO_2, O_3, NO_2, CO, and PM2.5, as well as several atmospheric variables, such as the velocity of the wind, wind direction, temperature, humidity, and pressure. The air quality database has been acquired from the Air Quality Open Data Platform (Air Quality Open Data Platform, 2021; Air Quality Open Data Platform, 2022). PM2.5 levels have been calculated for an Indian province using ANFIS models optimized with IGA.

ANFIS

ANFIS is a hybrid model that combines ANN with fuzzy inference. It is often used in diverse fields to address intricate and non-linear issues. This tool was created using the Sugeno fuzzy model. ANFIS often uses back propagation (BP) or a combination of BP and least-square (LS) prediction to calculate the values for membership functions. ANFIS utilizes the Takagi-Sugeno FIS, which includes a consistent output or a linear mixture of input parameters. ANFIS can create a relationship between input and output that utilizes human expertise. It does this by using hybrid learning techniques to allocate input-output information pairings.

The ANFIS structure is employed in simulation to simulate quadratic operations, forecast turbulent time series, and detect interactive non-linear elements in the control structure. ANFIS offers a superior option to current time-series models like ANN. The system can comprehend and evaluate many types of data, including mathematical, language-related, and rational data. Additionally, it can learn autonomously, govern itself, and enhance the accuracy of its predictions.

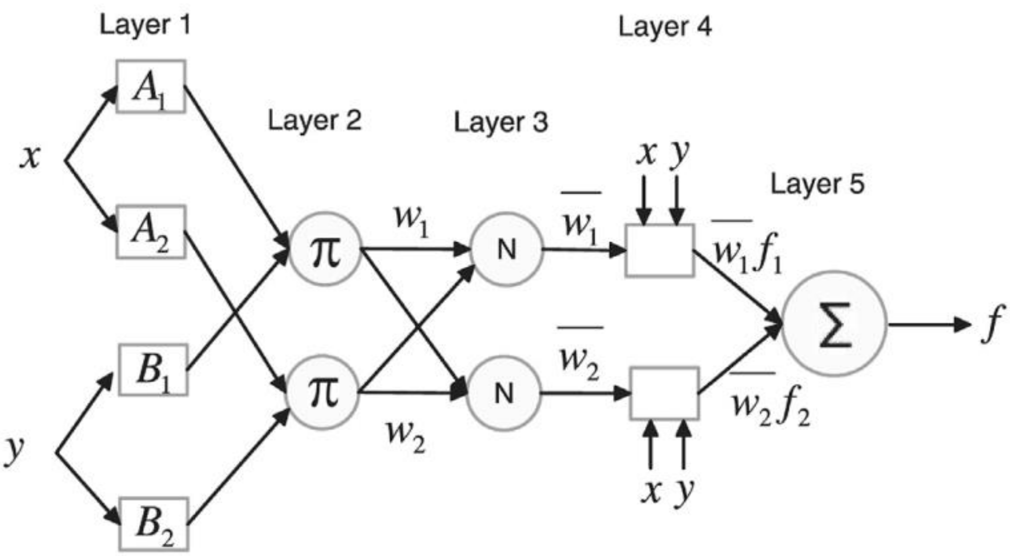

Figure 1. Overall configuration of ANFIS

Fig. 1 depicts the overall configuration of ANFIS, which consists of a single output (z) and two inputs (x, y). The ANFIS rule comprises two categories of Takagi-Sugeno if-then rules, as seen below:

$$Rule\ 1: If\ x\ is\ A1\ and\ y\ is\ B1;\ then\ f\ =\ p1\,x\ +\ q1\,y\ +\ r1 \quad (1a)$$
$$Rule\ 2: If\ x\ is\ A2\ and\ y\ is\ B2;\ then\ f\ =\ p2\,x\ +\ q2\,y\ +\ r2 \quad (1b)$$

The variables $A1, A2, B1, and\ B2$ are classified as regressive factors, whereas the variables $p1, p2, q1, q2, r1, and\ r2$ are classified as linear factors. The first layer, the fuzzification layer, involves the input variables x and y fed into the $A1, B1, A2, and\ B2$ nodes. In fuzzy theory, $A1, A2, B1, and\ B2$ have been employed to allocate the membership functions as communicative tags. ANFIS architecture has five levels.

Level 1: The level 1, also known as the fuzzification level, utilizes member functions to derive fuzzy groups from input values. This process calculates membership scores within the range of [0,1]. Various membership operations, including general bell operation, triangle, trapezium, etc., can be employed to determine membership principles. The shape of the member function is determined by factors such as $\{ai, bi, ci\}$, which are referred to as the basis or predecessor factors used in ANFIS training. The membership levels of each member function have been determined as follows:

$$L_i^1 = \gamma_{Ai}(x) \quad (2)$$

$$\gamma_{Ai}(x) = gbellmemfunc(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \quad (3)$$

Level 2: The level 2, also known as the rule level, determines the firing weights (W_i) for each rule using the membership values collected in the fuzzification level. The computation of W_i value is achieved by multiplying the membership values in the following manner:

$$L_i^2 = W_i = \gamma_{Ai}(x).\gamma_{Bi}(y), i = 1,2,3,4; \ j = 1,2 \quad (4)$$

Level 3: The standardization level computes the generalized firing weights ($\overline{W_i}$) for each rule utilizing the firing strain obtained from the preceding layer. The standardized firing weight of the ith rule is determined by dividing the firing weight of the ith rule by the sum of the firing weights.

$$L_i^3 = \overline{W_i} = \frac{W_i}{\sum_{i=1}^{4} W_i}, i = 1,2,3,4 \quad (5)$$

Level 4: The defuzzification level calculates the outcome of every rule by multiplying the standardized firing weights with a first-order polynomial. The procedure for the computation of the output is provided in Equation (5).

$$L_i^4 = \overline{W_i} f_i = \overline{W_i}(p_i x + q_i y + r_i) \quad (6)$$

The variable set $\{p_i, q_i, r_i\}$ correspond to first-order polynomials. The variables used in ANFIS training are considered concluding or subsequent factors.

Level 5: The summation level, also known as the defuzzification level, calculates the final output of ANFIS by adding up the outputs acquired from the defuzzification level.

$$L_i^4 = \sum_i \overline{W_i} f_i \quad (7)$$

The discrepancy between the observed and anticipated output of ANFIS is referred to as the error. The error value in the effective ANFIS model is minimal. Nevertheless, a drawback of the ANFIS model is the lack of interpretability in its weight values, making it unable to articulate a concise model. Nevertheless, it is extensively used in literature due to its several benefits, including the ability to learn from instances, not relying on assumptions about the underpinning model, handling inadequate and partial data, and being cognizant of machine learning and optimization methods.

Improved Genetic Algorithm

A broad GA is a stochastic search technique that adapts and optimizes globally by replicating species' genetic and biological processes in their natural setting. The GA search method is an iterative procedure combining survival and detection to search for solutions. This study presents a novel approach to address the issue of circular channels by introducing a new route discovery method. This method effectively minimizes the number of states needed to achieve extensive coverage. This approach establishes the state's priority first and then eliminates the newly produced states without altering the coverage status. The IGA employs a random technique to direct the coded variable space, treating each chromosome in the population as an object. This facilitates an evolutionary search to identify the ideal solution. The study predicts air pollution and identifies its components like SO2, O3, and PM2.5. Fig. 2 represents the overall sequence of steps in the IGA.

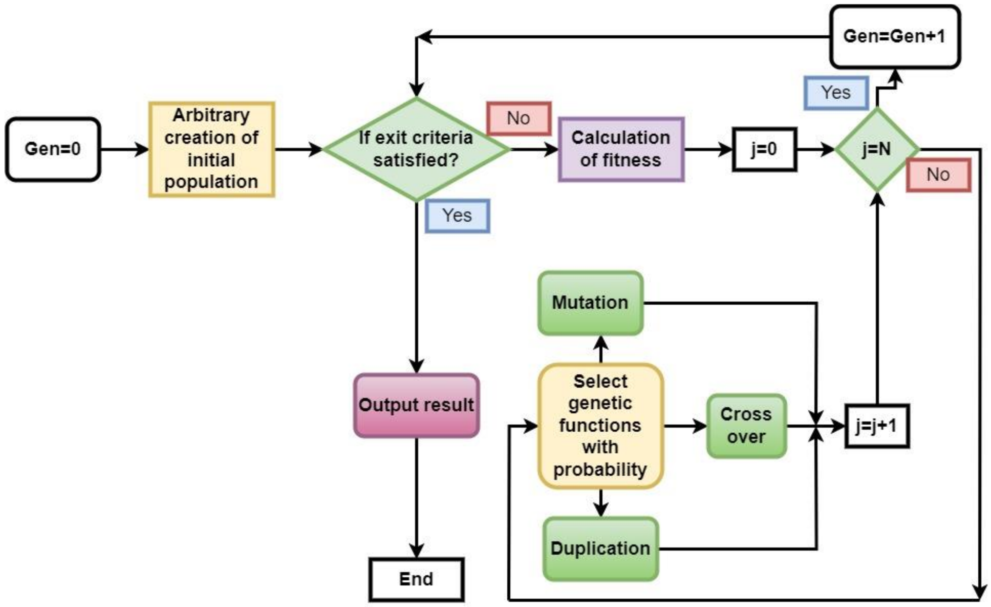

Figure 2. Overall sequence of steps in the IGA

Fig. 2 illustrates that there is a fixed number of people in the initial population, which is randomly produced. Each person is represented using chromosome-based coding. Next, each individual's fitness is computed to evaluate whether it satisfies the optimization requirements. If this condition is met, the most efficient person will be produced. Simultaneously, it also has the most favorable solution. If the circular calculation fails to match the conditions, it will persist in screening. During the screening process of regenerated people, those with high fitness will have a greater likelihood of being picked.

In contrast, those with poor fitness will be less likely to be chosen. Using a specific technique of variation and crossover, the ideal solution is examined in the next generation of the population chosen by Shuai. The most efficient set of solutions may be achieved by reciprocal calculation.

The IGA surpasses conventional optimization methods due to its utilization of a population as its search space instead of a single solution. Additionally, the IGA employs a fitness function in the evolutionary process, enabling it to address various fitness functions and limitations. Notably, the IGA does not rely on deterministic approaches. The state transfer rule utilizes probability, enabling it to conduct global search effectively. When employing an IGA to accomplish the optimum air pollution prediction, it is important to consider self-moderation. This requires designing a suitable fitness function to assess the effectiveness of the test data.

Integrated ANFIS-GA

The first traditional ANFIS technique used a mixed learning methodology for training. The learning methodology used the Gradient Descent (GD) algorithm to identify the hypothesis factors, while the Least Square Estimation (LSE) method was used to calculate the consequent variables. Nevertheless, there is a potential danger of being trapped at the local minimum because these approaches rely on derivatives. Utilizing metaheuristic approaches, as opposed to derivative-based algorithms, yields more efficiency in performance. For this research, it is advisable to use metaheuristic algorithms like IGA to train ANFIS due to these factors. The optimal model is achieved by adjusting the ANFIS parameters using IGA to minimize the discrepancies between the true output values and the anticipated output values obtained by ANFIS.

Results and Discussion

To validate the performance of the air pollution prediction system, actual statistics are evaluated around the same time. Air pollution data, including Fine Particulate Matter (FPM), CO, SO2, O3, and NO2, is gathered from the Air Quality Open Data Platform (Air Quality Open Data Platform, 2022). The forecasting data suggested by the framework were compared with traditional techniques using various assessment indicators. Short-term projected results, in addition to the long-term projection, were carried out for the year 2022. The optimization methods considered for analysis are ANFIS, ANFIS-PSO, ANFIS-GA, and the proposed ANFIS-IGA.

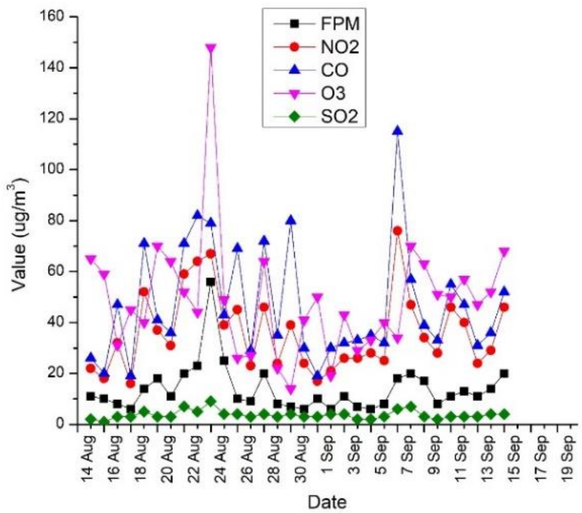

Figure 3. Predicted output of various air pollutants using the proposed ANFIS-IGA from 14th August 2022 to 15 September 2022

Fig. 3 displays the concentrations of several pollutants (measured in µg/m3) from 15th August 2022 to 15th September 2022, utilizing short-term forecasting for the proposed ANFIS-IGA. There was a substantial decrease in pollution levels between August 25th, 2022 and September 5th, 2022. There have been notable alterations in the NO, NO2, and FSP levels, and their rise has been observable.

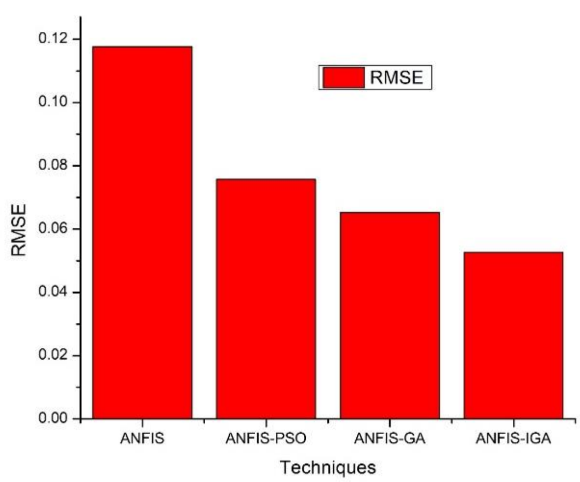

Figure 4. RMSE values of various optimization methods in predicting air pollution

Fig. 4 depicts the RMSE values of various optimization methods in predicting air pollution. The RMSE value for the basic ANFIS model is 0.11765, representing the performance of the adaptive neuro-fuzzy inference system without any optimization. By integrating PSO with ANFIS, the RMSE is substantially reduced to 0.075684. This indicates a significant improvement in the precision of predictions. The use of ANFIS-GA leads to further improvement, resulting in a decrease of the RMSE to 0.065248. An RMSE score of 0.052658 is obtained by incorporating an Improved Genetic Algorithm (ANFIS-IGA), demonstrating the exceptional ability of this approach to reduce prediction errors. The findings demonstrate that integrating metaheuristic algorithms improves the accuracy of ANFIS in forecasting air pollution levels, with ANFIS-IGA exhibiting the highest degree of performance among the assessed approaches.

Conclusion

The study used an Adaptive Network Fuzzy Inference System and an Improved Genetic Algorithm (ANFIS-IGA) to forecast air pollution levels. This study aimed to overcome this limitation by improving the accuracy of daily air pollution forecasting by analyzing time-series data using ANFIS modeling. Data on air pollution, namely Fine Particulate Matter (FPM), CO, SO_2, O_3, and NO_2, is collected via the Air Quality Open Data Platform. This study analyzes and forecasts air pollution levels in indoor and outdoor environments using the ANFIS-IGA model. The model's efficacy was improved and tuned specifically for the use of IGA. The findings demonstrate that the ANFIS-IGA framework, as presented, outperformed alternative models, as seen by the Root Mean Square Error (RMSE) value of 0.052658.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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