



Noise Robust Hybrid ANFIS-ARIMA Model for Air Pollution Time Series Forecasting

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Abstract

This research investigates the performance of a hybrid forecasting approach that integrates the Auto-Regressive Integrated Moving Average (ARIMA) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) models for air pollution time series prediction. The study utilizes daily concentrations of nitrogen dioxide (NO₂) and ozone (O₃) obtained from air quality monitoring stations. Data preprocessing included handling missing values, normalization, and decomposition into trend, seasonal, and residual components, followed by training

and testing partition. The individual ANFIS model was first applied to predict pollutant concentrations, showing reliable performance with R² values exceeding 0.90 for both NO₂ and O₃. To enhance accuracy, a hybrid ARIMA–ANFIS model was developed, where ARIMA captured linear patterns and ANFIS modeled the nonlinear residuals. The evaluation was performed under both clean and noisy conditions, with Gaussian noise added at levels of 10%, 20%, and 50% to assess robustness. Results indicated that the hybrid model achieved superior performance on clean data, with an MSE of 0.000338, RMSE of 0.018378, R² of 0.993286, and SMAPE of 4.01%. Although performance slightly declined under noisy conditions, the model maintained strong predictive ability, achieving R² values of 0.983286, 0.954630, and 0.790016 for 10%, 20%, and 50% noise, respectively. These findings confirm that the hybrid ARIMA–ANFIS framework is not only highly accurate but also robust against disturbances, making it a suitable and reliable model for forecasting air pollutant concentrations in real-world scenarios where data uncertainty is common.

Keywords: Air Pollution Forecasting, Time Series, ANFIS, ARIMA, Hybrid Model, Noise Robustness, Machine Learning

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Introduction

Air quality is a global issue that is receiving increasing attention because of its serious impact on human health and environmental sustainability. The World Health Organization (WHO) reports that more than 7 million premature deaths each year are related to exposure to air pollution, especially fine particulate pollutants such as PM_{2.5}, nitrogen dioxide (NO₂), and ozone (O₃) (Organization, 2025). These pollutants have been proven to contribute to an increased risk of chronic respiratory diseases, cardiovascular disorders, and lung cancer (Manisalidis et al., 2020). Therefore, air quality monitoring and forecasting systems are becoming very important not only for health risk mitigation, but also as a basis for public policy formulation and sustainable urban planning.

Conventional statistical methods have long been used to model time series data in the context of air quality, one of which is the Autoregressive Integrated Moving Average (ARIMA). The ARIMA model has the advantage of capturing linear patterns, so it is often applied to data with clear trends and seasonality (Wilson, 2016). However, the limitation of ARIMA lies in its inability to represent the non-linear patterns that often appear in complex environmental data. In addition, ARIMA performance decreases significantly when data is affected by *noise* or *outliers*, which is common in air quality sensor measurements (Chodakowska et al., 2021). This poses its own challenges in producing reliable predictions in real conditions. Alternatively, artificial intelligence-based methods have developed rapidly, one of which is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a hybrid system that combines the ability of *fuzzy logic* to handle uncertainty with artificial neural networks in the learning process (Jang et al., 1997).

The advantage of ANFIS lies in its flexibility in capturing complex non-linear patterns, making it able to produce more accurate predictions than purely statistical methods in many cases of environmental data (Ruf et al., 2022). However, although ANFIS excels in the aspect of non-linearity, the model has also been shown to be sensitive to the presence of *noise*, which can reduce the stability of prediction results (Rahajoeningroem & Aria, 2013). To overcome these limitations, a *hybrid approach* between ARIMA and ANFIS has begun to be developed. The main concept of this approach is to harness the power of ARIMA in capturing linear patterns, while ANFIS is used to model non-linear components. Several previous studies have reported that the combination of the two is able to improve prediction accuracy in a variety of domains, including environmental monitoring and Internet of Things (IoT)-based systems (Fitriyati & Yunita Wijaya, 2022). This approach is considered more adaptive to the diversity of data patterns, so it has the potential to provide a more comprehensive solution than the use of a single model.



However, a review of the current literature shows that most studies related to the ANFIS–ARIMA hybrid model focus more on improving predictive accuracy without emphasizing the *robustness* aspect of the model to noisy data conditions. In fact, in practice, air quality data often contains *noise* due to sensor errors, extreme weather conditions, or other external interference. Previous studies have even shown that ARIMA's performance decreases drastically when *noise levels* are high enough (Chodakowska et al., 2021), while ANFIS's sensitivity to *noise* has also been reported. Thus, there is a significant research gap related to the robustness evaluation of the ANFIS-ARIMA *hybrid* model on *noisy data*, especially in the context of air pollution forecasting.

Based on this background, this study aims to design and develop an ANFIS-ARIMA hybrid model that is able to improve the accuracy and durability of air quality prediction. The focus of the research is not only on predictive performance in clean data conditions, but also on robustness evaluation when the model is tested with data containing *Gaussian noise*, *outliers*, and sensor errors. In addition, this study compares the performance of *hybrid* models with single models (ARIMA and ANFIS) to provide a comprehensive analysis. Thus, this research is expected to make an academic contribution to the development of more reliable forecasting models, while supporting practical applications in real data-based air quality monitoring systems.

Methods

This study was designed as an experimental analytical study that utilized secondary data from air quality monitoring stations. The data collected were in the form of average daily concentrations of nitrogen dioxide (NO₂) and ozone (O₃) for a full year, resulting in 365 observations for each pollutant. The initial hourly data is first converted into a daily average to form a more structured time-series dataset (Vatresia et al., 2025). The preprocessing stage is carried out through four main steps. First, the detection and imputation of lost values is carried out by the linear interpolation method so that the continuity of the data is maintained (Muzakki et al., 2024). Second, the data is normalized using the min–max scale so that all variables are within the range [0, 1], which serves to accelerate convergence during model training (Chan et al., 2025). Third, the dataset was then decomposed into three components, namely trend, seasonal, and residue, using the STL (Seasonal-Trend decomposition based on Loess) approach to facilitate the identification of long-term patterns and seasonal fluctuations (Özüpak et al., 2025). Fourth, the data is divided into two subsets, namely 70% (≈255 days) and 30% (≈110 days) test data. In addition, additional experiments were conducted by simulating partial deletion of data on a subset of the test to assess the adaptability of the model to conditions of incomplete data availability (Iftikhar et al., 2024).

Three models were used in this study, namely ARIMA (Auto Regressive Integrated Moving Average), ANFIS (Adaptive Neuro-Fuzzy Inference System), and ANFIS–ARIMA



hybrid model. ARIMA was chosen for its ability to capture linear patterns over time series (Vatresia et al., 2025), while ANFIS is used to model non-linear patterns through the integration of fuzzy logic and neural networks (Jang et al., 1997). A hybrid model is built by combining the two, where the residual results of ARIMA predictions are studied by ANFIS to capture non-linear dynamics that ARIMA cannot explain (Wang et al., 2023). To test robustness, test data is given two types of interference. First, Gaussian noise is added with noise-to-signal ratios of 10%, 20%, and 50%. Second, outlier injections were carried out at the end of the time sequence to simulate extreme events in the observation (Ifikhar et al., 2024). Performance evaluation was carried out using three main metrics, namely Root Mean Square Error (RMSE), Mean Squared Error (MSE), and determination coefficient (R^2). Model robustness is analyzed by comparing performance degradation (RMSE/MSE increase and R^2 decrease) when noise or outliers are introduced into the test data (Estrada et al., 2020). The dependent variables in this study were prediction accuracy (measured by performance metrics), while independent variables included model type (ARIMA, ANFIS, Hybrid) and interference level (0%, 10%, 20%, 50%, and outlier).

Results and Discussion

This research uses the Python programming language, where the input data comes from daily air pollution time series, specifically nitrogen dioxide (NO_2) and ozone (O_3) concentrations collected from air quality monitoring stations. Predictions in this research are carried out using the Adaptive Neuro-Fuzzy Inference System (ANFIS) model and a hybrid model combining ARIMA and ANFIS (ARIMA-ANFIS). The evaluation results of these models are compared to analyze the performance differences between individual ANFIS and the hybrid ARIMA-ANFIS approach. In Table 1 is presented the result of a comparison of individual ANFIS evaluations.

Table 1 ANFIS CO and NO2

NO	Parameter	MSE	RMSE	R^2
1	NO_2	0.0052	0.0719	0.9223
2	O_3	0.0040	0.0636	0.9136

Based on Table 1, the performance of the ANFIS model on the parameters of nitrogen dioxide (NO_2) and ozone (O_3) showed fairly good results with relatively small MSE and RMSE values. For NO_2 , the model yields an MSE value of 0.0052 and an RMSE of 0.0719, indicating that the model's prediction error is relatively low. The R^2 value of 0.9223 also indicates that the ANFIS model is able to explain more than 92% of the actual data variation, so it can be said to be very suitable for NO_2 concentration forecasting. Meanwhile, for the O_3 parameter, the MSE value of 0.0040 and the RMSE of 0.0636 are also quite small, indicating a low prediction error rate. However, the R^2 value of 0.9136 was slightly lower than NO_2 , although it remained in the strong



category. This suggests that the ANFIS model can still capture the main patterns of O_3 data, but the predictions are slightly more varied than those of NO_2 . Overall, these results show that ANFIS is quite reliable in modeling air pollution data, both for NO_2 and O_3 , with high predictive ability indicated by an R^2 value above 0.90.

Building upon the result of the individual ANFIS model, further experiments were carried out by integrating ARIMA with ANFIS into a hybrid ARIMA-ANFIS model. This hybrid approach aims to combine the strengths of ARIMA in capturing linear temporal dependencies with ANFIS, which is powerful in modeling non linear relationships. The evaluation results of the hybrid model are presented in Table 2, which includes testing under clean conditions as well as under noise disturbances of 10%, 20%, and 50%.

Table 2 Evaluation ARIMA - ANFIS

Scenario	MSE	RMSE	R^2	SMAPE(%)
Clean	0.000338	0.018378	0.993286	4.01
Noise 10%	0.000854	0.029230	0.983286	10.06
Noise 20%	0.002349	0.048465	0.954630	17.19
Noise 50%	0.013197	0.114880	0.790016	39.13

As presented in Table 2, the Hybrid ARIMA–ANFIS model exhibited excellent predictive performance under clean conditions, achieving an MSE of 0.000338, RMSE of 0.018378, R^2 of 0.993286, and SMAPE of only 4.01%. Compared to the standalone ANFIS model, this represents a significant improvement in accuracy and explanatory power, with R^2 increasing from around 0.92 (NO_2) and 0.91 (O_3) to nearly 0.99. This demonstrates that the hybrid approach is far more effective at minimizing prediction errors and capturing both linear and nonlinear dynamics in air pollution data. When subjected to noise disturbances of 10%, 20%, and 50%, the model performance experienced some degradation, which is expected given the increased irregularity in the data. Nevertheless, the hybrid model maintained strong predictive ability. At 10% noise, the R^2 value was still as high as 0.983286 with SMAPE of 10.06%, which indicates that the model is able to handle moderate levels of uncertainty while still producing reliable forecasts. Even at 20%



noise, the model preserved good predictive power with $R^2 = 0.954630$ and SMAPE = 17.19%, suggesting robustness in the presence of substantial data fluctuations. Only at the highest noise level (50%) did the model show significant performance deterioration, with R^2 dropping to 0.790016 and SMAPE rising to 39.13%.

Overall, the comparison between ANFIS and Hybrid ARIMA–ANFIS highlights the advantages of the hybrid framework. While ANFIS alone provides reliable predictions with R^2 above 0.90, integrating it with ARIMA substantially enhances forecasting accuracy, as evidenced by the higher R^2 and lower error values. Moreover, the robustness analysis under noisy conditions further demonstrates the practicality of the hybrid model for real-world applications, where air quality data often contain noise due to sensor errors, environmental variability, or data collection limitations. These findings confirm that the Noise Robust Hybrid ARIMA–ANFIS model is not only accurate but also resilient, making it a promising tool for air quality forecasting and environmental decision support systems

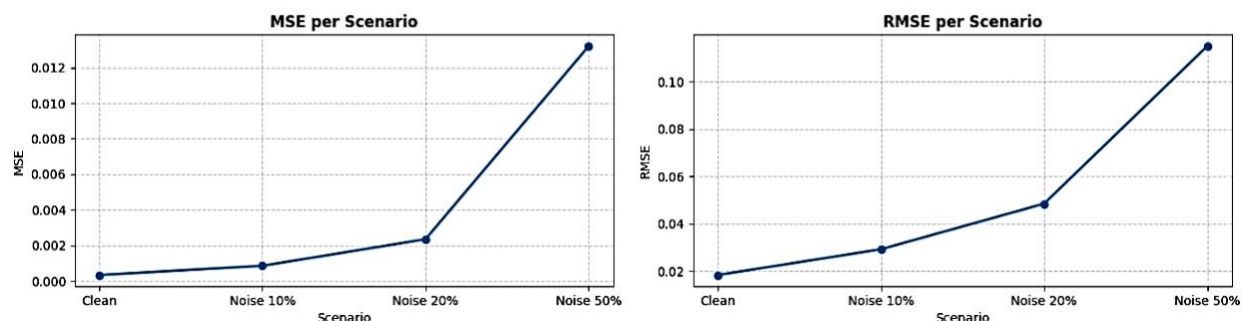


Fig 1 Evaluation MSE and RMSE

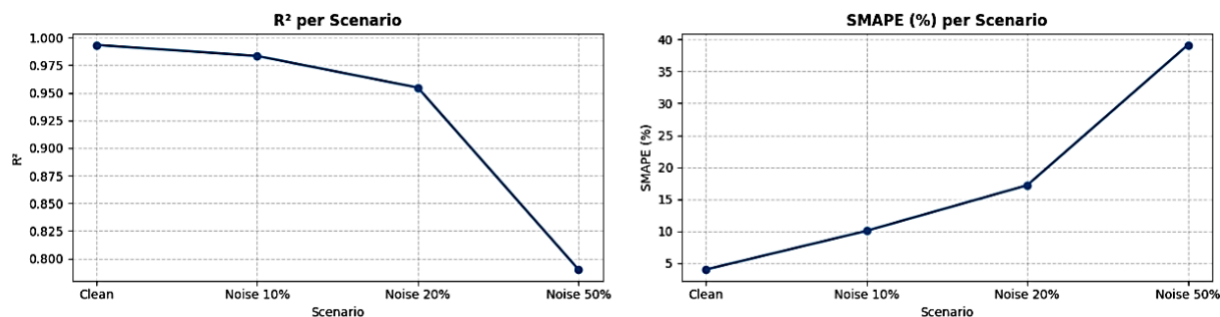


Fig 2 Evaluation R2 and SMAPE



Conclusion and Recommendation

Based on the results of the study, it can be concluded that the ANFIS model is able to provide a fairly good prediction performance in modeling the concentration of air pollutants, both for the NO_2 and O_3 parameters, with an R^2 value above 0.90. This shows that ANFIS can effectively capture non-linear patterns in air pollution time series data. However, the integration of ARIMA with ANFIS in the form of the ARIMA–ANFIS Hybrid model has been proven to result in superior performance. In the clean data, the hybrid model achieved a very high level of accuracy with MSE of 0.000338, RMSE of 0.018378, and R^2 of 0.993286. These results confirm that the hybrid approach is able to capture linear and non-linear patterns more comprehensively than a single ANFIS.

In addition, noise resistance testing shows that the ARIMA–ANFIS Hybrid model has good robustness. Despite the decrease in performance as the noise level increases, the model retains reliable predictive capabilities up to a noise level of 20%. A significant drop in performance was only seen at a noise level of 50%, which represents extreme conditions on the time series data. Overall, this study confirms that Hybrid ARIMA–ANFIS is a more effective and robust approach to air quality forecasting than a single ANFIS. With its ability to handle uncertainty and data fluctuations, this model has the potential to be widely applied in monitoring and decision-making systems related to air pollution control.

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