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Predictive Performance Evaluation of ARIMA and Hybrid ARIMA-LSTM Models for Particulate Matter Concentration

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ABSTRACT

This study objectively evaluates prediction models for particulate matter policy for industrial stakeholders by comparing the ARIMA (Auto Regressive Integrated Moving Average) and hybrid ARIMA-LSTM (Long Short-Term Memory) models for predicting air quality data in industrial environments. For PM 1.0 concentration, the ARIMA model has an RMSE of 8.29 and an error ratio of 0.45, while the hybrid ARIMA-LSTM model achieves an RMSE of 3.54 and an error ratio of 0.22. For PM 2.5 concentration, the ARIMA model shows an RMSE of 6.61 and an error ratio of 0.66, compared to the hybrid ARIMA-LSTM model's RMSE of 2.68 and an error ratio of 0.19. The best ARIMA models identified are (2,0,1) for PM 1.0 and (1,0,1) for PM 2.5. The hybrid ARIMA-LSTM model outperforms ARIMA, with improved RMSE and error ratio values by approximately 57.30% and 51.11% for PM 1.0, and 59.46% and 71.21% for PM 2.5, respectively. This superior performance is due to the hybrid model's ability to handle variable-length sequences and capture long-term relationships, making it more resistant to noise and enhancing prediction accuracy.

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1. INTRODUCTION

Air quality is becoming a critical issue for public health and environmental sustainability as urbanization picks up speed. Particulate matter (PM) is one of the issues with air quality since it affects air pollution. A mixture of tiny solid and liquid particles that are present in the air is known as particulate matter, or simply "particulate matter" [1], [2]. There are many other sources of particles, such as dust, chemicals emitted from factories and other industries, and the combustion of fossil fuels [3], [4].

Due to their small size, these particles have the potential to harm people's health by getting inside the respiratory system. PM1.0, or particulate matter smaller than 10 micrometers, can enter the human lung; PM2.5, or fine dust smaller than 2.5 micrometers, can enter the bloodstream and body and have an impact on bodily organs [5], [6].

PM2.5 is made up of tiny airborne particles that are 25 micrometers or smaller than PM1.0, which is made up of particles that are 10 micrometers or less. PM1.0 and PM2.5 are examples of small particles that can reach the human respiratory system by inhalation. Due to their small size, these particles have the ability to pass through blood vessels and lung tissue, which can lead to a number of health issues [7], [8]. Lung cancer, heart disease, stroke, and respiratory disorders are among the health issues brought on by PM1.0. As a result, it's critical to keep an eye on the levels of PM1.0 and PM2.5 in the environment and to limit how much exposure people get to these particles [9], [10].

In order to identify the better performance model that will be used to predict air quality data from the industrial environment as an objective assessment for industrial stakeholders related to particulate matter policy, this research compares the hybrid ARIMA-LSTM with the ARIMA model. The hybrid ARIMA - LSTM model is being proposed in this research since it has the ability to capture long-term dependencies, handle variable-length sequences, and be robust to noise, which can achieve higher prediction accuracy [11], [12],[13]–[16] while ARIMA is a univariate (single variable) time series-based forecasting and prediction technique that has a higher accuracy for short-term prediction[17], [18].

In contrast, LSTM (Long Short-Term Memory), a recurrent neural network, excels at capturing long-term dependencies and non-linear relationships, making it robust against the complexities and noise in sequential data like air quality measurements. By integrating ARIMA's linear modeling capabilities with LSTM's ability to manage variable-length sequences and long-term dependencies, the hybrid ARIMA-LSTM model provides a more accurate and adaptable approach to predicting particulate matter concentrations (PM 1.0 and PM 2.5), effectively handling both short-term trends and long-term patterns in diverse industrial air quality data.

2. METHOD

In the study, the process of creating an ARIMA and Hybrid ARIMA-LSTM model was carried out in several stages, as depicted in Figure 1 and Figure 2.

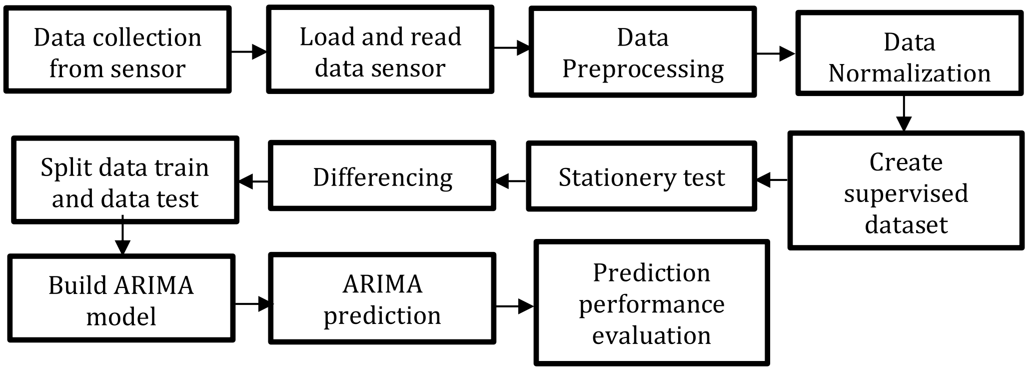


Figure 1. ARIMA research method

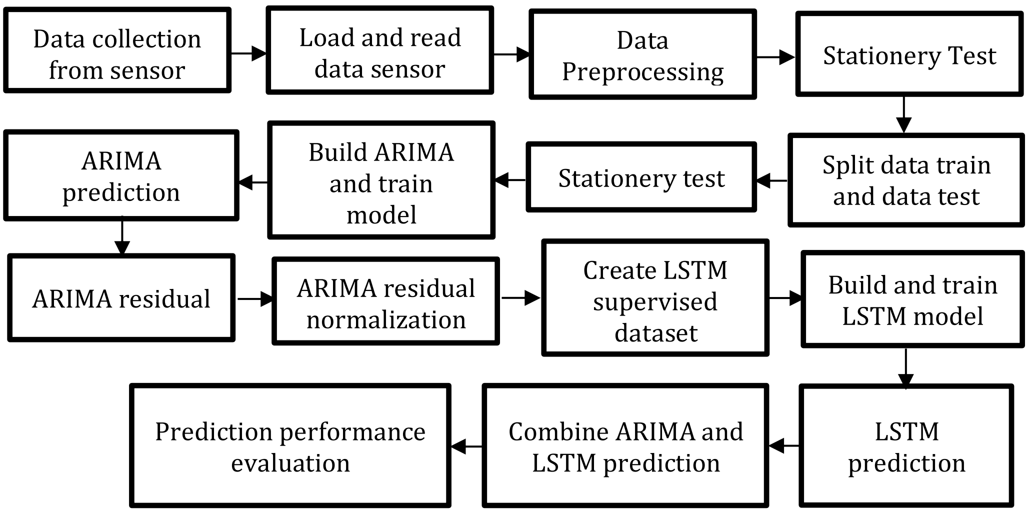


Figure 2. Hybrid ARIMA-LSTM research method

The following is a quick explanation of each phase in the study approach for the ARIMA model, taken from Figure 1 and Figure 2 above.

a. The initial stage of gathering all the research data obtained from the sensors is data collection. It will use the PM1.0 and PM2.5 attributes to predict air quality values. 310.080 pieces of data total, collected between November 2023 and February 2024, were included in the analysis.
b. The research phase involves loading and reading data. sensor loads data and reads it to determine its properties and content.

c. The goal of data preprocessing is to clean up and prepare the raw data for feeding into a statistical model or machine learning algorithm. The present study employs data preprocessing techniques such as removing superfluous data columns, indexing datetime data, resampling data into an hour, removing outliers, and removing zero and NaN values.
d. Normalizing the data comes next, following preparation. Setting and ensuring that the numerical values of various attributes are on a similar scale is the primary goal of data normalization. which will support machine learning models' interpretability, efficiency, and stability.
e. A supervised dataset for a supervised learning scheme must be created in order to forecast the next data values based on the previous value sequence.
f. To ensure that the ARIMA model meets its assumptions and is robust and accurate in capturing the underlying patterns in time series, the stationery test is the step that determines whether each feature is stationary.
g. The goal of differencing is to stabilize a time series. A fundamental presumption of many timeseries models, such as ARIMA, is stationarity. A time series can be made non-stationarity-free by subtracting trends and seasonality.
h. Before predicting the dataset, split data training and split data testing are used to separate the data into sets of data. The resampled data in this stage totals 2.827, which will be divided into two data tests: a 20% data test (consisting of 566 data) and an 80% data test (consisting of 2.261 data). The dataset that contains the split data will be resampled into hourly date times to minimize computation effort.
i. The process of creating the ARIMA model parameter involves looking for and locating the values of the p, d, and q parameters. This model will be utilized to make predictions. The autoarima function will determine the ARIMA model (p,d, and q).
j. The LSTM model is built to leverage the ability to capture and learn complex sequential patterns from time-series or sequential data and handle sequences of data where there are long-term dependencies or where the temporal dynamics of the data are important.
k. Calculating the ARIMA residual will allow for leveraging the strengths of both the ARIMA and LSTM models, potentially leading to better prediction accuracy and capturing a broader range of patterns in the data.
l. Normalizing ARIMA residuals ensures that they are compatible with the LSTM model's training process, leading to more stable training, improved convergence, and potentially better predictive performance in the Hybrid ARIMA-LSTM model.
m. Combining ARIMA and LSTM models means allowing the model to leverage the strengths of both ARIMA and LSTM models, correct errors, reduce uncertainty and ultimately improve the accuracy of the predictions.
n. The most important stage in forecasting the dataset's future values is data prediction. The prediction will employ divided data steps (point g) and the data train to forecast the data test that was previously set.
o. Following the forecast, an assessment of the prediction's performance will be conducted in order to appraise ARIMA and Hybrid ARIMA-LSTM models. In this study, error ratio and RMSE are used to evaluate performance.

2.1. Auto Regressive Integrated Moving Average (ARIMA)

ARIMA is an effective time series forecasting method that captures the underlying patterns and trends inside a time series by combining autoregression, differencing, and moving average components [19], [20]. For forecasting future values based on past data, the ARIMA model offers a reliable framework.

The acronym ARIMA (p, d, q) stands for the ARIMA model, where 'p' denotes the AR component's order, 'd' stands for the differencing order, and 'q' stands for the MA component's order [21], [22]. Accurate modeling requires careful parameter selection. There are a number of tests that may be used to verify if the time series is suitable for modeling, however, before using ARIMA, validation and stationarity assessment are crucial conditions using the Augmented Dickey-Fuller Test (ADF) [23]–[25]. The following is how ARIMA can be written as an equation in mathematics;

$$y_t = C + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_p \epsilon_{t-q} + \epsilon_t \quad (1)$$

where y_t represents the dependent variable at time t, C is the model's intercept, $\varphi_1 \ldots \varphi_p$ represents autoregressive parameters, $\theta_1 \ldots \theta_p$, represents the parameters of the moving average, and ϵ_t represents an error term at time t.

2.2. Long Short Term Memory (LSTM)

It's a type of recurrent neural network (RNN) architecture designed to overcome the limitations of traditional RNNs in capturing long-term dependencies in sequential data. LSTM has the ability to identify and predict data that has been retained for an extended period of time [26]. Figure 3 displays the architectural drawings of LSTM utilized in this research.

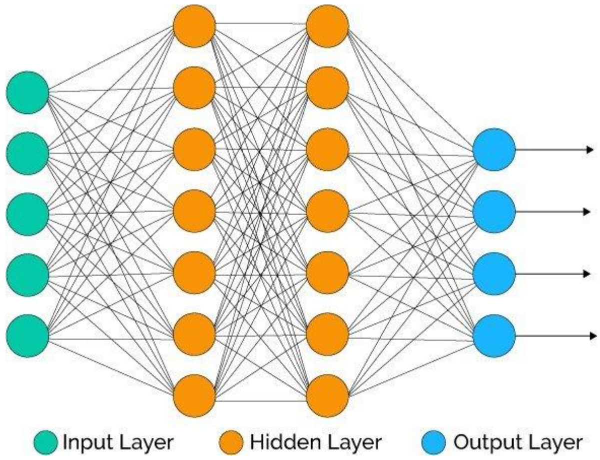


Figure 3. LSTM research model

According to Figure 2, the sequential approach LSTM model used in this work has four layers, namely:

- Input Layer
  Most of the time, sequential data, like the time sequence in time series data, is fed into the input layer of LSTMs. A sigmoid activation function will regulate the next gate, which is regulated by the input gate in each LSTM cell, and select the information from the input sequence data to pass [27], [28].
- Hidden Layer
  It plays a crucial role in processing and comprehending long-term information in sequential data, which makes it possible for neural networks to perceive and represent increasingly intricate links in that data sequence. Two (2) hidden layers are used by the LSTM model in this study to achieve network stability.
- Output Layer
  Its purpose is to process information through all time steps in sequential input data and produce output from the full LSTM network [29], [30] . The output layer is primarily responsible for transforming the internal representations generated by LSTM cells into a format that is consistent with the model's objectives. The output layer represents each feature that will be predicted, i.e., PM1.0 and PM2.5.

2.3. Root Mean Square Error (RMSE)

It is a technique for assessing a model's performance. The root mean square error (RMSE) determines the average of the squared discrepancies between the actual and model-predicted data. A lower root mean square error (RMSE) indicates higher model quality [31], [32]. RMSE is generally stated by the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{n}(Y_{obs} - Y_{pred})^2} \quad (2)$$

where N represents the number of data, Yobs represents the actual value, and Ypred represents the prediction value.

2.4. Error Ratio

The error ratio, which is derived by dividing the root mean square error (RMSE) by the standard deviation of feature data, is a metric used to evaluate the difference or error. The model's performance will decline as the error increases with an increasing error ratio. In terms of math, the error ratio is defined as follows:

$$Error\ ratio\ = \frac{RMSE}{\sigma} \tag{3}$$

where RMSE represents the Root Mean Square Error and σ represents the standard deviation of feature data.

2.5. Akaike Information Criterion (AIC)

The goodness-of-fit value (AIC) is a method used to estimate the prediction error to determine the relative quality of the statistical model for a particular dataset. In determining the best multiple linear regression model, the model with the smallest AIC value is considered the best model [33], [34]. Generally, the equation for model goodness-of-fit is defined as:

$$AIC\ =\ 2p\ -\ 2\ log\ L \tag{4}$$

where p represents the number of parameters in the model, and L represents the likelihood function of the model.

3. RESULT AND DISCUSSION

3.1. Data Preprocessing

Timeseries data plots for the PM1.0 and PM2.5 features are shown in Figures 4–5 below.

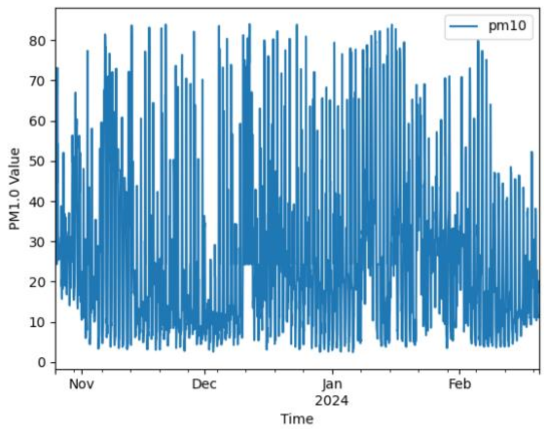


Figure 4. PM1.0 time series data observed in Nov 2023-February 2024 and recorded daily

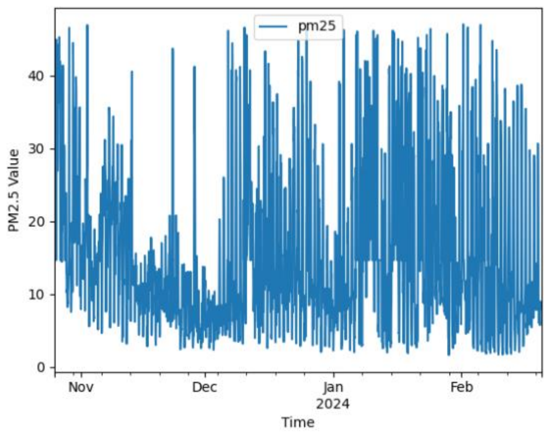


Figure 5. PM2.5 time series data observed in Nov 2023-February 2024 and recorded daily

As seen in Figures 4-5, the readings of PM1.0 and PM2.5 measurements exhibit significant data fluctuations, indicating that variations in sensor data readings can provide insights into the characteristics of particulate matter PM1.0 and PM2.5. PM1.0 and PM2.5 are seasonal data based on observation, which indicates the presence of seasonality in the PM1.0 and PM2.5 data.

3.2. Stationery Test

Table 1 presents the results of the stationery test for each feature in this research. Table 1 shows that the null hypothesis of non-stationarity has been rejected because each feature's p-value is less than the significant value of 0.05. This indicates that the features won't require a differencing process to obtain stationarity.

Table 1 Stationery test result

Features	p-value	Stationery Result
PM1.0	0.000018	Stationery
PM2.5	6.043795e-07	Stationery

3.3. ARIMA and LSTM Models

In this study, the ARIMA model is determined using autoarima to obtain the best model by selecting the best model based on the smallest AIC value. The results of the ARIMA model search with autoarima are shown in the following Table 2.

Table 2. ARIMA model and AIC value

Features	ARIMA model (p,d,q)	AIC Value
PM1.0	(2,0,1)	22182.271
PM2.5	(1,0,1)	14888.650

Based on Table 2, the ARIMA model equations for PM1.0 and PM2.5 are shown in Table 3.

Table 3. ARIMA model equation

Features	ARIMA model (p,d,q)	ARIMA equation
PM1.0	(2,0,1)	$y_t = 2.0817 + 1.6254 y_{t-1} - 0.6947 y_{t-2} + 0.7895 \varepsilon_{t-1} + \varepsilon_t$
PM2.5	(1,0,1)	$y_t = 15.0288 + 0.7660 y_{t-1} - 0.0234 \varepsilon_{t-1} + \varepsilon_t$

The LSTM model that has been built for this research is shown in Table 4.

Table 4. LSTM research model

Layer (type)	Output Shape	Param
lstm_2 (LSTM)	(None, 32)	6784
dense_6 (Dense)	(None, 32)	1056
dense_7 (Dense)	(None, 16)	528
dense_8 (Dense)	(None, 1)	17
Total Params		8385
Trainable Params		8385
Non-Trainable Params		0

As depicted in Table 4, the LSTM model for this study consists of four layers, i.e.:

- The input layer is denoted by lstm_2, with a total of 6.784 parameters.
- The first hidden layer is denoted by dense_6, with a total of 1.056 parameters.
- The second hidden layer is denoted by dense_7, with a total of 528 parameters.
- The output layer is denoted by dense_8, with a total of 17 parameters.

The parameter calculations for each parameter are listed as follows:

- Input layer
  Units = 32
  Input shape = (1, 20)
  params=(6×((32+1+1)×32)))+(8x32) = 6.784 parameter

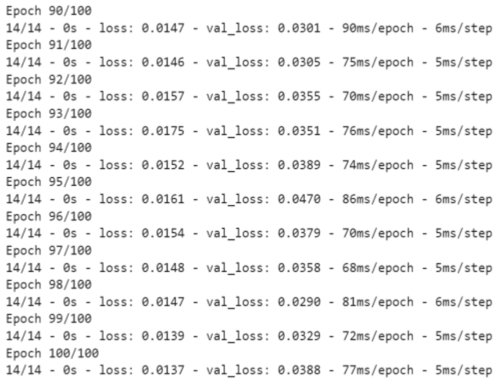
- First Hidden Layer
  Input dimension = 32
  Units = 32
  params=(32+1)×32=1.056 parameter

- Second Hidden Layer
  Input dimension: 32

Units = 16
params=(32+1)×16 = 528 parameter

- Output Layer
  Input dimension: 16
  Units = 1
  Params = (16+1)×1 =17 parameters

With two hidden layers and fewer parameters, the model is less likely to overfit or underfit the training data, especially when the training dataset is limited, effectively trains faster than those with more parameters, and has a lower computational complexity. To validate the loss model, training and validation losses need to be performed. The training and validation loss results for the LSTM model are shown in Figures 6-7.



```
Epoch 90/100
14/14 - 0s - loss: 0.0147 - val_loss: 0.0301 - 90ms/epoch - 6ms/step
Epoch 91/100
14/14 - 0s - loss: 0.0146 - val_loss: 0.0305 - 75ms/epoch - 5ms/step
Epoch 92/100
14/14 - 0s - loss: 0.0157 - val_loss: 0.0355 - 70ms/epoch - 5ms/step
Epoch 93/100
14/14 - 0s - loss: 0.0175 - val_loss: 0.0351 - 76ms/epoch - 5ms/step
Epoch 94/100
14/14 - 0s - loss: 0.0152 - val_loss: 0.0389 - 74ms/epoch - 5ms/step
Epoch 95/100
14/14 - 0s - loss: 0.0161 - val_loss: 0.0470 - 86ms/epoch - 6ms/step
Epoch 96/100
14/14 - 0s - loss: 0.0154 - val_loss: 0.0379 - 70ms/epoch - 5ms/step
Epoch 97/100
14/14 - 0s - loss: 0.0148 - val_loss: 0.0358 - 68ms/epoch - 5ms/step
Epoch 98/100
14/14 - 0s - loss: 0.0147 - val_loss: 0.0290 - 81ms/epoch - 6ms/step
Epoch 99/100
14/14 - 0s - loss: 0.0139 - val_loss: 0.0329 - 72ms/epoch - 5ms/step
Epoch 100/100
14/14 - 0s - loss: 0.0137 - val_loss: 0.0388 - 77ms/epoch - 5ms/step
```

Figure 6. LSTM model epoch and loss

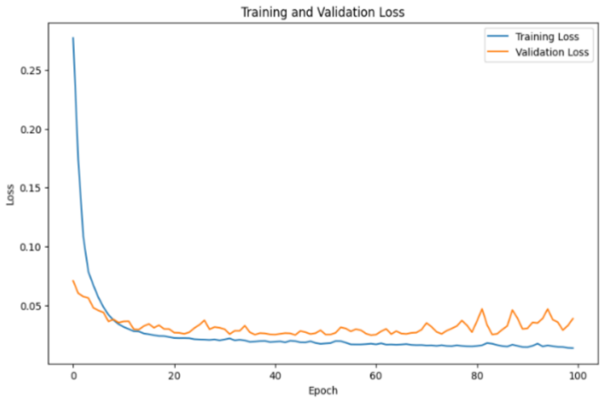


Figure 7. LSTM model training loss and validation loss plot

From Figures 6-7, we can see that using 100 epochs, the training and validation losses gradually decreased and were relatively balanced during the last 10 epochs. The training loss value is 0.0137 and the validation loss value is 0.0388 in the last epoch, which means there is no underfit or overfit for the LSTM model, which indicates that the model can be performed to predict the data.

3.4. Model Prediction Result

Figures 8–11 display the prediction findings for PM1.0 and PM2.5 based on the ARIMA and Hybrid ARIMA-LSTM models, and Table 4 displays the performance of the prediction assessment using RMSE and error ratio metrics.

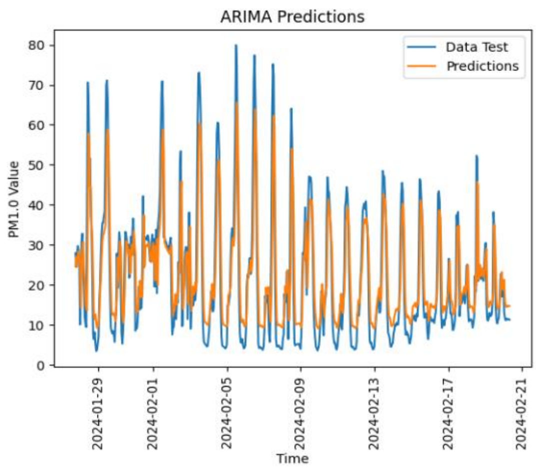


Figure 8 ARIMA PM1.0 prediction result

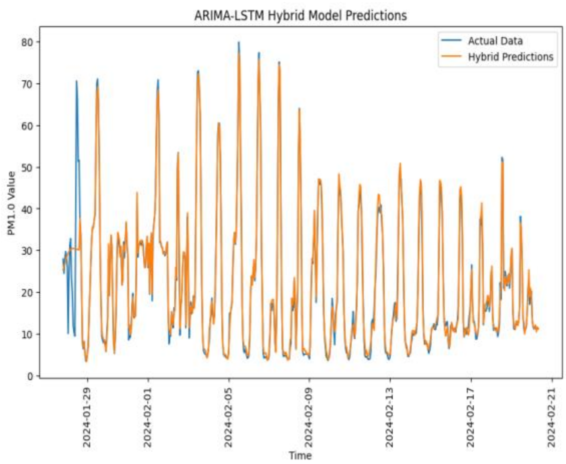


Figure 9 Hybrid ARIMA-LSTM PM1.0 prediction result

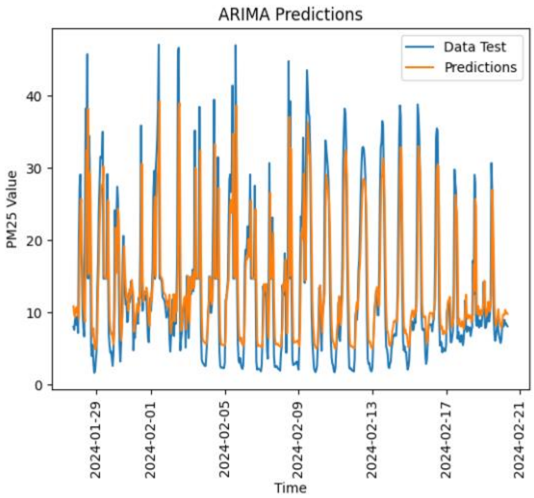


Figure 10 ARIMA PM2.5 prediction result

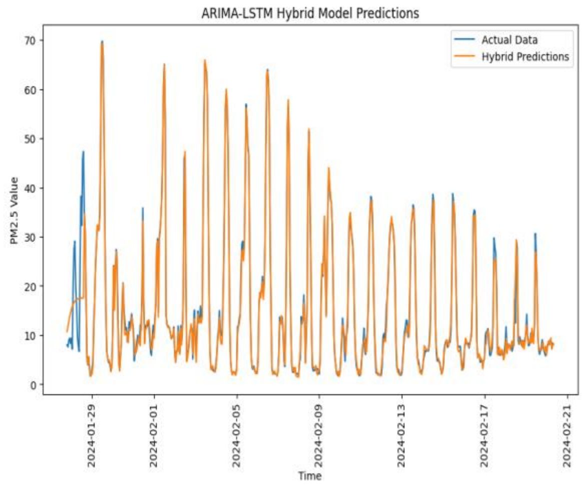


Figure 11 Hybrid ARIMA-LSTM PM2.5 prediction result

Based on Figures 8 and 10, it can be seen that the ARIMA model cannot predict the peak and valley from the original data since PM1.0 and PM2.5 have data fluctuation that brings unstable data values, and ARIMA has its limitations where it can't work properly when it meets the fluctuating data, while from Figures 9 and 11, the Hybrid ARIMA-LSTM model seems struggle to predict the data before January 29, 2024, it may caused by the additional noise or variability into the data, especially the original data contained high-frequency fluctuations or irregularities, but then start from January 29,2024 the prediction is good and improve than the ARIMA model since Hybrid ARIMA-LSTM model is able to capture long-term dependencies and handle variable-length sequences to gain robustness to noise which can achieve higher prediction accuracy.

Table 5. Prediction evaluation metrics

Features	RMSE ARIMA Model	RMSE Hybrid ARIMA-LSTM Model	Error Ratio ARIMA Model	Error Ratio Hybrid ARIMA-LSTM Model
PM1.0	8.29	3.54	0.45	0.22
PM2.5	6.61	2.68	0.66	0.19

From Table 5, we can see that the RMSE and error ratio values for the Hybrid ARIMA-LSTM model, respectively, are improved over the ARIMA model by around 57.30%, 51.11% for PM1.0, and 59.46%, 71.21% for PM2.5, which validates that the Hybrid ARIMA-LSTM model has a better prediction accuracy than the ARIMA model.

4. CONCLUSION

The research on air quality utilizing PM 1.0 and PM2.5 characteristics is presented in this article. The Hybrid ARIMA-LSTM model outperforms the ARIMA model in terms of PM1.0 and PM2.5 value prediction. The ARIMA model provides an RMSE value of 8.29 and an error ratio of 0.45 for PM1.0 concentration and an RMSE value of 6.61 and an error ratio of 0.66 for PM2.5 concentration. Conversely, the Hybrid ARIMA-LSTM model yields an RMSE value of 3.54, an error ratio of 0.22 for PM1.0, an RMSE value of 2.68, and an error ratio of 0.19 for PM2.5 concentration.

The ARIMA model cannot predict the peak and valley from the original data since PM1.0 and PM2.5 have data fluctuation that brings unstable data values, and ARIMA has its limitations where it can't work properly when it meets the fluctuating data. Meanwhile, the Hybrid ARIMA-LSTM model seems to struggle to predict the data before January 29, 2024, but starting from January 29, 2024, the prediction is better and improves than the ARIMA model since the Hybrid ARIMA-LSTM model can capture long-term dependencies and handle variable-length sequences to gain robustness to noise, which can achieve higher prediction accuracy.

Future research could explore optimizing the hybrid ARIMA-LSTM model by tuning its parameters and incorporating additional features, such as weather conditions or other environmental factors, to further enhance its prediction accuracy. Investigating the integration of other machine learning or deep learning models, like Convolutional Neural Networks (CNNs) or Gradient Boosting Machines (GBMs), could also improve the model's ability to capture complex patterns in air quality data. Additionally, expanding the study to include more diverse datasets from different industrial environments or geographic locations could provide insights into the model's generalizability and robustness. Lastly, exploring real-time prediction systems with continuous data updates could help in developing more responsive and adaptive air quality forecasting models.

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