

## Intelligent Dust Monitoring System Based on IoT

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### ABSTRACT

Dust is a frequent contributor to health risks and changes in the climate, one of the most dangerous issues facing people today. Desertification, drought, agricultural practices, and sand and dust storms from neighboring regions bring on this issue. Deep learning (DL) long short-term memory (LSTM) based regression was a proposed solution to increase the forecasting accuracy of dust and monitoring. The proposed system has two parts to detect and monitor the dust; at the first step, the LSTM and dense layers are used to build a system using to detect the dust, while at the second step, the proposed Wireless Sensor Networks (WSN) and Internet of Things (IoT) model is used as a forecasting and monitoring model. The experiment DL system train and test part was applied to dust phenomena historical data. Its data has been collected through the Iraqi Meteorological Organization and Seismology (IMOS) raw dataset with 170237 of 17023 rows and 10 columns. The LSTM model achieved small time, computationally complexity of, and layers number while being effective and accurate for dust prediction. The simulation results reveal that the model's mean square error test reaches 0.12877 and Mean Absolute Error (MAE) test is 0.07411 at the same rates of learning and exact features values of vector in the dense layer, representing a neural network layer deeply is connected to the LSTM training proposed model. Finally, the model suggested enhances monitoring performance.

**Keywords:** IoT (Internet of Things), Dust prediction, WSN (Wireless Sensor Network), Deep Learning (DL), Long Short-Term Memory (LSTM).

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## نظام مراقبة الغبار على أساس إنترنت الأشياء

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### الخلاصة

يساهم الغبار بشكل متكرر في المخاطر الصحية والتغيرات في المناخ ، وهو يعد من أحد أخطر المشكلات التي تواجه الناس اليوم. ويؤدي التصحر والجفاف والممارسات الزراعية والعواصف الرملية والترابية من المناطق المجاورة إلى هذه المشكلة. تم اقتراح الانحدار الجديد القائم على التعلم العميق للذاكرة قصيرة المدى لزيادة دقة التنبؤ بالغبار والمراقبة. يتكون النموذج المقترح من مرحلتين لكشف الغبار ومراقبته ؛ في المرحلة الأولى ، يتم استخدام ذاكرة طويلة قصيرة الامد والطبقات الكثيفة لبناء نظام يستخدم للتنبؤ ورصد الغبار ، بينما في المرحلة الثانية ، يتم استخدام نموذج شبكة الاستشعار و إنترنت الأشياء المقترح كنموذج للتنبؤ والمراقبة. تم تطبيق تدريب نظام التعلم العميق وجزء الاختبار على البيانات التاريخية لظاهرة الغبار. تم جمع بياناتها من خلال مجموعة البيانات الأولية لهيئة الانواء الجوية وعلم الزلازل العراقية مع 170237 من 17023 صفًا و 10 أعمدة. حقق نموذج التعلم العميق وقتًا أقل وتعقيدًا حسابيًا وعددًا من الطبقات بينما كان أكثر موثوقية من الخوارزميات الأخرى المطبقة على التنبؤ بالغبار. كشفت النتائج أن اختبار متوسط الخطأ المربع للنموذج يصل إلى 0.12877 ومتوسط اختبار الخطأ المطلق هو 0.07411 في نفس معدلات التعلم ونفس قيم متجه الميزات في الطبقة الكثيفة ، والتي تمثل طبقة شبكة عصبية متصلة بعمق بتدريب النموذج المقترح . أخيرًا ، يعزز النموذج المقترح أداء التنبؤ المراقبة.

**الكلمات المفتاحية:** إنترنت الأشياء, التنبؤ بالغبار, شبكة الاستشعار اللاسلكي, التعلم العميق, ذاكرة طويلة قصيرة الامد.

## 1. INTRODUCTION

According to the World Health Organization (WHO), dust kills seven or more than a million people worldwide, and nine out of 10 people breathe it. Dust causes respiratory issues and heart and lung disease hospitalization (**Manisalidis et al., 2020**). Long-term dust exposure damages plant leaves, affecting people and plants (**Haleem et al., 2019**). The study area consists of five stations located in the governorates of central and southern Iraq that have certified World Meteorological Organization (WMO) standards, as shown in **Table 1**.

**Table 1.** The area study

No.	Province/state	Station id	Longitude (° ")	Latitude (° ")
1	Baghdad - Airport	650	44.24	33.18
2	Kut	664	45.49	32.30
3	Karbala	656	44.03	32.34
4	Najaf	670	44.19	31.57
5	Hilla	657	44.07	32.07

Of all the provinces in Iraq, Baghdad, the capital city, has the highest population density. Twenty-one percent of the nation's population resides in the city. With a population of



almost 9 million and a total area of 5169 km<sup>2</sup>, this province is a popular travel destination for business, religious, and economic travelers (**Shafiqu and Hanna, 2016**). There are seven million people living in the provinces of Kut, Karbala, Najaf, and Hilla in addition to Baghdad. In the central parts of Iraq, the precise cause of sand and dust storms at specific wind speeds, directions, and ranges of visibility (RoV) is unknown (**Awadh, 2023; Ghazal, 2020**). The terms "sandstorm" and "dust storm" are often used interchangeably since the difference between them is minimal (**Shi et al., 2020; Joodi, 2023**). However, some experts differentiate between the two Based on soil particle size. When the particles are between 0.6 and 1 millimeter, it is a sandstorm, if smaller than 0.6 mm it is a dust storm. Desert dust storms are most commonly caused by the wind carrying particles of silt and clay measuring over 0.5 mm in diameter (**Darvish et al., 2023**). Dust is a common feature of arid and semi-arid climates, which experience climatic variation that causes sand and dust to travel distances long and rise, resulting in dust storms the phenomenon known (**Correa et al., 2023**).

As predicting dust storms is a pressing concern in contemporary times, DL has presented many research prospects (**Booz et al., 2019**). DL has become a valuable tool by accurately forecasting dust and addressing all issues related to dust changes in the study area (**Gholami and Mohammadifar, 2022**). One way to accomplish this is by implementing an artificially intelligent procedure that employs artificial DL algorithms such as (LSTM) and a dense layer in the last layer network (**El-Habil and Abu-Naser, 2022; Kubheka, 2023**), these algorithms can simulate input data nonlinear with synthetic mechanism to dust study (**Parveen et al., 2022**). The sensor station enters the test data on the trained DL system, which is formed via a cloud, where the sensor station consists of a dust sensor to detect all dust particles in the atmosphere (**Ganji et al., 2023**). The wind direction and speed sensors were used for the speedy detection of dust and to inform the authorities to take the necessary measures to reduce the effects of Harmful negatives (**Ghadi and Salman, 2022**). This paper provides useful information about dust levels from five different governorates whose data were collected from (IMOS) from 2018 to 2022, whose advantages are low cost and low energy, as well as many sensors that can connect to it, and ease of understanding and programming.

The increasing expansion of the Internet of Things systems and sensors has led to heightened awareness of dust monitoring. Here overview of some studies provides about dust prediction and monitoring. In (**He et al., 2016**), the concentration of PM10 was studied in urban using deep neural networks to forecast. The study by (**Hojaiji et al., 2017**) used convolutional neural networks (CNNs) to forecast dust concentration levels in dry and semi-arid climatic zones employing meteorological data, and air quality monitoring station information. Models for satellite-based dust storm forecasting were trained using (CNNs) and (LSTM) networks by (**Pullan et al., 2020**), to train the model. Dust concentrations were measured using meteorological and satellite data. Forecast dust storms by using DL, the network was built using a deep neural network, dust storm forecasting method was applied to Ahvaz, Iran, in a case study (**Querol et al., 2019**). Researchers found that hybrid methodologies are better at identifying dust storms and estimating horizontal visibility than conventional image processing techniques and statistical models. Data from air quality monitoring stations and meteorological data were used to train the model. The study presents a novel approach by introducing a fast hybrid deep neural network prediction model, representing a big improvement over the previous technique. In (**Li et al., 2021; Saleh, 2023**). In (**Li et al., 2021; Saleh, 2023**), In this article, a deep-learning method is presented for monitoring and predicting open-pit dust. Using dust monitoring data from the



mine, the authors construct a deep learning model based on CNNs and LSTMs. Statistical models are compared with the model for predicting real-time dust concentrations. With DL, dust concentrations are predicted more accurately and with fewer errors than with statistical models. Monitoring and warning of high dust concentrations in real time reduces dust's health and safety risks. In (Zhu et al., 2023; Joodi, et al., 2022), For health reasons, indoor air quality needs to be monitored. There are air quality monitoring systems available. They're expensive and hard to come by. Thus, very few individuals use them. The Internet of Things (IoT) has made monitoring indoor air quality (IAQ) easier, and a lot of research has been done on IAQ monitoring using IoT. An inexpensive Internet of Things gadget is the IAQ monitoring system. The Message Queuing Telemetry Transport (MQTT) protocol allows real-time display of IoT sensor data on a dashboard. AI is used to anticipate future CO<sub>2</sub> concentrations by analyzing CO<sub>2</sub> data. approach can forecast a steady state with a 5.5% error margin using calculated CO<sub>2</sub> concentration. In (Paithankar, 2023), The development of industry and transportation has made monitoring air quality a priority these days. introduce an innovative Internet of Things-based air quality monitoring solution. Every city in the country has put in place a hardware-software air quality monitoring system. The findings demonstrate that the recommended method can reliably track changes in air quality and identify trends in those changes.

The aim of this work develop an accurate, fast, and reliable dust forecasting system. A variety of error types are computed, such as Mean Square Error (MSE), Root Mean Absolute Error (RMAE), and Root Mean Square Error (RMSE). Climate change and non-essential information disruptions like temperature, precipitation, and humidity could affect the results of regression and identification in the proposed weather variable forecasting system, a WS, WD, and RoV-based Using wind to anticipate dust.

## 2. SYSTEM DESIGN AND IMPLEMENTATION

### 2.1 Proposed Model LSTM-Based Prediction

Neural networks are superior to others, recurrent neural networks (RNNs), and are a well method for time series forecasting (Tagliabue et al., 2021). RNN loops allow networks to communicate temporally in a single layer. using both current input and historical data to make a ruling. An issue with RNNs is gradient vanishing, which can be problematic when dealing with large quantities of data in time series the study by (Kumari and Singh, 2022). This issue can be resolved by the upgraded RNN with a memory issue, LSTM. LSTM consists of four layers, input gate, forget gate, output gate, and updated. Compared to RNN, forget gate input data is high storage. By systemizing information flow and avoiding gradients from inflating, LSTM addresses this challenge of difficult time series. These are issues with traditional RNNs (Low, 2020). Accordingly, LSTM is a state-of-the-art technique for time series prediction (Li et al., 2019). In this work, the data was first split into two portions: 30% was set aside for testing and 70% for training. Following this, the data underwent reprocessing. Second, to test the suggested method, performance metrics for various stages were read by referring to various periods and proving the system's effectiveness. Ultimately, following the suggested system's success, it was linked to a sensing station equipped with WS, WD, and RoV sensors. The proposed station's data was then processed to track these phenomena and forecast dust. **Fig. 1** depicts the proposed model architecture. **Table 2.** illustrates the architecture that proposes an LSTM model with a monitoring system. **Table 3.** illustrates the IMOS types of dust appearing by number code.

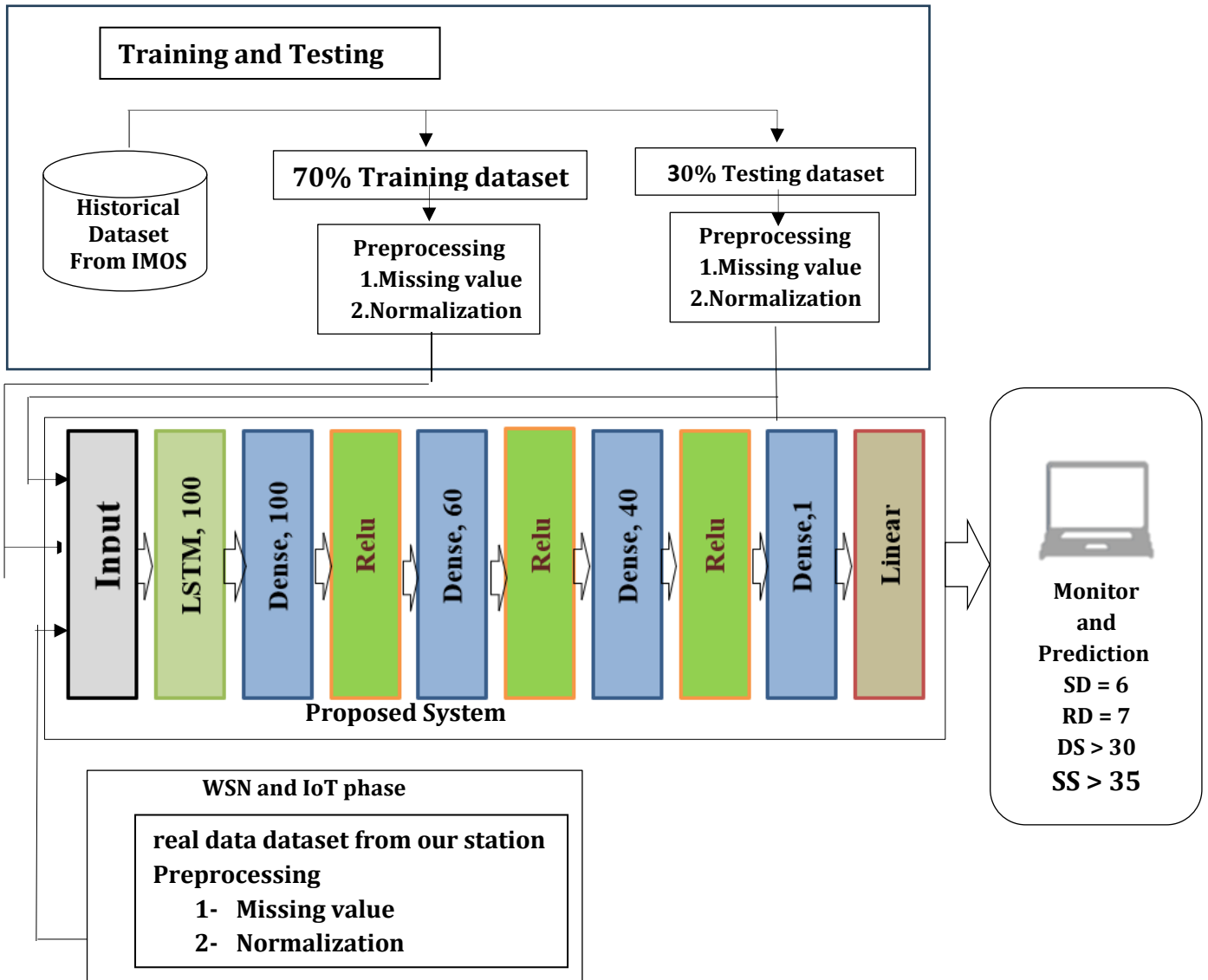


Figure 1. Flowchart of the proposed methodology.

Table 2. The architecture proposes an LSTM model with a monitoring system

Layer (Type)	Output Shape	Parameters
LSTM	100	80400
Dense-1	100	10100
Dense-2	60	6060
Dense-3	40	3050
Dense-4	1	51
Activation function 1	Relu =3	0
Activation function 2	Linear =1	0
Optimizer	Last dense layer	ADAM
Batch Size	125	0
Epochs	100	0
Loss function	MAE, MSE, RMAE, RMSE	0
Lookbacks (Test)	Time index (Hourly)	10,50,100,200,300,400)

**Table 3.** IMOS types of dust appearing by number code

Events type	Horizontal visibility (km)	Wind speed (m/sec)	Particle diameter (µm)	Number code
Suspended Dust (SD)	0 – less than 10	0 – 7	Less than1	6
Rising Dust (RD)	1 – less than 10	>8	1 – 10	7
Dust Storm (DS)	Less than 1	>8	Less than100	>30
Sand Storm (SS)	Less than1	>8	250	>35

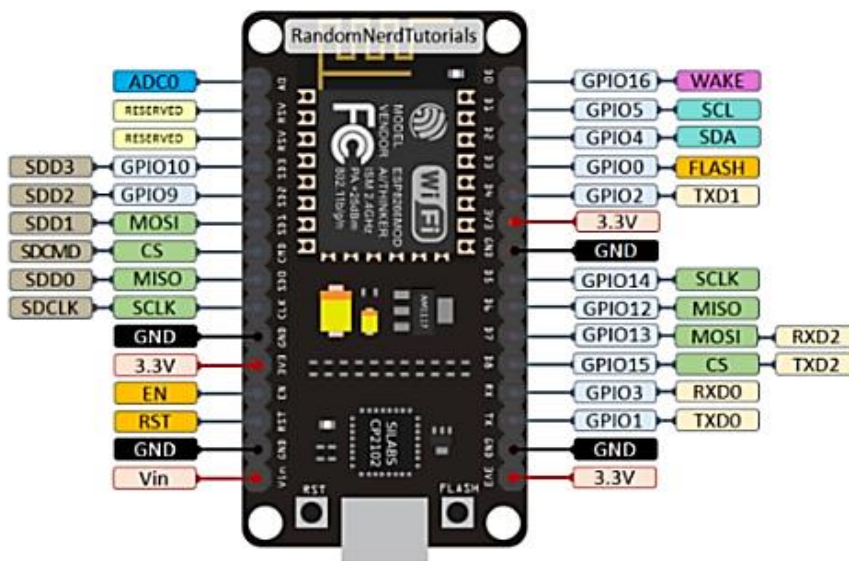
## 2.2 Hardware Specification

### 2.2.1 Experimental Setup

Experiments and results were aggregated on a computer device running by Windows 20 hertz version 64-.bit, processor worked at 2.80 GHz, Intel 8-core, and RAM with 8192 MB. The prediction system on algorithms used Python version 3.6.5 writing window with coupling by Keras, TensorFlow was applied to DTR, SGD, GBR, BRR, and LR.

### 2.2.2 ESP8266 NodeMCU

ESP8266 NodeMCU is a node microcontroller unit and Wi-Fi Module, as shown in **Fig. 2**. The ESP8266 is a cheap Wi-Fi chip with a TCP/IP stack and a microcontroller. It allows the system to connect to Wi-Fi and operates at 3.3V (Tulenkov et al., 2018; Abd Halim et al., 2023).



**Figure 2.** Wi-Fi Module (ESP8266)

### 2.2.3 Dust sensor DSM501A

Dust sensor affordable dust sensor module is the DSM501A. Greater than 1 micron-diameter fine particles can be detected by it (Mallewari and Mohana, 2023). **Fig. 3** shows dust sensor DSM501A.





**Figure 3.** Dust sensor DSM501A

#### 2.2.4 Wind speed and wind direction

Wind direction sensor, it shows the wind's azimuth direction relative to a fixed location. An anemometer measures wind speed. Meteorology, weather stations, environmental monitoring, renewable energy systems, aviation, and other wind data applications use wind speed sensors (Shi et al., 2019; Salih and Saleh, 2022). Fig. 4 illustrates the wind speed and wind direction sensors.



**Figure 4.** (a) wind direction and (b) wind speed sensors.

### 3. RESULTS AND DISCUSSION

#### 3.1 Dataset and Pre-Processing

IMOS and its accredited stations spread across Iraq collect hourly historical data about the devices used for monitoring and the location of the stations. In central Iraq, five stations were tested in five governorates. As illustrated in the following diagram, the raw data contain dust phenomena such as wind speed (WS), wind direction (WD), visibility range (RoV), circumference (W1W1), past weather (WW), as well as time and date. in **Table 4**. After dividing the data into two parts and processing it by normalization improved the data quality, as in Eq. (1). normalized range [0, 1] Data gaps can occur due to equipment faults or other uncontrollable factors. Multiple missing values were removed from data records. Only one missing weight could be filled using linear interpolation (Ajmeera and Vasumathi, 2020; Pallavi et al., 2020). Data processing yielded 17,023 valid sets out of 17237.

$$x_{range} = (x - x_{min}) / (x_{max} - x_{min}) \quad (1)$$



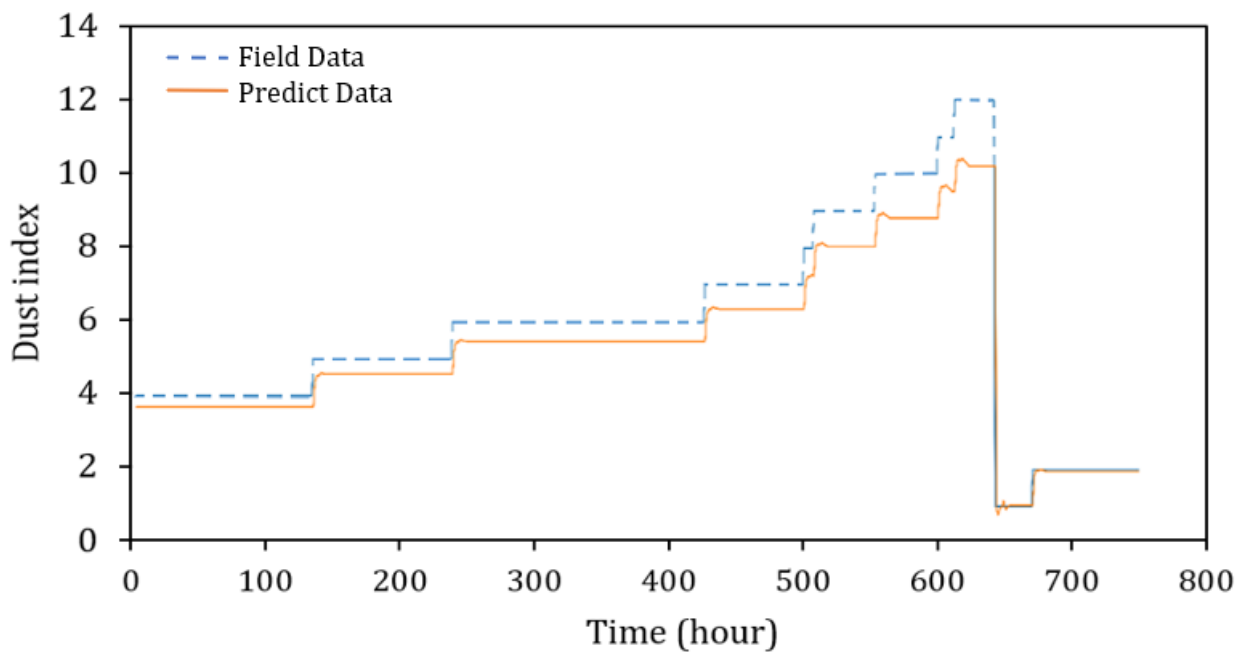
Where  $x$  is the original value,  $x_{min}$  and  $x_{max}$  represent the minimum and maximum values of the feature in the dataset, respectively.

**Table 4.** IMOS dataset dust phenomena used in our experiment

Station	Year	Month	Day	Hour	RoV	WD	WS	WW	W1W1
650	2018	01	01	13	57	240	01	06	11
650	2018	01	01	14	57	160	02	06	00
650	2018	01	01	15	58	130	02	06	11
650	2018	01	01	16	56	140	02	06	11
650	2018	01	01	17	56	160	04	06	00
650	2018	01	01	18	57	160	01	06	00
650	2018	01	01	19	57	170	02	06	00
650	2018	01	01	20	57	170	03	06	00

### 3.2 Training

The effect of lookback on accuracy was analyzed in how changing the lookback value affects the accuracy metrics of the LSTM model. Plotting these metrics against different lookback hourly values can help visualize the relationship between lookback and prediction. From **Figs. (5 - 10)**, it can be shown that all the types of errors decreased when the lookback time index increased, which processed the dataset. The binary cross-entropy loss across the training and testing sets was evaluated using a batch size of 125.100 epochs used throughout the training procedure, and a look back time index hourly with 10, 50, 100, 200, 300, and 400 value dept was selected. **Fig. 5** shows the variance between the field data and the predicted data at the lookback value of 10 hours.



**Figure 5.** The accuracy with 10 lookbacks time index.

**Fig. 6** shows the variance between the field data and the predicted data at the lookback value of 50 hours.



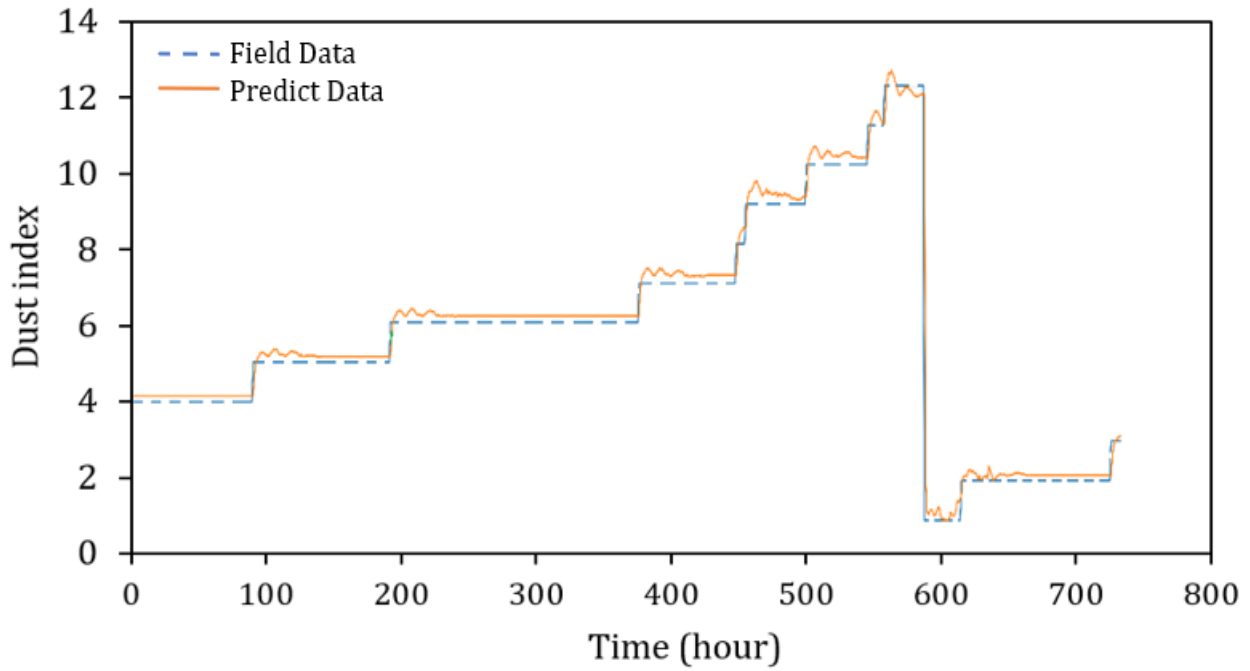


Figure 6. The accuracy with 50 lookbacks time index.

Fig. 7 shows the variance between the field data and the predicted data at the lookback value of 100 hours.

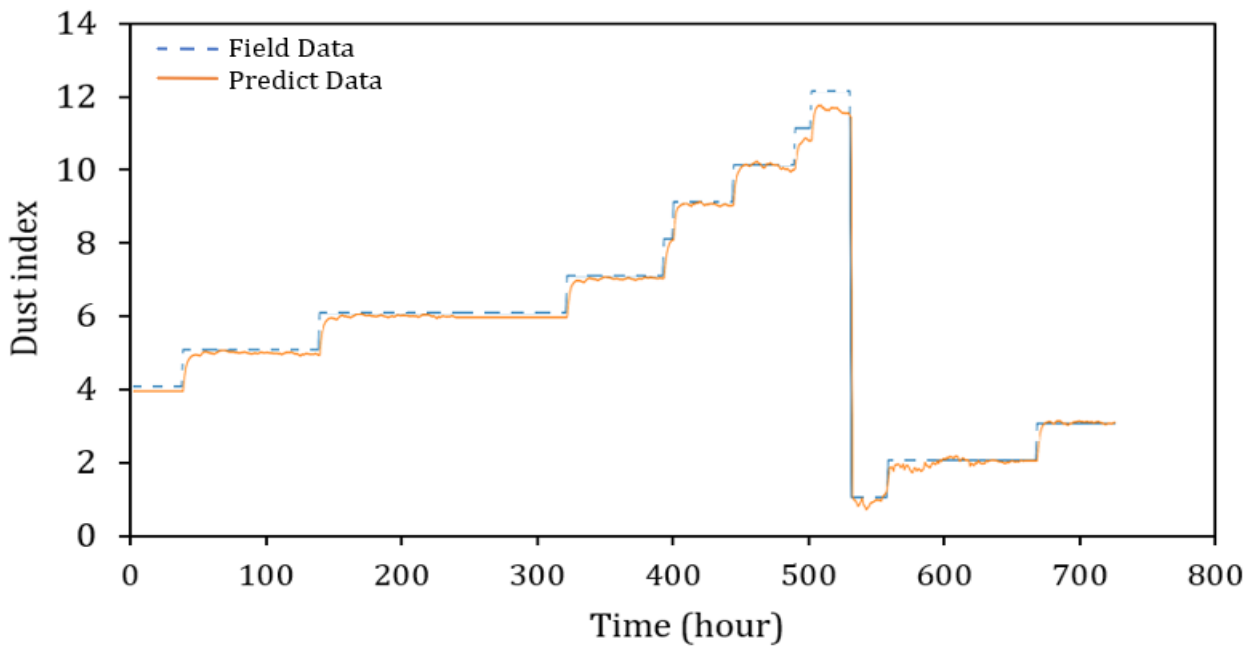


Figure 7. The accuracy with 100 lookbacks time index.

Fig. 8 shows the variance between the field data and the predicted data at the lookback value of 200 hours.

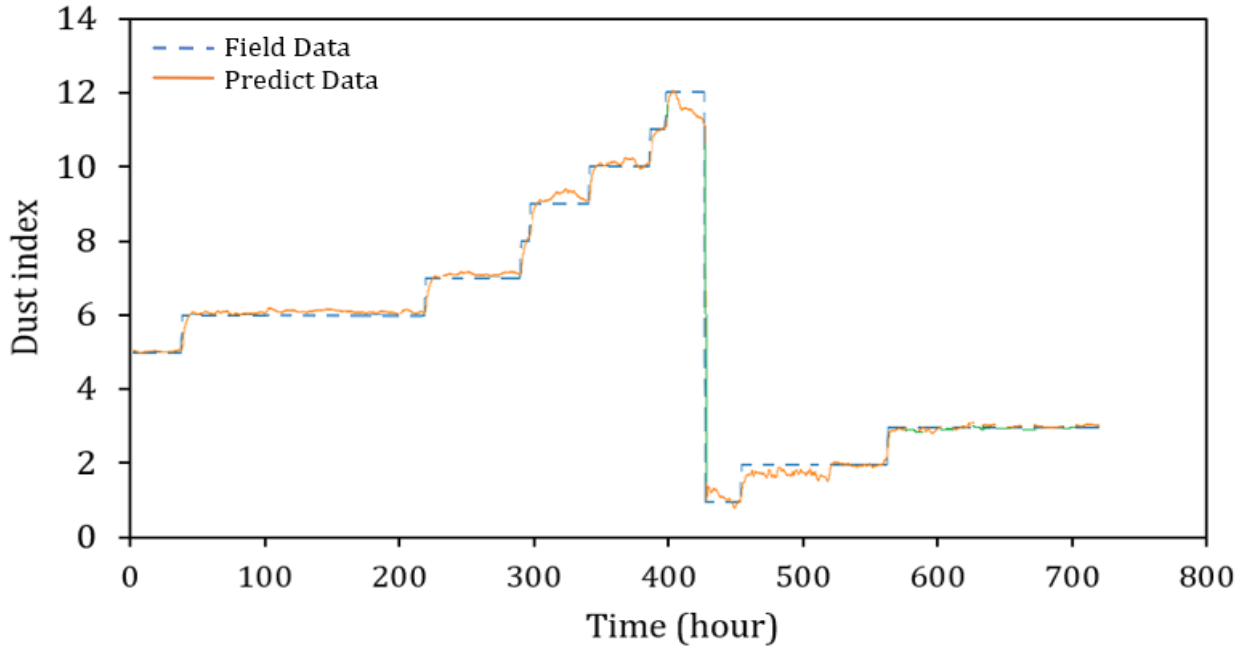
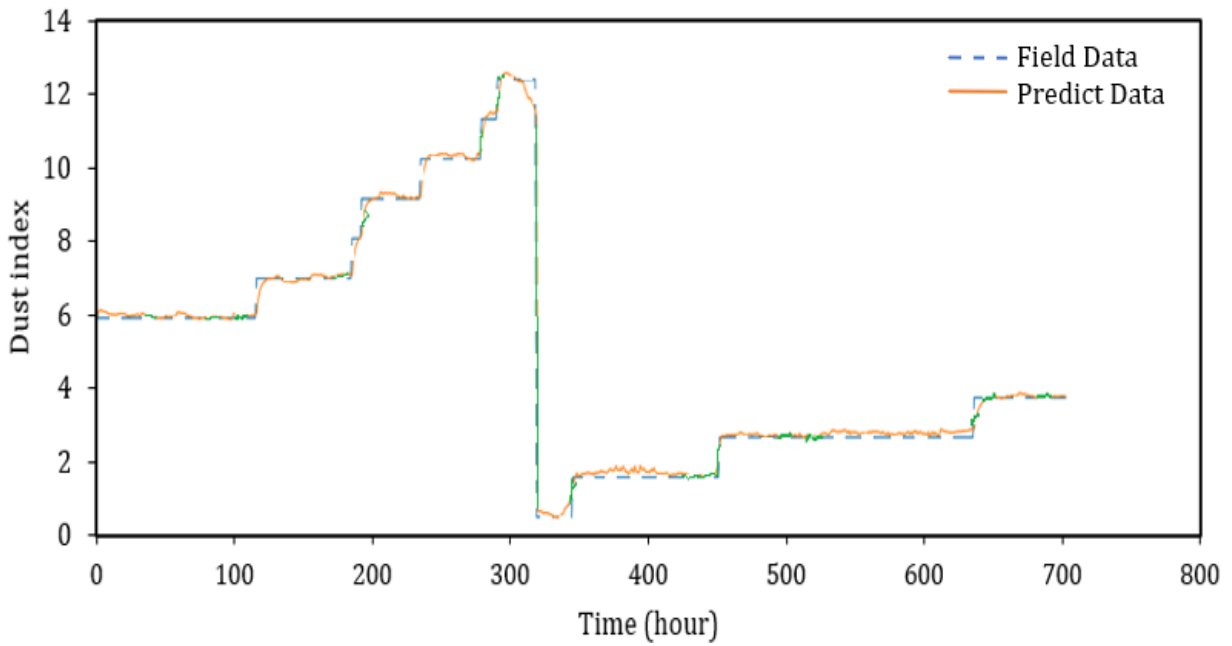
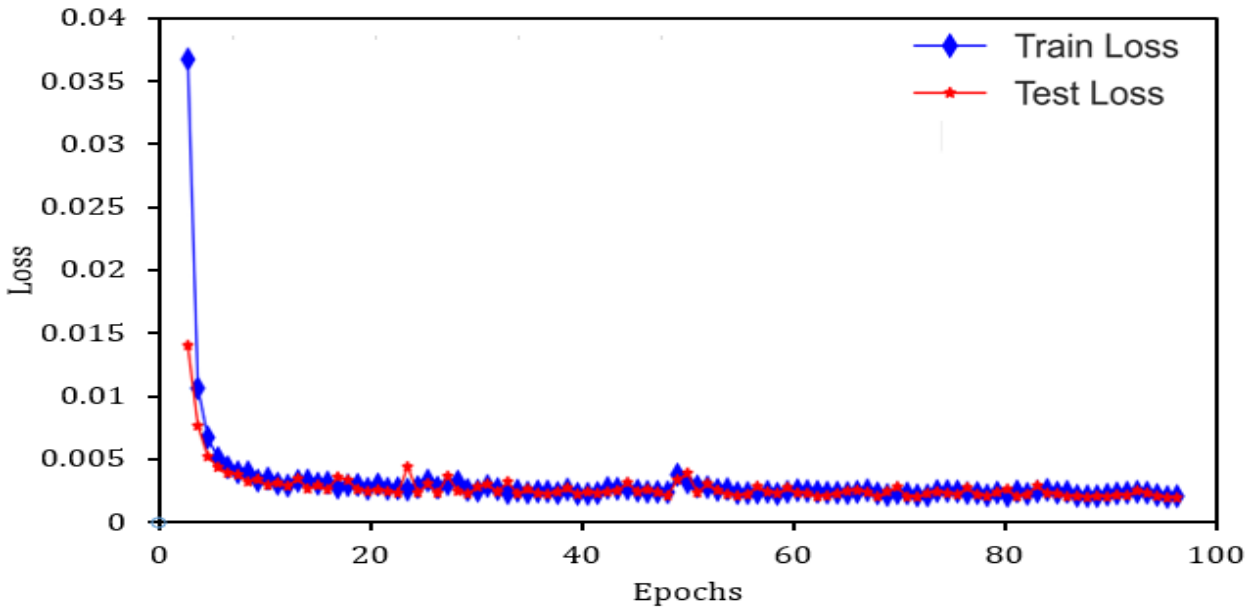


Figure 8. The accuracy with 200 lookbacks time index.

Fig. 9a shows the variance between the field data and the predicted data at the lookback value of 300 hours, with dataset augmentation. The loss estimates for training and testing data decreased as shown in Fig. 9b.



(a)



(b)

Figure 9. (a) the accuracy with 300 lookbacks time index, (b) dataset values with train and test loss.

Fig. 10 shows the variance between the field data and the predicted data at the lookback value of 400 hours.

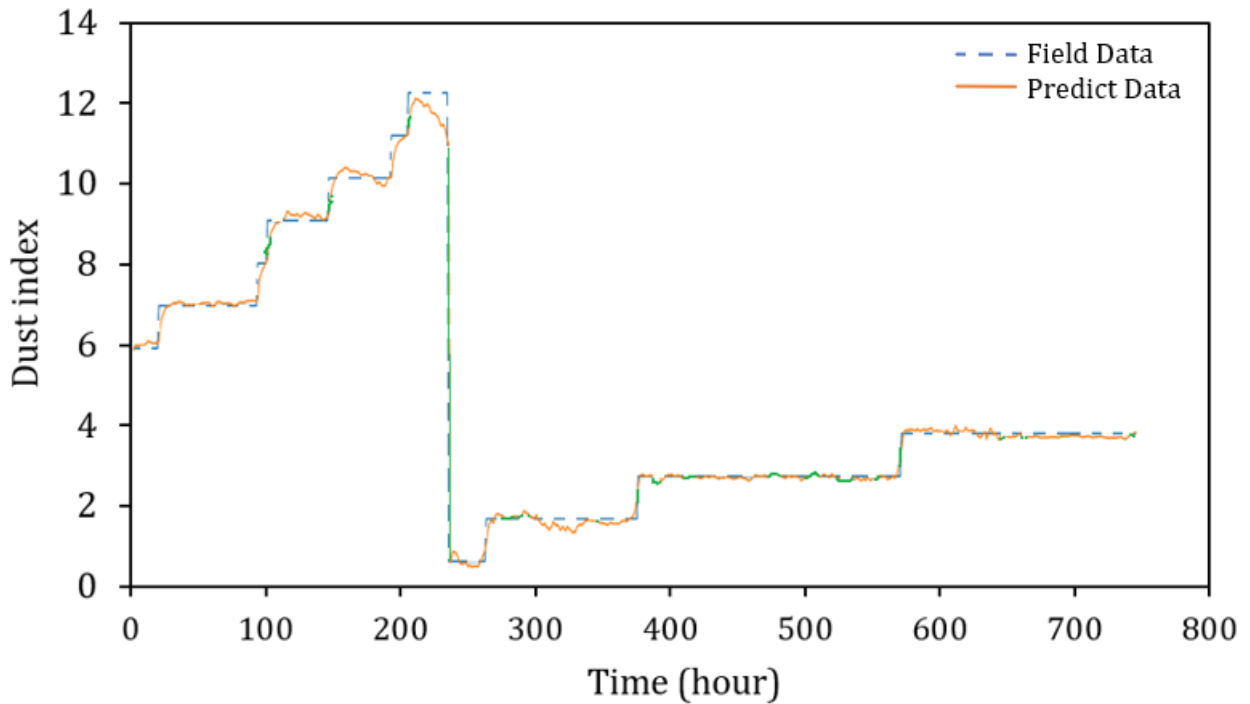


Figure 10. The accuracy with 400 lookbacks time index.



### 3.3 Performance

The prediction models are assessed using four assessment measures: (RMSE), (MAE), (RMAE), and (MSE) as tabulated in **Table 5**. was computed average by the difference between the original values and forecasted values using MAE (**Hodson, 2022; Warrens and Jurman, 2021**). As a result, we can assess the symmetry between the actual data and the forecast value. By using MAE can calculated by using Eq. (2), and **Fig. 11**. shows the MAE with different lookbacks.

$$MAE = \frac{1}{N} \times \sum_{i=1}^N |O_i - P_i| \tag{2}$$

Where  $O_i$  represents the projected values,  $N$  is the sample size, , and  $P_i$  represents the actual values. MSE is the average squared difference between actual and anticipated values. It is utilized to assess the precision of regression problems.

MSE is calculated by using Eq. (3), and **Fig. 12**. shows the MSE with different lookbacks.

$$MSE = \frac{1}{N} \times \sum_{i=1}^N |O_i - P_i|^2 \tag{3}$$

By smaller RMAE better model performance is shown, with a value of zero signifying perfect prediction accuracy. RMAE is calculated by using Eq. (4), and **Fig. 13**. shows the RMAE with different lookback.

$$RMAE = \frac{1}{N} \sum_{i=1}^N \frac{|O_i - P_i|}{A_i} \tag{4}$$

On the other hand, RMSE stands for Root Mean Squared Error (*RMSE*), a commonly used metric to measure the difference between predicted and actual values in a regression problem. It is calculated as the square root of the average of the squared differences between predicted and actual values. Finally,

RMSE is calculated by using Eq. (5), and **Fig. 14**. shows the RMSE with different lookback.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (P_i - O_i)^2} \tag{5}$$

**Table 5.** Evaluating error in each hybrid model with a set with different lookback times.

Performance measures	Lookback of Hyper LSTM					
	10	50	100	200	300	400
MAE	0.50508403	0.20370877	0.13753016	0.11979844	0.09994719	0.09080752
MSE	0.43776502	0.16743952	0.14521642	0.10679299	0.08255273	0.07897825
RMAE	0.71069264	0.45134108	0.37085059	0.34611912	0.3013428	0.31614426
RMSE	0.66163813	0.40919374	0.38107272	0.32679197	0.28731992	0.2810307

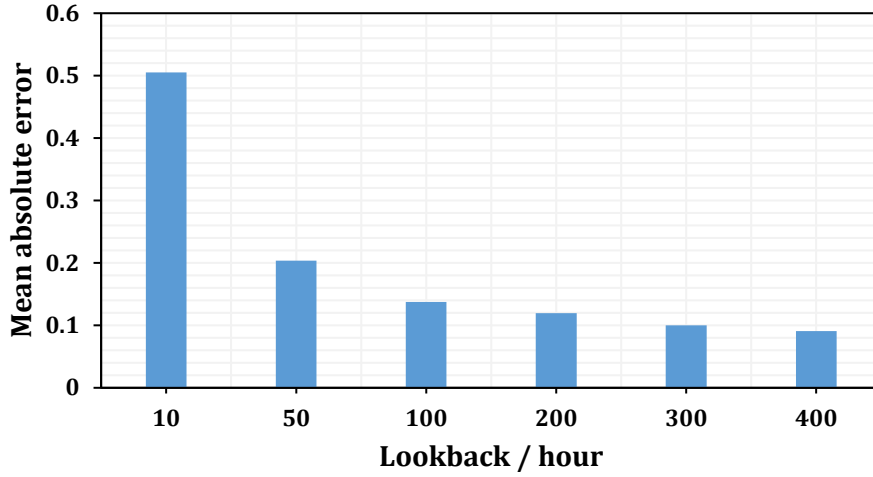


Figure 11. MAE for different time indexes (lookback/hour).

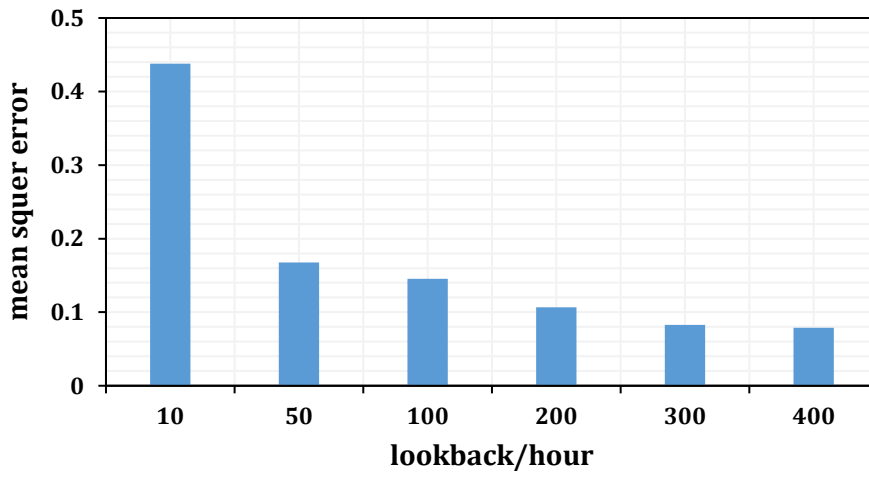


Figure 12. MSE for different time indexes (lookback/hour).

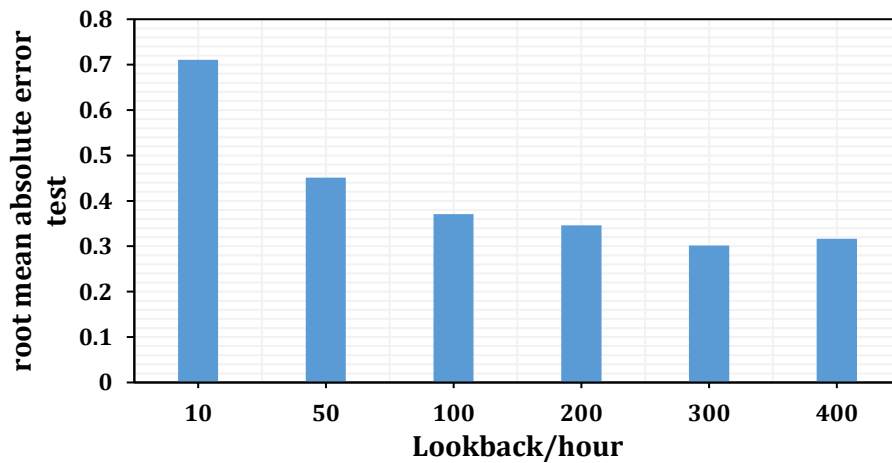
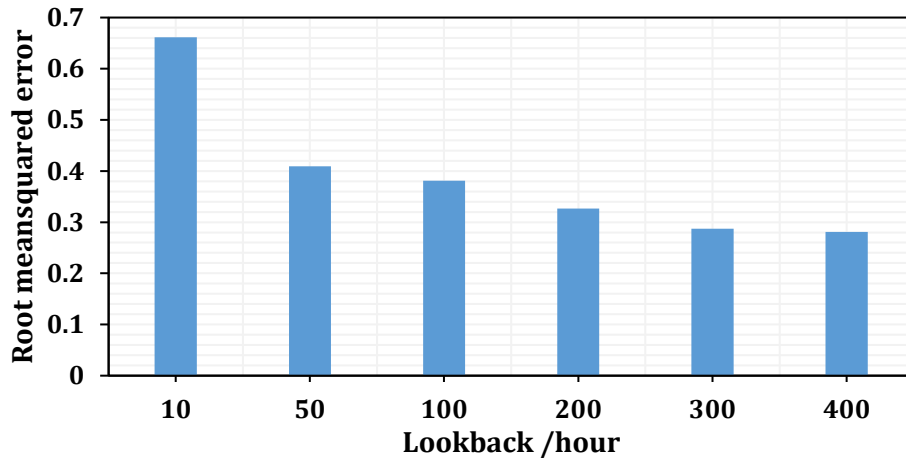


Figure 13. RMAE for different time indexes (lookback/hour).



**Figure 14.** RMSE for different time indexes (lookback/hour)

### 3.4 Test Prediction System

To monitor dust through different dust phenomena related to weather and climate using WSN and IoT. Accessing a deep-trained system from anywhere (a weather station containing sensors and monitoring devices) via the Cloud, which is installed on the roof of a building to obtain dust phenomena correctly and is transferred to the computer as a cloud via the HTTP protocol between the NodeMCU installed in the terminal to the calculator by connecting them to Wi-Fi with the same network defined by the advanced IP scanner program after designing an interface via Python; Dust phenomena such as wind speed, direction, and visibility are monitored based on a built-from-scratch proposed LSTM training model for dust forecasting. **Fig. 15** shows the equipment station it contains a wind speed sensor, wind direction sensor, dust sensor DSM501A, and MAX485 TTL to RS485 module converter.



**Figure 15.** Compact station from the top view





## 5. CONCLUSIONS

This work presented a monitoring dust phenomena and dust prediction, through WSN and IoT, within a proposed LSTM. With two parts, the DL part is applied to an hourly historical dataset collected by IMOS. The main idea is to enable the system to test the proposed system. The second part is a simple cloud-based system with regression applied to online data from the sensors used in our experiment. The main idea is to enable the system to monitor and forecast dust. To monitor dust through different dust phenomena related to weather and climate using WSN and IoT. Accessing a deep-trained system from anywhere (a weather station containing sensors and monitoring devices) via the Cloud.

### Nomenclature

Symbol	Description
$N$	Sample Size
$O_i$	Projected Values
$P_i$	Actual Values
$A_i$	Actual Value For The I-Th Data Point

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### Credit Authorship Contribution Statement

Ali Y. Hassan: Writing – original draft. Muna Hadi Saleh: Writing – review & editing, Validation, Conceptualization.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## REFERENCES

- Abd Halim, A.A., Mohamad, R., Rahman, F.Y.A., Harun, H. and Anas, N.M., 2023. IoT based smart irrigation, control, and monitoring system for chilli plants using NodeMCU-ESP8266. *Bulletin of Electrical Engineering and Informatics*, 12(5), pp. 3053-3060. Doi: [10.11591/eei.v12i5.5266](https://doi.org/10.11591/eei.v12i5.5266)
- Awadh, S.M., 2023. Impact of North African sand and dust storms on the Middle East using Iraq as an example: Causes, sources, and mitigation. *Atmosphere*, 14(1), p.180. Doi: [10.3390/atmos14010180](https://doi.org/10.3390/atmos14010180)
- Booz, J., Yu, W., Xu, G., Griffith, D. and Golmie, N., 2019. A deep learning-based weather forecast system for data volume and recency analysis. In *2019 International Conference on Computing, Networking and Communications (ICNC)*, pp. 697-701. IEEE. Doi:[10.1109/ICNC.2019.8685584](https://doi.org/10.1109/ICNC.2019.8685584)
- Chicco, D., Warrens, M.J. and Jurman, G., 2021. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression analysis evaluation. *PeerJ Computer Science*, 7, P.e623. Doi:[10.7717/peerj-cs.623/table-1](https://doi.org/10.7717/peerj-cs.623/table-1)



Correa, M.A., Franco, S.A., Gómez, L.M., Aguiar, D. and Colorado, H.A., 2023. Characterization methods of ions and metals in particulate matter pollutants on PM<sub>2.5</sub> and PM<sub>10</sub> samples from several emission sources. *Sustainability*, 15(5), P. 4402. [Doi: 10.3390/su15054402](https://doi.org/10.3390/su15054402)

Darvishi Bolorani, A., Soleimani, M., Papi, R., Neysani Samany, N., Teymouri, P. and Soleimani, Z., 2023. Sources, drivers, and impacts of sand and dust storms: a global view. In *Dust and Health: Challenges and Solutions* (pp. 31-49). Cham: Springer International Publishing. [Doi:10.1007/978-3-031-21209-3\\_3](https://doi.org/10.1007/978-3-031-21209-3_3)

El-Habil, B.Y. and Abu-Naser, S.S., 2022. Global climate prediction using deep learning. *J Theor Appl Inf Technol*, 100, p.24.

Gholami, H. and Mohammadifar, A., 2022. Novel deep learning hybrid models (CNN-GRU and DDL-RF) for the susceptibility classification of dust sources in the Middle East: a global source. *Scientific Reports*, 12(1), p.19342. [Doi: 10.1038/s41598-022-24036-5](https://doi.org/10.1038/s41598-022-24036-5)

Joodi, M.A., Saleh, M.H. and Kadhim, D.J., 2022. A proposed 3-stage CNN classification model based on augmentation and denoising. *International Journal of Nonlinear Analysis and Applications*. pp. 1–20. [Doi: 10.22075/IJNAA.2022.27970.3770](https://doi.org/10.22075/IJNAA.2022.27970.3770)

Joodi, M.A., Saleh, M.H. and Khadhim, D.J., 2023. Proposed face detection classification model based on Amazon Web Services Cloud (AWS). *Journal of Engineering*, 29(4), pp.176-206. [Doi: 10.31026/j.eng.2023.04.12](https://doi.org/10.31026/j.eng.2023.04.12)

Haleem, A.M., Al-Obaidy, A.H.M. and Haleem, S.M., 2019. Air quality assessment of some selected hospitals within Baghdad city. *Engineering and Technology Journal*, 37(1), pp.59-63. [Doi: 10.30684/etj.37.1C.9](https://doi.org/10.30684/etj.37.1C.9)

He, H., Gao, Y. and Zhang, Z., 2016, May. The urban road dust monitoring system based on ZigBee. In *2016 Chinese Control and Decision Conference (CCDC)* (pp. 1793-1796). IEEE. [Doi: 10.1109/CCDC.2016.7531272](https://doi.org/10.1109/CCDC.2016.7531272)

Hodson, T.O., 2022. Root-Mean-Square Error (RMSE) or Mean Absolute Error (MAE): When to use them or not. *Geoscientific Model Development*, 15(14), pp. 5481-5487. [Doi:10.5194/gmd-15-5481-2022](https://doi.org/10.5194/gmd-15-5481-2022)

Hojaiji, H., Kalantarian, H., Bui, A.A., King, C.E. and Sarrafzadeh, M., 2017, March. Temperature and humidity calibration of a low-cost wireless dust sensor for real-time monitoring. In *2017 IEEE Sensors Applications Symposium (SAS)* (pp. 1-6). IEEE. [Doi: 10.1109/SAS.2017.7894056](https://doi.org/10.1109/SAS.2017.7894056)

Kubheka, S., 2023. South African inflation modelling using bootstrapped long short-term memory methods. *SN Business & Economics*, 3(7), p.110. [Doi:10.1007/s43546-023-00490-9](https://doi.org/10.1007/s43546-023-00490-9)

Kumari, S. and Singh, S.K., 2022. Machine learning-based time series models for effective CO<sub>2</sub> emission prediction in India. *Environmental Science and Pollution Research*, pp.1-16. [Doi: 10.1007/s11356-022-21723-8](https://doi.org/10.1007/s11356-022-21723-8)

Li, L., Zhang, R., Sun, J., He, Q., Kong, L. and Liu, X., 2021. Monitoring and prediction of dust concentration in an open-pit mine using a deep-learning algorithm. *Journal of Environmental Health Science and Engineering*, 19, pp. 401-414. [Doi: 10.1007/s40201-021-00613-0](https://doi.org/10.1007/s40201-021-00613-0)

Li, Y., Zhu, Z., Kong, D., Han, H. and Zhao, Y., 2019. EA-LSTM: Evolutionary attention-based LSTM for time series prediction. *Knowledge-Based Systems*, 181, p.104785. [Doi: 10.1016/j.knosys.2019.05.028](https://doi.org/10.1016/j.knosys.2019.05.028)

Low, R., Cheah, L. and You, L., 2020. Commercial vehicle activity prediction with imbalanced class



distribution using a hybrid sampling and gradient boosting approach. *IEEE Transactions on Intelligent Transportation Systems*, 22(3), pp.1401-1410. [Doi:10.1109/TITS.2020.2970229](https://doi.org/10.1109/TITS.2020.2970229)

Malleswari, S.M.S.D. and Mohana, T.K., 2022. Air pollution monitoring system using IoT devices. *Materials Today: Proceedings*, 51, pp.1147-1150. [Doi:10.1016/j.matpr.2021.07.114](https://doi.org/10.1016/j.matpr.2021.07.114)

Manisalidis, I., Stavropoulou, E., Stavropoulos, A. and Bezirtzoglou, E., 2020. Environmental and health impacts of air pollution: a review. *Frontiers in public health*, 8, p.14. [Doi:10.3389/fpubh.2020.00014](https://doi.org/10.3389/fpubh.2020.00014)

Ganji, A., Youssefi, O., Xu, J., Mallinen, K., Lloyd, M., Wang, A., Bakhtari, A., Weichenthal, S. and Hatzopoulou, M., 2023. Design, calibration, and testing of a mobile sensor system for air pollution and built environment data collection: The urban scanner platform. *Environmental Pollution*, 317, p.120720. [Doi:10.1016/j.envpol.2022.120720](https://doi.org/10.1016/j.envpol.2022.120720)

Ghadi, N.M. and Salman, N.H., 2022. Deep learning-based segmentation and classification techniques for brain tumor MRI: A review. *Journal of Engineering*, 28(12), pp.93-112. [Doi: 10.31026/j.eng.2022.12.07](https://doi.org/10.31026/j.eng.2022.12.07)

Ghazal, N.K., 2020. Monitoring dust storm using Normalized Difference Dust Index (NDDI) and brightness temperature variation in Simi arid areas over Iraq. *Iraqi Journal of Physics*, 18(45), pp.68-75. [Doi: 10.30723/ijp.18.45.68-75](https://doi.org/10.30723/ijp.18.45.68-75)

Paithankar, D.N., Pabale, A.R., Kolhe, R.V., William, P. and Yawalkar, P.M., 2023. Framework for implementing air quality monitoring system using LPWA-based IoT technique. *Measurement: Sensors*, 26, p.100709. [Doi: 10.1016/j.measen.2023.100709](https://doi.org/10.1016/j.measen.2023.100709)

Pallavi, S., Ramya Laxmi, K., Ramya, N. and Raja, R., 2020. Study and analysis of modified mean shift method and Kalman filter for moving object detection and tracking. In *Proceedings of the Third International Conference on Computational Intelligence and Informatics: ICCII 2018* (pp. 821-828). Springer Singapore. [Doi:10.1007/978-981-15-1480-7\\_76](https://doi.org/10.1007/978-981-15-1480-7_76).

Parveen, S., Kumar, S.S., MohanRaj, P., Jabakumar, K. and Ganesh, R.S., 2022. Design of a dense layered network model for epileptic seizures prediction with feature representation. *International Journal of Advanced Computer Science and Applications*, 13(10). pp. 218-223. [Doi:10.14569/IJACSA.2022.0131027](https://doi.org/10.14569/IJACSA.2022.0131027)

Pullan, P., Gautam, C. and Niranjana, V., 2020, October. Air quality management system. In *2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCon)* (pp. 436-439). IEEE. [Doi: 10.1109/GUCon48875.2020.9231233](https://doi.org/10.1109/GUCon48875.2020.9231233)

Querol, X., Tobías, A., Pérez, N., Karanasiou, A., Amato, F., Stafoggia, M., García-Pando, C.P., Ginoux, P., Forastiere, F., Gumy, S. and Mudu, P., 2019. Monitoring the impact of desert dust outbreaks for air quality for health studies. *Environment International*, 130, p.104867. [Doi:10.1016/j.envint.2019.05.061](https://doi.org/10.1016/j.envint.2019.05.061)

Saleh, M.H., Ayesh, A.N. and Sathyaprakash, P., 2023. Development prediction algorithm of vehicle travel time based traffic data. *Periodicals of Engineering and Natural Sciences*, 11(1), pp.197-207. [Doi: 10.21533/pen.v11i1.3447](https://doi.org/10.21533/pen.v11i1.3447)

Mohammed, Q.S.A.A.D. and Sa'ur, R.H., 2016. Data base for dynamic soil properties of seismic active zones in Iraq. *Journal of Engineering*, 22(7), pp.1-18. [Doi:10.31026/j.eng.2016.07.01](https://doi.org/10.31026/j.eng.2016.07.01)

Salih, Z. and Saleh, M.H., 2022. Attitude and altitude control of quadrotor carrying a suspended payload using genetic algorithm. *Journal of Engineering*, 28(5), pp. 25-40.



[Doi:10.31026/j.eng.2022.05.03](https://doi.org/10.31026/j.eng.2022.05.03)

Shi, L., Zhang, J., Zhang, D., Igbawua, T. and Liu, Y., 2020. Developing a dust storm detection method combining Support Vector Machine and satellite data in typical dust regions of Asia. *Advances in Space Research*, 65(4), pp.1263-1278. [Doi: 10.1016/j.asr.2019.11.027](https://doi.org/10.1016/j.asr.2019.11.027)

Shi, M., Yeatman, E.M. and Holmes, A.S., 2019, November. Energy harvesting piezoelectric wind speed sensor. In *Journal of Physics: Conference Series* (Vol. 1407, No. 1, p. 012044). IOP Publishing. [Doi 10.1088/1742-6596/1407/1/012044](https://doi.org/10.1088/1742-6596/1407/1/012044)

Tagliabue, L.C., Cecconi, F.R., Rinaldi, S. and Ciribini, A.L.C., 2021. Data driven indoor air quality prediction in educational facilities based on IoT network. *Energy and Buildings*, 236, p.110782. [Doi:10.1016/j.enbuild.2021.110782](https://doi.org/10.1016/j.enbuild.2021.110782)

Tulenkov, A., Parkhomenko, A., Sokolyanskii, A., Stepanenko, A. and Zalyubovskiy, Y., 2018, September. The features of wireless technologies application for Smart House systems. In *2018 IEEE 4th International Symposium on Wireless Systems within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS)* (pp. 1-5). IEEE. [Doi: 10.1109/IDAACS-SWS.2018.8525842](https://doi.org/10.1109/IDAACS-SWS.2018.8525842)

Zhu, Y., Al-Ahmed, S.A., Shakir, M.Z. and Olszewska, J.I., 2022. LSTM-based IoT-enabled CO<sub>2</sub> steady-state forecasting for indoor air quality monitoring. *Electronics*, 12(1), p.107. [Doi. 10.3390/electronics12010107](https://doi.org/10.3390/electronics12010107)