2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)

System for Detecting and Forecasting PM2.5 Concentration Levels Using Long Short-Term Memory and LoRa

Wei Song[1,2,*], Jinkun Han[1], Junwei Xie[1], Yanning Gao[1], Liangliang Song[3]
[1] North China University of Technology, Beijing, China
[2] Beijing Key Lab on Urban Intelligent Traffic Control Technology, Beijing, China
[3]ThingPark China, Beijing, China
[*] sw@ncut.edu.cn

***Abstract*—Atmospheric particulate matter, such as PM2.5, contributes to air pollution negatively affecting human health. Many factors determine the change of PM2.5 concentration levels, which can be very sudden, nonlinear, and uncertain. Hence, traditional methods are not always suitable for predicting the exact amount of PM2.5 in the air. Effective forecasting of PM2.5 levels can tell people the air condition and support country's sustainable development; hence, forecasting PM2.5 values has an important social and long-term economic significance. This study proposes a system for monitoring the amount of PM2.5 and other pollutants in the air using the long-range wireless data communication technology LoRa and a cloud-based system model, which includes a proprietary terminal device. LoRa's excellent characteristics, such as low-power consumption and long range, allow effectively obtaining a history of PM2.5 readings. A PM2.5 prediction model based on a long short-term memory (LSTM) cyclic neural network is utilized to predict the next few hours' PM2.5 values and carry out an air quality index analysis of PM2.5. Experiments using atmospheric pollutant datasets collected specifically for this study from the North China University of Technology in 2019 show that the system can analyze well the PM2.5 datasets and accurately predict the hourly variation trend of PM2.5.**

Keywords—IoT; LoRa; LSTM; Deep Learning; PM2.5

I. INTRODUCTION

PM2.5 is a particulate matter with a diameter of less than or equal to 2.5 µm. It is one of the atmospheric pollutants that can damage human respiratory, cardiovascular, and cerebrovascular systems [1], or even cause lung cancer, when its concentration reaches high levels [2]. Moreover, a high-level concentration of PM2.5 can block people's eyesight, causing inconveniences or even leading to serious traffic accidents [3].

Many countries around the world are paying more attention to monitoring air quality due to its deterioration in recent years. Acquiring the exact amount of PM2.5 in the air at any given time can inform residents and allow them to arrange their outdoor activities reasonably. In particular, PM2.5 values should be detected frequently in areas with dense population to protect people with low immunity, such as students and patients [4]. However, simply monitoring PM2.5 values only captures the current state of the environment. Only predicting PM2.5 values in advance can allow people to plan preventive measures in advance and protect their health effectively. Accordingly, this study proposes a smart system for effective monitoring of PM2.5 values and their prediction for the next few hours using LoRa and long short-term memory (LSTM) technologies.

The proposed system consists of four parts: a terminal device, a LoRa gateway, a cloud server, and an application. The first three components relate to the LoRa technology. In the application part, the system utilizes a LSTM model trained on PM2.5 datasets to make accurate predictions.

The low-power wide-area network (LPWAN) LoRa is a revolutionary wireless access technology for the Internet of Things (IoT) that has the advantages of long range, low-power consumption, low cost, and wide coverage compared with Wi-Fi, Bluetooth, and ZigBee [5]. LoRa is suitable for IoT terminal devices that transmit small amounts of data over long distances and use the battery-powered mode. As a LPWAN technology, LoRa has a mature industrial chain with well-developed commercialization.

The existing LPWAN technologies can operate in either authorized or unauthorized spectrum. The majority of LPWANs are currently deployed in the unauthorized spectrum known as the ISM band. An authorized spectrum is expected to become available in the future once LPWAN technologies based on cellular networks mature. Compared with the authorized spectrum LPWAN technologies, the unauthorized spectrum LPWAN technologies have the characteristics of flexible network construction, fast speed, low deployment cost, and fast commercialization, enabling their easy, large-scale commercial installation [6].

LSTM is a recurrent neural network proposed by Hochreiter and Schmidhuber in 1997 that can solve the problems of gradient explosion and gradient dispersion [7]. When the number of network layers increases, the ability of the subsequent nodes to perceive the previous nodes becomes weak, and the network forgets the earlier information over time. This phenomenon can be effectively solved by LSTM. Furthermore, LSTM can input multiple variables and be used for time series prediction [8].

978-1-7281-2980-8/19/$31.00 ©2019 IEEE
DOI 10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00151

Meteorological and pollution data should be preprocessed before training the proposed LSTM model to ensure the validity of the data and improve the model's accuracy. In the data preprocessing stage, the missing values are removed and the remaining data are normalized. The collected datasets used in this study are time series sorted by time. The training dataset is composed of the input X and output Y.

The rest of this paper is organized as follows. Section 2 provides an overview of related work. Section 3 introduces the proposed system. Section 4 outlines the performance evaluation of the proposed system. Section 5 concludes the paper.

II. RELATED WORK

Monitoring PM2.5 has never stopped since people have become aware of the environmental crisis. In China, the rapid growth of industrialization and urbanization has led the air pollution to become a serious issue in the last 20 years. The particulate matter is the sixth-ranking mortality risk factor of the world, and many major diseases are associated with the long-term exposure to PM2.5. Facing PM2.5 pollution, the Chinese government and society are highly challenged to develop better policies to balance the relationship between the economy and environment [9]. Forecasting the amount of PM2.5 in the air at given times can allow the citizens to plan in advance and avoid the periods of severe air pollution to ensure their physical health.

Several systems for detecting PM2.5 levels have been proposed recently. For example, Wang has introduced a PM2.5 detection system based on STM32 MCU control and a TV to show the results [10]. The drawback of the system is its limited distance coverage, which is suitable only for organizations building their own local detection system. Dai has investigated the indoor air quality using a Wi-Fi monitoring sensor [11], which supports long-distance transmission but is limited by the Wi-Fi coverage area. A PM2.5 detection system with a long transmission distance not restricted by a Wi-Fi, SIM card, or wire has not been developed yet. This paper proposes such a system based on the LoRa technology.

LoRa is a new wireless IoT technology that has evolved recently and gained great popularity due to its low-power consumption. It uses a battery and transfers a small amount of data at short intervals over a long range. LoRa can accomplish a longer distance transmission compared with other low-consumption IoT protocols, such as BLE, Z-wave, W-Mbus, and ZigBee (Figure 1). Taking ZigBee as an example, its transmission distance is 10–100 m; hence, it is suitable only for small projects, where data are transferred over small distances. Another advantage of LoRa is its low cost compared with Wi-Fi, 3G, and 4G networks. While 2G network is also of low cost, with the advent of the 5G technology, many of the cellular providers are discontinuing 2G services for supporting the operation of IoT devices [12].

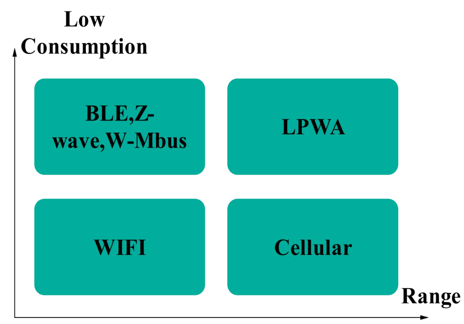


Fig. 1. Comparison of IoT protocols

LoRa has incomparable advantages when it comes to security. Traditional IoT devices usually do not include any secret keys, or their configuration is very complex. For example, Nguyen has proposed an identity-based cryptography system guaranteeing high safety of ZigBee transmission [13]. However, the installation process and structure of the system are more complex compared with those of a system based on public secret keys. On the other hand, while the public secret key technology secures the transmission to the target devices, it does not ensure the security of the sending device. LoRa uses the received signal strength indicator (RSSI) to generate a secret key, whereas different devices have their own RSSIs [14], which guarantee the safety of communication to the greatest extent. Compared with the ZigBee security method, LoRa uses a simpler security mechanism enabling its commercialization.

PM2.5 values in the next few hours depend on both the previous values and previous state of the environmental pollution. Traditional neural networks are not suitable for predicting such time series. According to the experimental results obtained by Zhang [15], LSTM achieves the lowest mean absolute percentage error when forecasting future values over time series compared with such algorithms as feedforward neural network and support vector machine. Hence, it is expected that LSTM will work well when forecasting PM2.5 values that change over time.

III. DETECTION AND FORECASTING SYSTEM

A. LoRa System

In a remote detection system, LoRa has the following advantages compared with traditional Internet, stand-alone Internet, and wireless sensors (Table 1). Due to the excellent features of LoRa, the proposed PM2.5 detection system can cover a large area.

TABLE I. COMPARISON OF THE ADVANTAGES AND DISADVANTAGES OF THE SENSORS

Sensor types	LoRa	Internet	Indepe n-dent	Wireless
Power supply	Battery	Wire	Battery	Battery
Networking	LoRaWAN	Wire	None	ZigBee or

mode				etc.
Distance	Over 2 km	No limitat-ions	No limitati-ons	<100m
Maintenance difficulty	Easy	Easy	Easy	Hard
Amount of gateway	A few	No limitat-ions	No limitat-ions	Many
Real-time warning	Support	Support	Not Support	Support
Cost	Low	High	Low	High

Figure 2 illustrates the principle of LoRa data transmission based on broadcasting. The green pointing arrows at the bottom of the figure represent the dataset upstream. Every terminal device uploads its datasets using broadcasting so that all nearby LoRa gateways can receive the data signal. The LoRa gateways that have received the datasets successfully upload the datasets to the cloud server, saves only one group of valid datasets from the same data. Meanwhile, all LoRa gateways also upload their IDs to the cloud server, which enables it to find the fastest and most efficient path toward the LoRa gateway, whose signal coverage area includes the target terminal device to return back the results or instructions. The LoRa gateway utilizes a broadcasting method to deliver datasets from the cloud server to the target terminal device as represented by the red pointing arrows in Figure 2. These datasets include the ID of the target terminal device helping it to judge whether to decrypt the datasets. Thus, only the correct device can get the intended information.

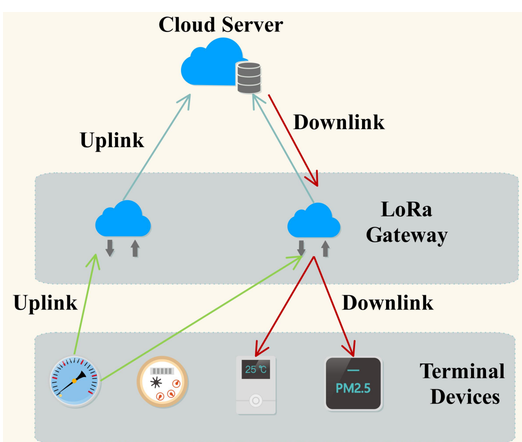


Fig. 2. Up- and downlinks of data transmission in LoRa

The proposed LoRa system can be connected to the cloud server via two pathways: activation-by-personalization (ABP) and over-the-air activation (OTAA). ABP is a simple connection pathway, but it has insecurities, which make it suitable only for private networks. As illustrated in Figure 3, three key parameters are configured to have the same values for the terminal device and cloud server working in the ABP mode: DevAddr, NwkSKey, and AppSKey. When the terminal device requests to join the network, the system compares the parameter values between the terminal and the cloud server to judge whether to connect. OTAA offers a high level of security that guarantees safe operation of the LoRa system. It works as follows. The parameters AppEUI, DevEUI, and AppKey are configured for the end node, which generates a random value (LoRa RSSI) to form DevNonce utilized to combine other parameters to generate NwkSKey and AppSKey for encrypting and decrypting datasets. The cloud server registers the transmitted DevEUI value and returns a corresponding DevAddr value, which is utilized in the later system communication. The OTAA mode is considered to be safer compared with the ABP mode due to the application of a protecting method to the communication.

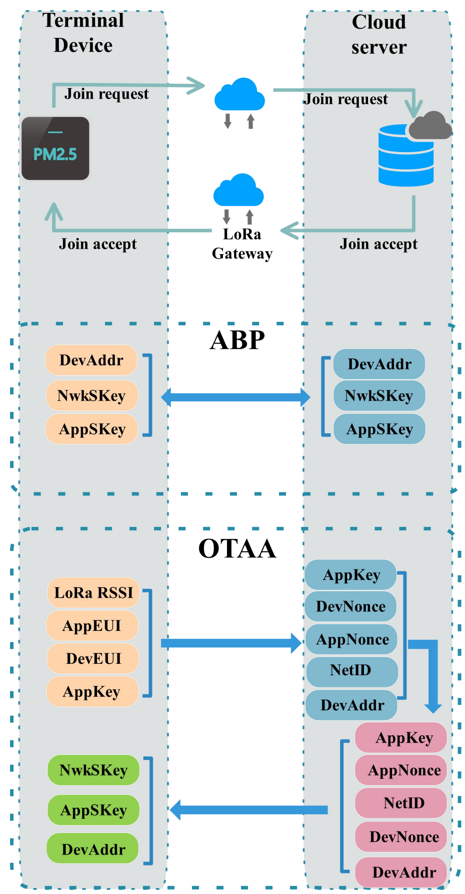


Fig. 3. LoRa security framework

B. System Architecture

The structure of the proposed system for detecting and forecasting PM2.5 values is illustrated in Figure 4. The system consists of four parts: a terminal device, a LoRa gateway, a cloud server, and an application. The terminal device is utilized to detect PM2.5 values and time. Afterwards, all vital datasets are packaged and encrypted to be transmitted to the LoRa gateway via the LoRa long-range wide-area network connection, a special transport protocol for the LoRa technology. The LoRa gateway does not do any other function except delivering datasets and checking their integrity. Then, these datasets are transmitted to the cloud server via Wi-Fi or any public network, where the datasets are saved, sorted by time and device IDs, and displayed on a webpage to enable judging whether terminal devices work well and the datasets are valid. The first three parts of the system implement the detection functionality that collects and saves datasets in preparation for analyzing and forecasting PM2.5 values. In the final part, the application requests the saved datasets from the cloud server to draw charts and analyze the situation of the local environment and air quality. It uses a deep learning method to forecast the next few PM2.5 values.

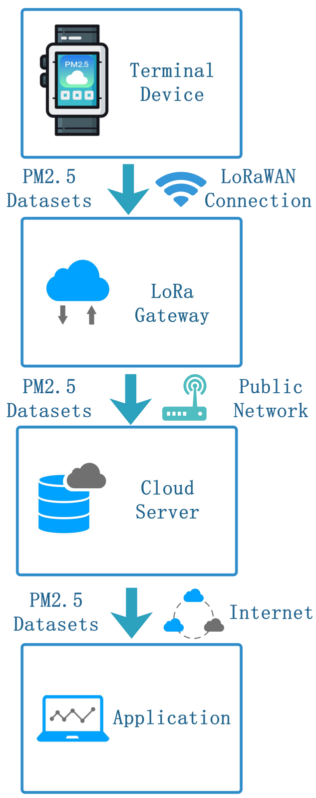


Fig. 4. Four parts of the proposed system

Figure 5 illustrates the internal data flow across the four system parts. All devices are initialized upon the start of the system and wait for the next manual input instructions to configure the system parameters. When the devices and cloud server start working (as illustrated by the blue pointing arrows in Figure 5), the terminal device transmits a special password to connect to the LoRa gateway and receives data encryption and decryption instructions from the cloud server. The LoRa gateway delivers the request to the cloud server, which then generates and returns new keys and a password to the gateway as illustrated by the green pointing arrows. When the terminal device finishes connecting, it begins collecting PM2.5 data, which are delivered to the cloud server by the LoRa gateway as illustrated by the red pointing arrows. Consequently, the application downloads the data from the cloud server, performs the analysis and forecasting, and visualizes the results.

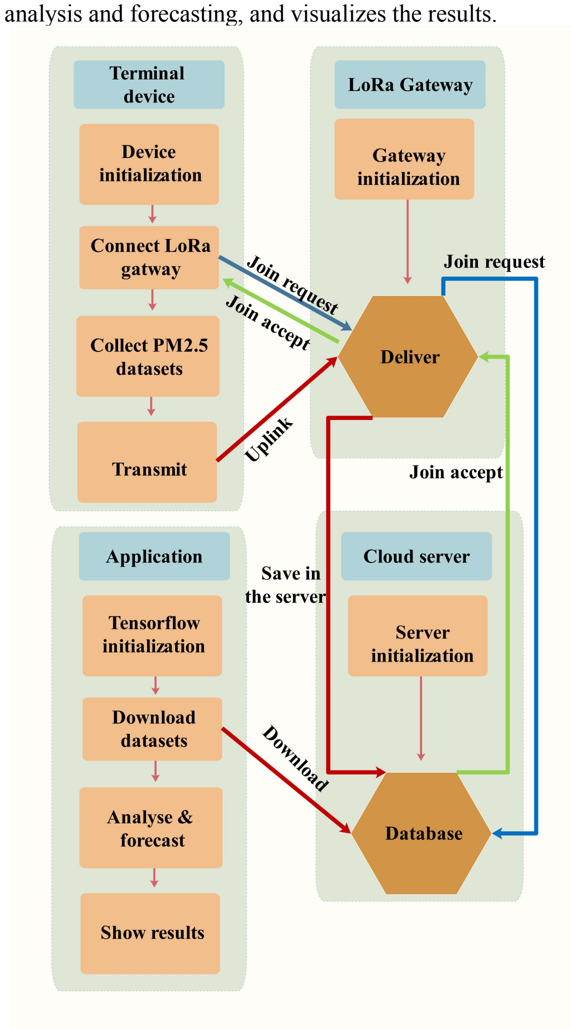
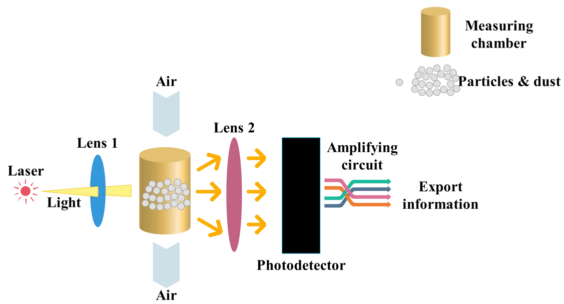


Fig. 5. Data flow across the four system parts

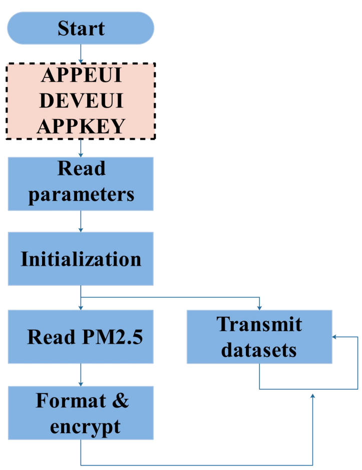
C. Terminal Device

An aerosol is a suspension of liquid or solid particles in the air. Fog, smoke, haze, mist, and dust are examples of atmospheric aerosols resulting from natural or human processes. They can be used as condensation nodules of water droplets and ice crystals (see atmospheric condensation nodules, atmospheric ice nuclei), absorbers, and scatterers of solar radiation and participate in various chemical cycles. They are important components of the atmosphere.

In the proposed system, the laser light scattering dust detector sucks in aerosols to the measuring chamber (Figure 6(a)). To initiate the measurement, a thin-layer light source is formed by the laser diode through the lens group. When a thin layer of light illuminates aerosols flowing through the measuring chamber, it produces scattering. The scattering intensity of light can be detected using a photoelectric detector, which produces electrical signals proportional to the mass concentration of illuminated aerosols. The detected scattering intensity of light is multiplied by the voltage calibration coefficient, which can be obtained by measuring aerosols of a specific concentration. The result of this procedure is the actual value of PM2.5.



(a) Structure of the laser light scattering dust detector



(b) Data flow in the terminal device

Fig. 6. Four parts of the whole system

When the terminal device starts working for the first time, three key parameters are required to be configured manually (Figure 6(b)). These parameters are saved in the main memory of the controlling board and utilized for connecting to the LoRa gateway, as well as encrypting and decrypting datasets. Once initialization is completed, the system starts reading PM2.5 data and transmitting them to the LoRa gateway at the same time. Thus, the first few data points reaching the cloud server might have invalid or null values. The collected PM2.5 datasets are being formatted, encrypted as a package, and delivered to the function responsible for transferring the data every 30 min.

D. Long Short-Term Memory Model

In the preprocessing stage, the absent data points are replaced with historical averages of two present data points before and after the absent point, whereas the instances with unreasonably high values generated by noise are eliminated. The remaining data points are normalized to be in the range of [0; 1] using the min–max scale method to accelerate the performance of the gradient descent algorithm used for the LSTM model training. In particular, every input X is replaced with its normalized value X' as

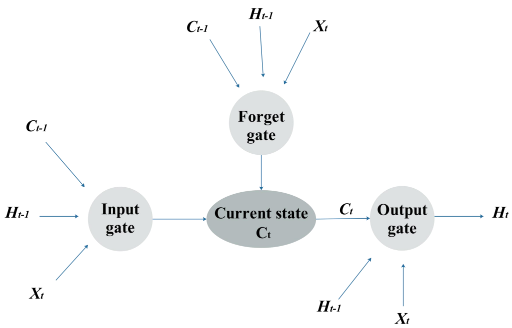
$$X' = (X - X_{min})/(X_{max} - X_{min}), \qquad (1)$$

Where X_{min} and X_{max} are the minimum and maximum values of raw data in one batch, respectively.

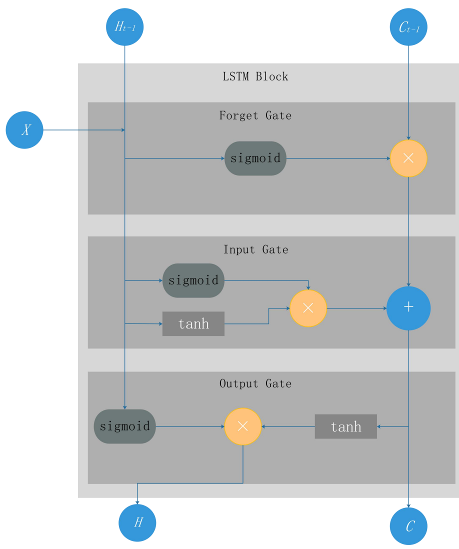
The input layer of the LSTM model is a 3D tensor *[batch-size, time-step, input-size]*, where *input-size* is the values of the considered environmental pollutant, PM2.5. Providing that the proposed LSTM is a time series model, different time steps would result in different levels of accuracy. Time step can be understood as the number of input variables used to predict the next variable. A suitable choice of the time-step value can effectively improve the accuracy of predictions. In this study, we investigated the performance of three different time-step values: 12 h (half of a day), 24 h (1 day), and 48 h (2 days).

An LSTM cell is divided into three parts: Input gate, Forget gate, and Output gate (Figure 7(a)). With the PM2.5 data coming in, the LSTM system starts analyzing the information included in the datasets; useful datasets which contribute significantly to the results are saved , whereas those of no use are discarded. In Figures 7(a) and 7(b), X represents the input value, H represents the output value, and C represents the cell state. Overall, the LSTM model utilizes the Forget gate, Input gate, and Output gate to achieve data filtering.

The input value X is combined with the last output value H_{t-1} in the Forget gate and then gets into the sigmoid layer, which outputs a vector of "1" and "0" values (Figure 7(b)). It means the proportion of the corresponding information which allowed to pass. For specific example, "1" means the information is totally saved, whereas "0" is totally thrown. Then, the vector is multiplied by the last cell state to lose a part of the information and achieve the goal "Forget." After forgetting the information, a cyclic neural network requires input values going through the sigmoid layer to decide on the datasets to be updated in the input gate. The tanh layer is then utilized to update the datasets and supply the newest memory. The temporary vector is generated by the sigmoid and tanh layer in the input gate. Then, the temporary vector add the vector from forget gate to generate a final vector. The combined datasets (X and H_{t-1}) and the final vector are processed by the sigmoid and tanh layers, respectively, and multiplied by each other to generate the current output value H and the next parameter of forget gate.



(a) A cell of the LSTM



(b) The structure of an LSTM cell

Fig. 7. Four parts of the proposed system

Before the LSTM model starts learning, its hyparameters are required to be configured manually (Figure 8). In machine learning, hyparameters are usually initialized to random values and then optimized to improve the model performance. In this study, the input PM2.5 data are processed using the min–max scale method and reshaped as a 3D vector specifying the batch_size, time_step, and input_size. During the LSTM model training process, the output values are fed into the loss function along with the true label values. The gradient descent method is used to optimize and adjust the hyparameters according to the value of the loss function. The loss function is defined as

$$Loss(x) = \frac{1}{N} \sum_{i=1}^{N} (y_i - p_i)^2 . \qquad (2)$$

The mean absolute error (MAE) and root mean square error (RMSE) are used to evaluate the model performance:

$$MAE = \frac{1}{N} \sum_{i=1}^{n} |(y_i - \hat{y}_i)|, \qquad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}, \qquad (4)$$

where N denotes the total number of samples, whereas y_i denotes the ith sample in the sample set. The MAE is a measure of the quality of an estimator; it is always nonnegative, and values closer to zero are better. The RMSE is the square root of the mean square error.

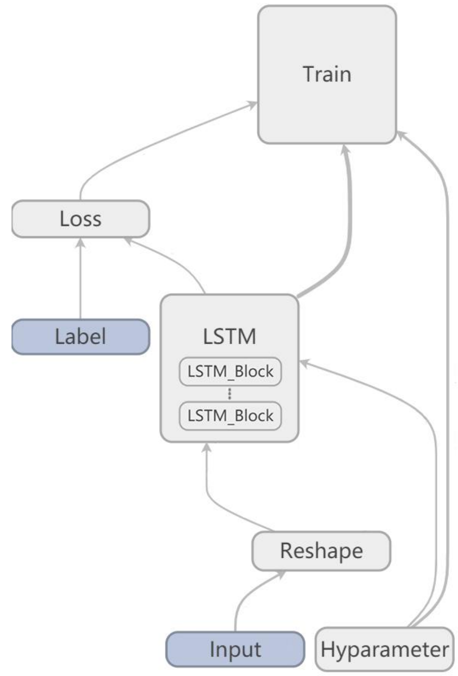


Fig. 8. Data flow of the LSTM system

IV. Experiments and Analysis

This section presents the analysis of the performance of the proposed LoRa-based system for PM2.5 detection and forecasting.

In the terminal and LoRa gateway parts, the system utilizes an Arduino Mega board, a laser dust sensor, a LoRa shield, and a LoRa gateway (Figure 9).

(a) Arduino Mega board

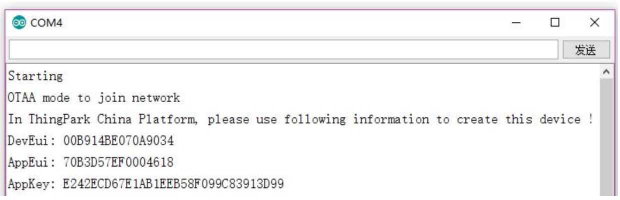
(b) PM2.5 sensor

(c) LoRa shield

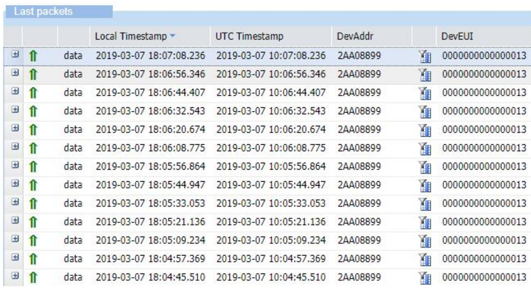
(d) LoRa gateway

Fig. 9. System terminal sensors, device, and gateway

Figure 10(a) shows a test of the terminal device. As can be seen, the terminal device successfully connects to the LoRa gateway using the OTAA mode and transmits the three key parameters (DevEUI, AppEUI, and AppKey) to the cloud server as a connection confirmation.

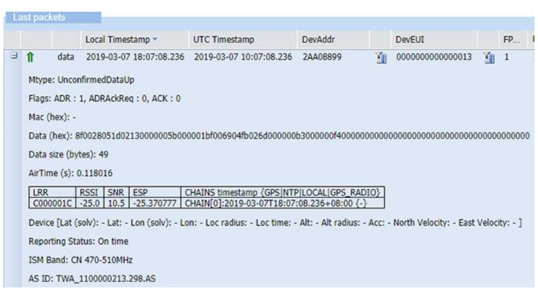


(a) Example of the terminal test


Last packets

			Local Timestamp	UTC Timestamp	DevAddr		DevEUI
⊞	⇑	data	2019-03-07 18:07:08.236	2019-03-07 10:07:08.236	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:06:56.346	2019-03-07 10:06:56.346	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:06:44.407	2019-03-07 10:06:44.407	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:06:32.543	2019-03-07 10:06:32.543	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:06:20.674	2019-03-07 10:06:20.674	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:06:08.775	2019-03-07 10:06:08.775	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:05:56.864	2019-03-07 10:05:56.864	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:05:44.947	2019-03-07 10:05:44.947	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:05:33.053	2019-03-07 10:05:33.053	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:05:21.136	2019-03-07 10:05:21.136	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:05:09.234	2019-03-07 10:05:09.234	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:04:57.369	2019-03-07 10:04:57.369	2AA08899		0000000000000013
⊞	⇑	data	2019-03-07 18:04:45.510	2019-03-07 10:04:45.510	2AA08899		0000000000000013

(b) Datasets in the cloud server


Last packets

			Local Timestamp	UTC Timestamp	DevAddr		DevEUI		FP...
⊟	⇑	data	2019-03-07 18:07:08.236	2019-03-07 10:07:08.236	2AA08899		0000000000000013		1

Mtype: UnconfirmedDataUp

Flags: ADR : 1, ADRAckReq : 0, ACK : 0

Mac (hex): -

Data (hex): 8f0028051d02130000005b000001bf006904fb026d000000b3000000f40000000000000000000000000000000000000000

Data size (bytes): 49

AirTime (s): 0.118016

LRR	RSSI	SNR	ESP	CHAINS timestamp {GPS|NTP|LOCAL|GPS_RADIO}
C000001C	-25.0	10.5	-25.370777	CHAIN[0]:2019-03-07T18:07:08.236+08:00 {-}

Device [Lat (solv): - Lat: - Lon (solv): - Lon: - Loc radius: - Loc time: - Alt: - Alt radius: - Acc: - North Velocity: - East Velocity: -]

Reporting Status: On time

ISM Band: CN 470-510MHz

AS ID: TWA_1100000213.298.AS

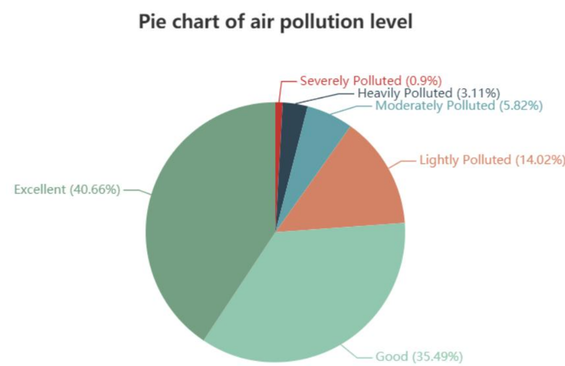
(c) Details of datasets

Fig. 10. Terminal test

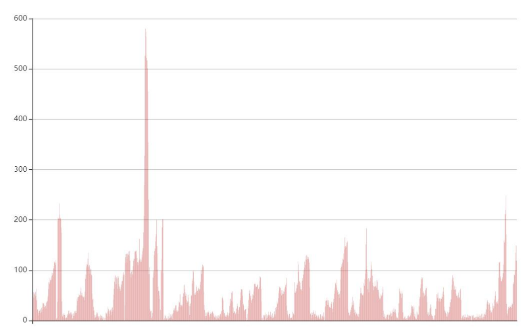
The collected datasets are saved to the cloud sever sorted by time (Figure 10(b)). In this study, the training datasets are from January 1 to February 20, 2019, and the terminal device uploads them every hour. These data are all hexadecimal and have a custom sorting format. Thus, if anyone wants to use the datasets, he or she must know the rules of decryption. The uploading method of hexadecimal also saves lots of memory and improves the communication speed when communicating between the terminal device and cloud server. If the transmitted datasets contain only numbers, this method can save over a half of the transmitting memory.

Fig. 11. Application in a real environment

In our experiment, the terminal device was fixed in the box as illustrated by the red rectangle in Figure 11. Thus, it could collect PM2.5 data outside without being impacted by rainy or snowy weather. The box allowed the air to go through without limitations, guaranteeing the accuracy of PM2.5 values.



(a) Analysis of the air pollution levels



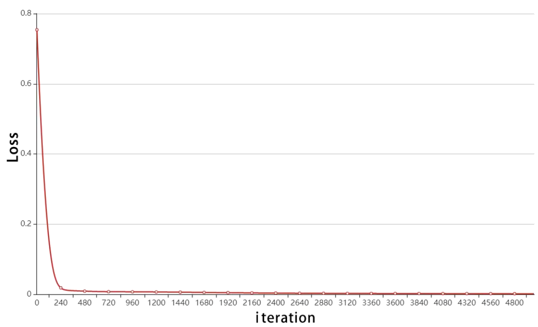
(b) Analysis of the air fluctuation

Fig. 12. Analysis of data in the real-environment experiment

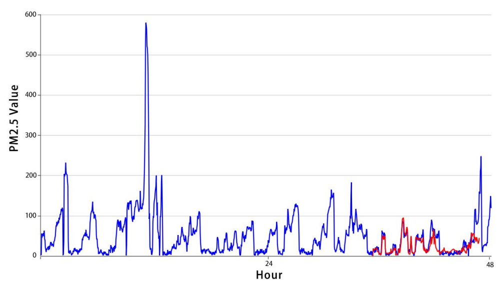
The data collected by the system in 50 days can be divided into the following air pollution levels: Excellent, Good, Lightly Polluted, Moderately Polluted, Heavily Polluted, and Severely Polluted (Figure 12(a)). According to Figure 12(b), the rule of fluctuation can be easily concluded and utilized to evaluate the effectiveness of the measures to reduce PM2.5.

TABLE II. A COMPARISON OF DIFFERENT TIME SLOTS FOR TRAINING

Time step	12 h	24 h	48 h
MAE	14.11	12.58	11.50
RMSE	25.29	22.93	18.65



(a) The loss of the LSTM model during training



(b) PM2.5 actual and forecasted values

Fig. 13. Performance of the system in the real-environment application

We found that the time step of 48 h resulted in the best performance (Table 2); hence, we used this value to assess the system performance. Figure 13(a) illustrates the loss generated at every step. After the iteration reaches 1580 time, the loss trend to be stable and close to zero. Figure 13(b) shows the actual PM2.5 values represented by the blue line and the forecasted values represented by the red line. As can be noticed from the figure, the forecasted values closely follow the trend of the actual data.

CONCLUSION

This paper proposed a smart system for detecting and forecasting PM2.5 values using LoRa and LSTM. Being of low power and long range, it satisfies the requirements of future IoT systems and provides a reliable reference for governmental work and people's lifestyle when it comes to air quality. Our experiments in a real environment demonstrated that the system is capable of accurately predicting PM2.5 values for the next few hours. In the future, the system can be used as a mobile application providing warnings about high air pollution levels in real time. For example, predicting future PM2.5 values can help people to decide whether to go outside.

ACKNOWLEDGMENT

This research was supported by National Natural Science Foundation of China (61503005), Beijing Young Topnotch Talents Cultivation Program (No. CIT&TCD201904009), North China University of Technology "The Belt and Road" Countries Talent Training Base Project, and "Yuyou" Project of North China University of Technology.

REFERENCES

[1] R.D. Brook, S. Rajagopalan, C.A. Pope and et al., "Particulate Matter Air Pollution and Cardiovascular Disease An Update to the Scientific Statement From the American Heart Association", Circulation, vol. 121, pp.2331-2378, June 2010.

[2] M. Kampa, E. Castanas, and T.K. Ahn, "Human health effects of air pollution", Environmental Pollution, vol. 151, pp.362-367, Jane 2008.

[3] S. Dhondt, L.X. Quynh, V.V. Hieu, and H. Luc, "Environmental health impacts of mobility and transport in Hai Phong, Vietnam", Stochastic Environmental Research and Risk Assessment, vol. 25, pp. 363-376, March 2011.

[4] P.V. Dorizas, M.N. Assimakopoulos, C. Helmis and et al., "An integrated evaluation study of the ventilation rate, the exposure and the indoor air quality in naturally ventilated classrooms in the Mediterranean region during spring", Science of The Total Environment, vol.502, pp.557-570, Jane 2015.

[5] A. Augustin, J.Z. Yi, T. Clausen and W.M. Townsley, "A Study of LoRa: Long Range & Low Power Networks for the Internet of Things", Sensors, vol.16, September 2016.

[6] G. Wibisono, G.P. Saktiaji and I. Ibrahim, "Techno-economic analysis of smart meter reading implementation in PLNBali using LoRa technology", 2017 International Conference on Broadband Communication, Wireless Sensors and Powering, pp.1-6, January 2018.

[7] S. Hochreiter, J. Schmidhuber, "Long short-term memory", Neural Computation, vol.9, pp.1735-1780, December 1997

[8] M. Wollmer, Z. Zhang, F. Weninger and et al. "Feature enhancement by bidirectional LSTM networks for conversational speech recognition in highly non-stationary noise", 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, May 2013.

[9] S. Li, B. Zou, J. You and et al., "Satellite-based China's PM2.5 pollution and associated premature mortality measurement over past two decades", Internation Archives of the Photogrammetry, Remote Sensing and Spatial Information Science, vol.42, pp.39-45, October 2018.

[10] X. Wang, "Application of PM2.5 alarm system based on embedded technology in urban air pollution monitoring", Chemical Engineering Transaction, vol.59, pp.715-720, 2017.

[11] X. Dai, J. L, X. Li and L. Zhao, "Long-term monitoring of indoor CO2 and PM2.5 in Chinese homes: Concentrations and their relationships with outdoor environments", Build and Environment, Vol .144, pp.238-247, October 2018.

[12] S. Devalal, and A. Karthikeyan, "LoRa Technology – An Overview", Proceedings of the 2nd International Conference on Electronics, Communication and Aerospace Technology, ICECA 2018, pp.284-290, September 2018.

[13] S.T. Nguyen and C. Rong, "ZigBee security using identity-based cryptography", Lecture Notes in Computer Science, vol.4610, pp.3-12, July 2007.

[14] W. Xu, S. Jha and W. Hu, "LoRa-Key: Secure Key Generation System for LoRa-based Network", IEEE Internet of Things Journal, 2018, December 2018.

[15] J. Zhang, K. Nawata, "A comparative study on predicting influenza outbreaks", Bioscience Trends, vol.11, October 2017.