Deep-Learning-Driven Proactive Maintenance Management of IoT-Empowered Smart Toilet

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***Abstract*—The recent proliferation of Internet of Things (IoT) sensors has driven a myriad of industrial and urban applications. Through analyzing massive data collected by these sensors, the proactive maintenance management can be achieved such that the maintenance schedule of the installed equipment can be optimized. Despite recent progress in proactive maintenance management in industrial scenarios, there are few studies on proactive maintenance management in urban informatics. In this article, we present an integrated framework of IoT and cloud computing platform for the proactive maintenance management in smart city. Our framework consists of: 1) an IoT monitoring system for collecting time-series data of operating and ambient conditions of the equipment and 2) a hybrid deep learning model, namely, convolutional bidirectional long short-term memory (CBLM) model for forecasting the operating and ambient conditions based on the collected time-series data. In addition, we also develop a naïve Bayes classifier to detect abnormal operating and ambient conditions and assist management personnel in scheduling maintenance tasks. To evaluate our framework, we deployed the IoT system in a Hong Kong public toilet, which is the first application of proactive maintenance management for a public hygiene and sanitary facility to the best of our knowledge. We collected the sensed data more than 33 days (808 h) in this real system. Extensive experiments on the collected data demonstrated that our proposed CBLM outperformed six traditional machine learning algorithms.**

***Index Terms*—Cloud computing, convolutional neural network (CNN), deep learning, Internet of Things (IoT), long short-term memory (LSTM), machine learning, proactive maintenance management.**

I. Introduction

As THE cost of Internet of Things (IoT) technology is gradually decreasing, IoT technology is gaining its popularity and is widely applied in different industrial scenarios and commercial sectors [1], [2], [3], [4], [5], [6], [7], [8], [9]. Driven by the big data collected by IoT sensors and information systems, the maintenance of the equipment installed in commercial facilities and venues can now be potentially scheduled proactively through forecasting its operating and ambient conditions. Management personnel can manage the scheduling of the maintenance task proactively by referring to the forecast on the operating and ambient conditions of commercial equipment. Currently, most of the studies on proactive maintenance management focus on industrial equipment [10] and are often driven by traditional machine learning models or analytics-driven engineering involving human intuition. Among these studies, industrial equipment is often installed in factories or industrial sites and is less likely to be subjected to the dynamic changes of the nearby personnel and social events. By contrast, the operating and ambient conditions of commercial equipment and public facilities are often affected by the dynamic changes in nearby personnel and social events. Meanwhile, it is difficult to quantitatively measure the effects of these dynamic changes on the operating and ambient conditions of commercial equipment with analytical models. Therefore, models introduced in existing studies may be inadequate in capturing the effects of these dynamic changes. These model may be unreliable in forecasting the operating and ambient conditions of commercial equipment and ultimately fail to assist management personnel to proactively schedule the maintenance of commercial equipment. Therefore, new models which can forecast the operating and ambient conditions of commercial equipment while capturing the effects of these dynamic changes have to be developed.

A. Motivation and Objective

The challenge of capturing the effects of the dynamic changes in nearby personnel and social events on the operating and ambient conditions of commercial equipment can be addressed with data-driven models, such as deep learning and the big data collected with IoT technologies. For example, high-level features can be extracted with deep learning models such as convolutional neural network (CNN) to reduce the dimensionality of the data subjected to model learning. As a representative type of deep neural network (DNN), CNN can extract high-level and hidden features in the data automatically through layers of abstraction [11], [12], [13] without domain-specific engineering skills and expert knowledge. On the other hand, time-series forecasting models, such as recurrent neural network (RNN) can learn to forecast the operating and ambient conditions of commercial equipment. It was demonstrated in existing literature that RNN such as long short-term

Manuscript received 11 February 2022; revised 6 September 2022; accepted 21 September 2022. Date of publication 12 October 2022; date of current version 24 January 2023. This work was supported in part by the LEO Dr. David P. Chan Institute of Data Science, Lingnan University, and in part by the Innovation and Technology Commission—The Government of the Hong Kong Special Administrative Region. *(Corresponding author: Kwan-Yeung Lee.)*

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Digital Object Identifier 10.1109/JIOT.2022.3211889

memory model (LSTM) [14] is ideal in predicting the status of industrial equipment and detecting anomaly in the time-series data collected with IoT sensors and information systems.

On the other hand, we are particularly interested in studying the operating and ambient conditions of the equipment installed in public hygiene and sanitary facilities, like public toilets. This is because the public hygiene facilities have become crucial to ensure our health, especially in the post-COVID-19 era [15]. Meanwhile, there are strong temporal variations within the complex conditions (such as facility configuration, temperature, humidity, number of users, and nearby social events), which serve as a good representation of the operating and ambient conditions that can be encountered by other commercial equipment and public facilities.

B. Main Contributions of This Article

The contribution of this article is threefold. First, we developed a proactive maintenance management framework, which consists of an IoT monitoring system for collecting data on the operating and ambient conditions of commercial equipment and a cloud platform for managing and analyzing the data collected. Second, we proposed a deep learning hybrid regression model called convolutional bidirectional long short-term memory (CBLM), which consists of a CNN for extracting high-level features hidden in our collected data and bidirectional LSTM (Bi-LSTM) for predicting the operating and ambient conditions in the future such that management personnel can then schedule the maintenance task accordingly. In addition, a naïve Bayes classifier is developed to assist management personnel in detecting abnormal operating and ambient conditions. Finally, our framework was deployed in a real public toilet and CBLM was evaluated with the data collected from our framework. To the best of our knowledge, this is the first work to forecast the operating and ambient conditions of toilet equipment for the proactive maintenance management purpose.

C. Organization of This Article

The remainder of this article is organized as follows. In Section II, we discuss the existing approaches in proactive maintenance management for different types of equipment. We first present our IoT and cloud-based monitoring framework in Section III and then elaborate on the CBLM model in Section IV-A and the naïve Bayes classifier in Section IV-B. In Section V, we discuss the real-world deployment of our IoT and cloud-based monitoring framework to a public toilet and analyze the results of the benchmark experiment performed on CBLM and naïve Bayes classifier with the real data that we collected. Finally, we conclude this article in Section VI.

II. Related Work

Proactive maintenance management has been conducted in industrial scenarios [8]. Industrial production lines are equipped with different kinds of sensors such that production processes can be constantly and automatically monitored and controlled by information systems. The big data collected by these sensors over a long period of time can be analyzed with data mining techniques and different kinds of models can then be constructed to solve different kinds of problems, such as detecting abnormal events in time-series data [16], [34], [35], [36], predicting or detecting the mechanical fault of machinery [37], [38], [39], predicting the energy consumption of machinery [40], [41], and detecting human activities [42]. These models can assist management personnel in improving the efficiency of production line.

One of the most obvious approaches in optimizing an industrial production process is to minimize its idling cost. If the internal status or the external operating and ambient conditions of the equipment can be accurately forecast, management personnel can then optimize the schedule for maintenance inspections such that the idle time of the production line can then be minimized. This practice of scheduling the maintenance task of equipment can be described as proactive maintenance management.

A. Scheduling Maintenance Task Through Analyzing the Status of Equipment

One typical approach of proactive maintenance management is to train models that can accurately predict the status of the equipment based on the raw data collected by its sensors. This approach is called predictive maintenance. Random forest is one of the most popular classification models adopted by other studies because of its robustness toward over-fitting [11]. It was demonstrated to be effective over different types of equipment, such as air compressors [17], wind turbines [18], and computer hard drives deployed in data centers [19]. Meanwhile, other classification models, such as support vector machine (SVM) and neural network were also applied in the field of predictive maintenance. For example, SVM was applied in predicting the failure of automotive transmission boxes [20] and rail network equipment [21]. On the other hand, a hybrid model of SVM and k-Nearest Neighbors (k-NN) was developed for detecting machinery failure caused by accumulative usage and stress on its components [22]. Meanwhile, the neural network was applied to industrial packaging robots [23] and engines [24]. Furthermore, IoT and fog computing have both gained their popularity in industrial sector due to the recent technological advancement and development in industry 4.0. As a result, traditional machine learning and deep learning predictive maintenance models can now be potentially learned with the data collected with IoT, edge, fog, and cloud computing technologies [43] as demonstrated in the following recent studies under industrial scenarios, such as production pipeline [25], [26], [27], [28] and nuclear power plant infrastructure [29].

B. Scheduling Maintenance Task Through Analyzing the Operating and Ambient Condition of Equipment

It is expected that the equipment which can be deployed in an industrial production line should have a reasonably high reliability. As a result, the distribution of data points sampled from abnormal equipment and normal equipment is more likely to be imbalanced, i.e., the number of normal data points is far more than that of abnormal data points.

TABLE I
COMPARISON OF EXISTING APPROACH VERSUS THE PROPOSED FRAMEWORK

	Data Acquisition			Feature Extraction and Selection		Prediction of Operating and Ambient Conditions/Anomaly Detection	
	Real-time Data Collection	Ambience Data	Operating Data	Based on Human Knowledge	Based on Machine Learning/Statistical Test	Traditional Machine Learning	Deep Learning
[16]	✓		✓	✓		✓	
[17]			✓		✓	✓	
[18]	✓		✓	✓	✓	✓	
[19]	✓		✓		✓	✓	
[20]			✓		✓	✓	
[21]			✓		✓	✓	
[22]			✓		✓	✓	
[23]			✓		✓	✓	
[24]			✓	✓		✓	
[25]	✓		✓		✓	✓	
[26]	✓		✓		✓		✓
[27]	✓		✓		✓	✓	
[28]	✓		✓		✓		✓
[29]	✓		✓		✓	✓	
[30]	✓		✓		✓		✓
[31]	✓		✓		✓	✓	
[32]			✓		✓	✓	
[33]			✓		✓	✓	
Our Framework	✓	✓	✓		✓		✓

This imbalanced distribution of data poses a challenge for the researchers to build robust models for predictive maintenance. To circumvent this limitation, other approaches in solving the problem of proactive maintenance management were proposed. For example, the performance of the equipment can be forecast based on its external operating conditions such that management personnel can beware of any potential abnormal behaviors of the equipment being affected in the future and schedule the maintenance task accordingly. For example, an abnormal photovoltaic (PV) system can be detected through analyzing the dynamic changes of the differences between the expected output against the actual output of its power production. The expected power production output of a PV system can be predicted by a neural network. The neural network can be trained to perform its prediction based on the operating conditions data, such as solar irradiance and PV panel temperature [16] or the power production output data of neighboring PV panels [30]. Other types of abnormal equipment can also be detected through analyzing its operating conditions as demonstrated by a recent study on the injection molding machine [31]. On the other hand, researchers can discover hidden knowledge and patterns, which can assist management personnel in scheduling the maintenance task, after analyzing the common characteristics found within each cluster partitioned by various clustering algorithms. For example, in a previous research, factors potentially associated to the failure of the transformer were discovered after researchers partitioned the data into clusters according to the concentration of gases dissolved in the insulating oil of a transformer with the k-mean clustering algorithm [32]. Similarly, another group of researchers performed clustering on the operating conditions of a selective laser melting machine tool and discovered four sets of faulty operating conditions [33].

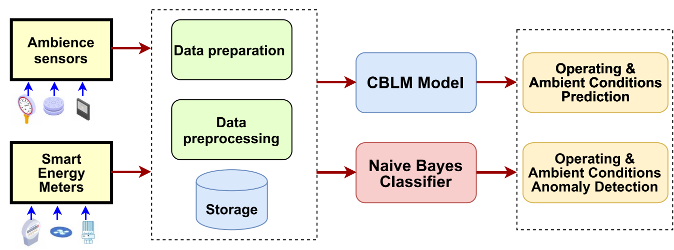

Fig. 1. Our framework for achieving the proactive maintenance management of public toilet.

In summary, there is no study on proactive maintenance management for urban informatics like public toilets despite previous research efforts in industrial scenarios. Different from industrial environment, public facilities are often affected by dynamical changes of nearby personnel and social events. To bridge this research gap, we propose an integrated framework of IoT and cloud system for proactive maintenance management of a public toilet. We also design a hybrid deep learning model to analyze the collected data. Different from existing approaches, our framework considers real-world scenarios, such as real-time data collection, general models, and robustness. The key differences between our framework and existing approaches are summarized in Table I.

III. SYSTEM OVERVIEW

In this section, we describe our IoT and cloud-based monitoring framework for collecting and forecasting the operating and ambient conditions of the equipment which can aid management personnel to schedule maintenance task proactively. The overall framework is illustrated in Fig. 1.

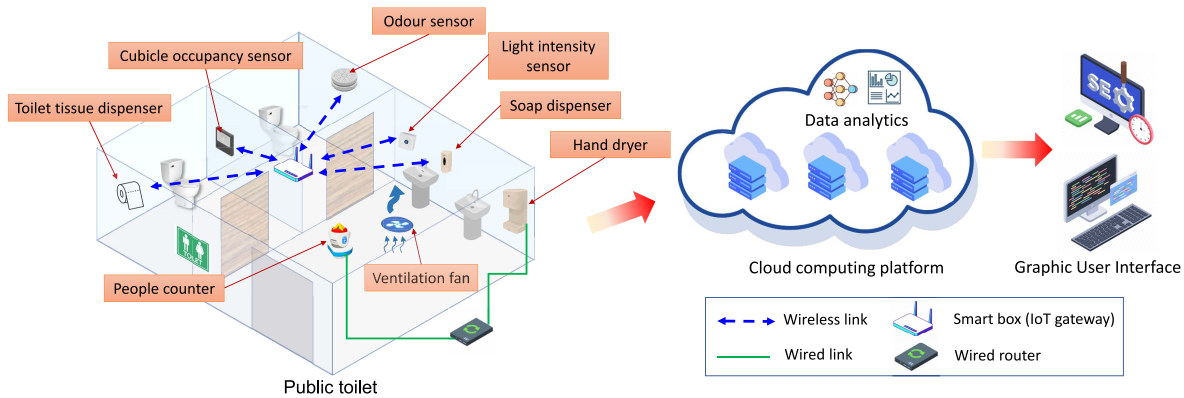

Fig. 2. Overview of the IoT monitoring system.

First, our integrated framework has an IoT monitoring system for collecting data on the operating and ambient conditions of different kinds of equipment with ambience sensors and smart energy meters. After that, the data collected is then preprocessed and cleaned. Finally, CBLM can then be learned with our cloud-based analysis platform to forecast the operating and ambient conditions of different kinds of equipment such that management personnel can then optimize the maintenance schedule in the future. On the other hand, a naïve Bayes classifier will also be included to assist management personnel in detecting abnormal operating and ambient conditions during their decision-making process. Our framework was developed and tested based on the data collected from a real toilet.

To collect data on the operating and ambient conditions of a toilet for our study, we installed ambience sensors, smart energy meters, and an IoT monitoring system in a Hong Kong public toilet. A systematic overview of our IoT monitoring system is shown in Fig. 2.

A. Collecting Data Through Ambience Sensors and Smart Energy Meters

1) Ambience Sensors: Ambience sensors, such as cubicle occupancy sensors, odor sensors, people counters, light intensity sensors, and remaining amount sensors for soap dispensers and toilet tissue dispensers, were installed in the toilet to establish a comprehensive monitoring on the ambient conditions of the equipment in the toilet. The data collected by these sensors is called ambience data and are sent to a smart box via wireless communications. These sensors can measure ambient conditions, including temperature, relative humidity, light intensity, ammonia (NH_3) gas concentration level, hydrogen sulfide (H_2S) gas concentration level, number of toilet users, soap level in dispensers, toilet paper availability in toilet paper holders, air quality, and cubicle occupancy.

To eliminate the cost of constructing and maintaining a wired network, most of the sensors that we selected for this project are designed to send the collected data to a smart box via wireless communications (data of some sensors are collected via wired links to the wired router). The wireless network is constructed based on a low-power wide-area network technique, namely, LoRa because of its excellent communication performance and low power consumption. The frequency band and emission power of all sensors are configured to comply with the requirements of Office of the Communications Authority (OFCA) of Hong Kong. The data collected by the IoT sensors is uploaded to the cloud platform through a smart box.

2) Smart Energy Meter: In order to collect the data on the operating frequencies and the level of the operational capacity of the electrical appliances (i.e., operating condition data), a smart energy meter is installed on each electrical circuit to monitor the electricity consumption of the corresponding circuits. Each electrical circuit is connected to only one type of electrical appliance. The data collected by the smart energy meters is uploaded to the cloud platform through the wired router.

3) Cloud Computing Platform: Our cloud computing platform can record, analyze, and forecast the operating and ambient conditions of toilet equipment. On the other hand, it can detect abnormal operating and ambient conditions of toilet equipment and alert management personnel.

4) Web-Based User Interface: The readings of the sensors and the results of the analysis performed under our cloud computing platform can be visualized with the Web-based user interface. Management personnel can monitor the status of the toilet in real time with the same user interface as well.

The user interface has two different user privilege levels.

1) General users can browse the current situation of the toilet, including the concentration levels of two common odors in toilets, the occupancy of the cubicles, and any shortage of toilet paper or soap. If one toilet has all cubicles being occupied, the potential users may go to another nearby toilet levels.
2) Staff users can browse the logs on the sensors' readings and receive alerts regarding abnormality predicted in the operating and ambient conditions of toilet equipment such as any shortage of toilet paper or soap, having stagnant water on floor, abnormal high level of odors. Management personnel can thus arrange cleaning and maintenance personnel to resolve the issues.

In this article, we aim at collecting data of the operating and ambient conditions of lighting devices and ventilation fans

TABLE II
ELECTRICAL DEVICES IN THE TOILET BEING MONITORED

Devices	Operating Conditions	Ambient Conditions
Lighting devices	Power consumption, electrical current, electrical power, electrical voltage, and electrical frequency	Light intensity, temperature, relative humidity, ammonia gas concentration level, number of toilet users, hydrogen sulfide gas concentration level, and air quality
Ventilation fans	Power consumption, electrical current, electrical power, electrical voltage, and electrical frequency	Temperature, relative humidity, light intensity, ammonia gas concentration level, number of toilet users, hydrogen sulfide gas concentration level, and air quality

such that we can predict the operating and ambient conditions of these two types of devices. Table II presents the details of the data being collected.

B. Analyzing the Operating and Ambient Conditions

After collecting data from smart energy meters and ambience sensors, the data need to be preprocessed and cleaned [44] before it can be used to train our CBLM model and naïve Bayes classifier. First, the smart energy meter data of the electric device will be merged with the ambience data into one data set such that the hidden association between these two kinds of data can be captured later through machine learning models. After that, since the sampling frequencies of the sensors are different from each other, the data set of each device will be resampled such that the sampling time interval of each variable is standardized to 15 min. Then, missing data are imputed through interpolation with existing data. Finally, normalization will be performed to regularize the scale of every variable to reduce bias during the learning process.

We finally obtained two data sets of operating and ambience conditions for two electric devices. One for the ventilation fans and another for the lighting devices. In particular, we list data statistics of the ventilation fans and the lighting devices in the Appendix. Each data set was then split into three sets, namely, a training set, a validation set, and a testing set, respectively, under a 80/10/10 ratio, which is the standard practice for deep learning models and machine learning models [45].

IV. ANALYSIS MODELS

After we preprocessed, cleaned, and integrated the data collected from the ambience sensors and smart energy meters, machine learning models can analyze the data so as to forecast the operating and ambient conditions through capturing the interactions among these conditions. For example, it is well known that the ambient temperature affects the operating current and life span of electrical motors and existing literature shows that there is a general inverse relationship between the lifespan of electric motors and the ambient temperature [46], [47]. However, there are other factors that can affect the operating current and life span of electrical motors, such as motor design, insulation material of coil wire, and material of the motors. Since the environment of a public toilet is highly dynamic, there may be multiple directional and nonlinear interactions among the operating and ambient conditions of different types of equipment in a public toilet, thereby affecting the lifespan of the equipment. Meanwhile, existing traditional machine learning approaches, such as random forest, Bayesian network, and SVM are not robust against noise in a dynamic environment and may fail to extract fault patterns of the equipment unless the environment is well-understood and relatively static.

On the other hand, a piece of equipment can be deployed in real-world scenarios only if it is sufficiently reliable. Therefore, the data on the operating and ambient conditions of the equipment collected during its normal state are expected to be far more abundant than the data collected during its abnormal state. Inspired by the fact that the longevity of a piece of equipment is correlated to its operating and ambient conditions, we addressed the above two challenges by modeling the problem of proactive maintenance management as a regression problem. Our solution is to construct a regression model which can predict the operating and ambient conditions in the future such that management personnel can then schedule the maintenance task accordingly.

Additionally, it is tedious for management personnel to inspect the operating and ambient conditions and detect anomaly by hand. Therefore, we have constructed another classification model for predicting if a given operating and ambient conditions is abnormal or not. This model can then assist the management personnel in detecting abnormal operating and ambient conditions.

A. Predicting Operating and Ambient Conditions With CBLM

In this section, we will discuss our regression model that can predict the operating and ambient conditions of the equipment in the future based on the operating and ambient conditions of the equipment collected by our IoT monitoring system in the past. Our regression model is a hybrid model called CBLM model, which comprises a Bi-LSTM stacking on top of a CNN. A CNN [48], [49], [50] typically comprises a series of convolution layers. Each neuron in the convolution layer is responsible for extracting localized relationships between the elements covered by its corresponding local receptive field through performing convolution with a common kernel shared across all local receptive fields. During the training of CNN, the parameters of these convolution layers can be optimized by backpropagation without the involvement of any prior knowledge. The correlations among different operating and ambient conditions can hence be extracted as high-level features through a nested hierarchy of kernels over a series of properly trained convolution layers. These high-level features are then feed into the Bi-LSTM network, which can be trained to forecast the operating and ambient conditions of the equipment. The overall structure of the CBLM

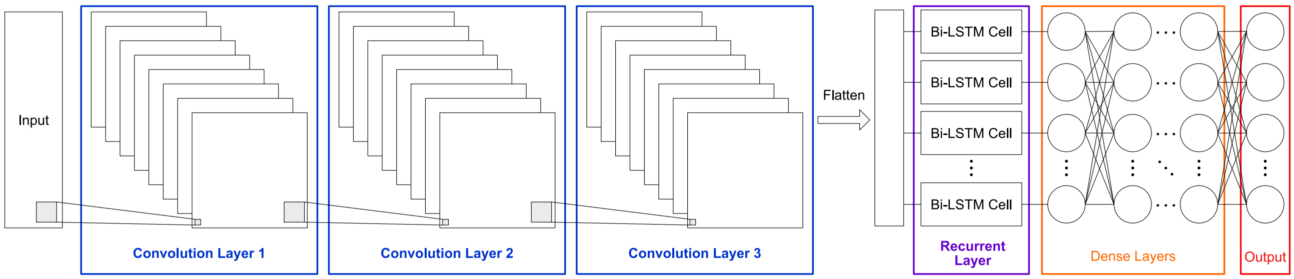

Fig. 3. Network structure of CBLM.

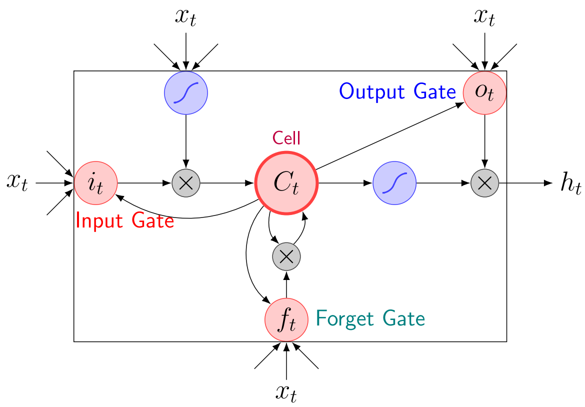

Fig. 4. Structure of an LSTM cell [51].

TABLE III
OPTIMIZED PARAMETERS FOR CBLM ON VENTILATION FANS

Parameter	Value
Optimal time lag	4s
Optimal number of units in CNN	66
Kernel size of CNN	5
Stride size of CNN	1
Activation function of CNN	Relu
Optimal number of units in Bi-LSTM	132
Activation function of Bi-LSTM	Relu
Activation function of dense layer	Linear

is shown in Fig. 3. We next elaborate on this model in detail.

As a subclass of RNNs, a Bi-LSTM network can model the changes of the operating and ambient conditions of the equipment by capturing long-term temporal associations in both forward and backward directions. A Bi-LSTM network is a collection of LSTM recurrent cells connected together in a specific topology followed by a series of dense neuron layer. An LSTM recurrent cell is the basic functional unit for capturing temporal associations. Fig. 4 depicts the architecture of an LSTM cell [51], where i_t, o_t, f_t, and c_t are the value of the input gate, output gate, forget gate, and cell state at time t, respectively, and h_t is the output of the cell at time t. The values of these terms can be computed by

$$f_t = \sigma\left(w_{f,h}h_{t-1} + w_{f,x}x_t + w_{f,c}c_{t-1} + b_f\right) \quad (1)$$
$$i_t = \sigma\left(w_{i,h}h_{t-1} + w_{i,x}x_t + w_{i,c}c_{t-1} + b_i\right) \quad (2)$$
$$o_t = \sigma\left(w_{o,h}h_{t-1} + w_{o,x}x_t + w_{o,c}c_t + b_o\right) \quad (3)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tanh\left(w_{c,h}h_{t-1} + w_{c,x}x_t + b_c\right) \quad (4)$$
$$h_t = o_t \circ \tanh(c_t). \quad (5)$$

Among them, $w_{f,h}$, $w_{f,x}$, $w_{f,c}$, $w_{i,h}$, $w_{i,x}$, $w_{i,c}$, $w_{o,h}$, $w_{o,x}$, $w_{o,c}$, $w_{c,h}$, and $w_{c,x}$ are weights and b_f, b_i, b_o, and b_c are bias. The internal state of an LSTM recurrent cell is controlled by its input and forget gates. The input gate and forget gate control how much information of the current input sample and the previous internal state has to be included while computing the current internal state, respectively. Meanwhile, the output gate computes the output of the LSTM cell based on its current internal state and its current input sample. The introduction of the gate mechanism significantly improves the performance of an LSTM recurrent cell over its predecessor (i.e., a basic recurrent cell) in modeling long-term temporal associations with approximately the same number of parameters [51], [52]. This improvement was empirically demonstrated in existing literature [53]. However, an LSTM recurrent cell has a limitation that it can only model the hidden relationships among the samples in one temporal direction. To model these relationships in both temporal directions, a Bi-LSTM network has two sets of hidden layers of recurrent cells such that each set of hidden layers is responsible for modeling relationships in one temporal direction [51].

CBLM is a complex model and has many parameters. To optimize the performance of CBLM, these parameters must be tuned. The search for an optimal set of parameters in the CBLM is characterized as a combinatorial optimization problem, which belongs to the class of nondeterministic polynomial (NP) hard problem. Therefore, we have applied $(\mu + \lambda)$ genetic algorithm [54] to search for a near-optimal set of parameters scholastically for ventilation fans and lighting devices. Tables III and IV list parameters for ventilation fans and lighting devices, respectively. The parameters of the genetic algorithm are shown in Table V.

Meanwhile, six baseline models were trained with traditional machine learning algorithms and can serve as a reference during the performance evaluation of CBLM.

B. Detecting Anomaly With Naïve Bayes Classifier

In this section, we will discuss our approach for detecting abnormal operating and ambient conditions with a naïve Bayes classifier. After a prediction model is properly validated,

TABLE IV
OPTIMIZED PARAMETERS FOR CBLM ON LIGHTING DEVICES

Parameter	Value
Optimal number of time lag	7s
Optimal number of units in CNN layer 1	70
Kernel size of CNN layer 1	5
Stride size of CNN layer 1	1
Kernel size of pooling layer 1	2
Stride size of pooling layer 1	2
Optimal number of units in CNN layer 2	140
Kernel size of CNN layer 2	3
Stride size of CNN layer 2	1
Kernel size of pooling layer 2	2
Stride size of pooling layer 2	2
Optimal number of units in CNN layer 3	280
Kernel size of CNN layer 3	3
Stride size of CNN layer 3	1
Activation function of all CNN and pooling layer	Relu
Optimal number of units in Bi-LSTM	140
Activation function of Bi-LSTM	Relu
Activation function of dense layer	Linear

TABLE V
OPTIMIZED PARAMETERS FOR GENETIC ALGORITHM HYPERPARAMETER TUNING OF CBLM

Parameter	Value
μ	2
λ	4
Number of generations	20
Selection	Roulette Wheel Selection
Crossover	Two-Point Crossover, Crossover Probability = 0.7
Mutation	binary flip mutation, mutation probability = 0.1
Fitness function	Root-Mean-Square Error (RMSE)
Fitness Evaluation Datasets	Validation Dataset

if there is a significant deviation between the predicted value and the real value of operating and ambient conditions (i.e., prediction errors) at a particular time t, then, we may assume that there is an anomaly at time t. Based on this assumption, we modeled the distribution of the prediction error of our prediction model as a multivariate Gaussian distribution and constructed a naïve Bayes classifier. Fig. 5 depicts an overview of the working flow of how we learn the naïve Bayes classifier.

Given a data point y_t at time t in an operating and ambient conditions data set, a prediction model can compute the predicted value of y_t based on the data point y_{t-1} at time $t-1$. The prediction error e_t between the predicted value and the actual value of y_t can then be computed. By randomly selecting 30% of the data points from an operating and

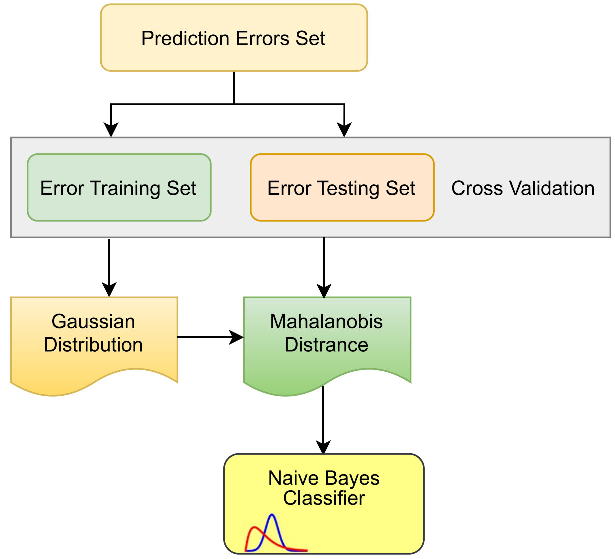

Fig. 5. Overview of anomaly detection.

ambient conditions data set and repeating the above operation on each selected data point, the prediction errors of these selected data points are calculated and divided into error training set and error testing set. After that, the distribution of the prediction errors is modeled as a multivariate Gaussian distribution and the corresponding parameters are estimated through maximum likelihood estimation under cross-validation. Then, the Mahalanobis distance of the prediction errors of each selected data point is obtained according to the Gaussian distribution [55]. By making another assumption that data point y_t is abnormal if the Mahalanobis distance of its prediction error e_t is in the top 10% of the distribution of the Mahalanobis distance, a status label can then be assigned to each selected data point in an unsupervised manner. Finally, a Gaussian naïve Bayes classifier can be learned with the training set and validated with the testing set.

After the naïve Bayes classifier is trained and validated, the classifier can then assist management personnel to identify if the operating and ambient conditions y_t at any particular time t is abnormal or not based on the difference between its predicted value and its actual value.

V. EVALUATION

To evaluate the overall effectiveness of our framework in achieving proactive maintenance management of commercial equipment, we first deployed our IoT monitoring system to a real smart public toilet. After collecting data on the operating and ambient conditions of the toilet equipment with our framework, we performed benchmark experiments on our CBLM and naïve Bayes classifier to evaluate their performance in predicting the future operating and ambient conditions of the toilet equipment and detecting anomalies.

A. Deployment of the IoT Monitoring System

We deployed our IoT monitoring system in a Hong Kong public toilet to test the operability of our system in

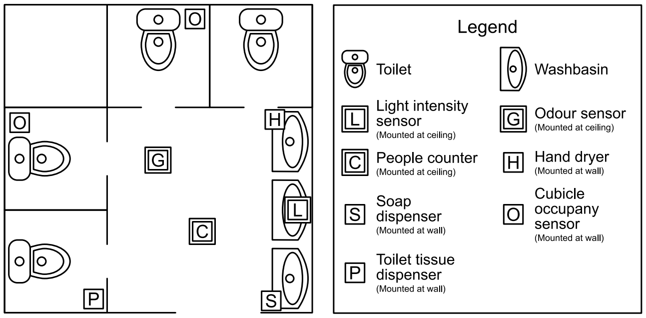

Fig. 6. Flour plan of sensor deployment.

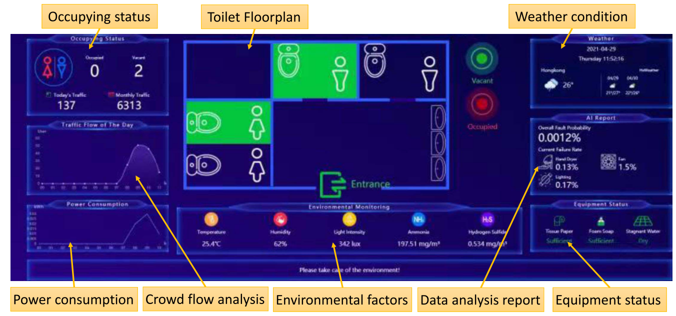

Fig. 7. GUI of IoT monitoring system.

collecting data of the operating and ambient conditions of toilet equipment in the real life scenarios and to collected enough data to support the evaluation of our CBLM and naïve Bayes classifier. We give the general deployment procedure of an ambient sensor in the IoT monitoring system as follows.

1) Preparing a power source for the sensor.
   a) Low-power sensor will be powered by a battery directly.
   b) Power-hungry sensor will be powered by a dc power adaptor instead of a high-capacity battery pack to reduce the maintenance cost.
2) Pairing the sensor with the smart box and assigning identification to the sensor.
3) Mounting the sensor according to its functionality.
   a) Odor level sensor or people counter should be mounted on ceiling.
   b) Light intensity sensor should be mounted on high position of wall with one meter from to ceiling.
   c) Cubicle occupancy sensors, soap dispensers with level sensors, or toilet paper holders with built-in sensors should already be built into the equipment.
4) Validating the sensor is operating correctly after the installation.

All ambient sensors were installed according to the above procedure and a floor plan visualizing the deployment location of the sensors in the toilet is shown in Fig. 6. Meanwhile, the smart energy meters were installed to the main smart box (the IoT gateway) such that each of them can be physically connected to the electrical circuit that it is supposed to be monitoring. Real deployment of these sensors is given in Fig. 8 in the Appendix.

After all ambient sensors, smart energy meters, and cloud platform are deployed, data collected can then be visualized and retrieved through the web-based dashboard GUI of our system as shown in Fig. 7.

B. Performance Benchmark on Our Framework

We performed benchmark experiments on CBLM and six other machine learning baseline models with the real data of ventilation fans and lighting devices collected from the implemented smart toilet to evaluate the performance of CBLM in predicting the operating and ambient conditions of toilet equipment. In addition, we performed a Proof of Concept (PoC) experiment to demonstrate the potential application of our

TABLE VI
EXPERIMENTAL RESULTS OF COMPARING SIX BASELINE MODELS AGAINST CBLM UNDER VENTILATION FANS

	RMSE	CV(RMSE)	MAE	R-Squared
RIDGE	8.81	1.02	6.25	0.970
SVR	6.73	0.78	5.79	0.993
LR	7.51	0.88	5.93	0.983
Extra Tree	6.61	0.76	5.57	0.994
Random Forest	8.72	1.01	6.08	0.972
XGBoost	5.94	0.68	4.28	0.993
Our CBLM	**5.11**	**0.55**	**3.88**	**0.995**

TABLE VII
EXPERIMENTAL RESULTS OF COMPARING SIX BASELINE MODELS AGAINST CBLM UNDER LIGHTING DEVICES

	RMSE	CV(RMSE)	MAE	R-Squared
RIDGE	26.39	1.56	11.39	0.944
SVR	29.01	1.73	12.51	0.949
LR	26.88	1.57	11.71	0.946
Extra Tree	29.32	1.75	12.84	0.938
Random Forest	35.91	2.15	13.74	0.907
XGBoost	31.46	1.88	12.98	0.935
Our CBLM	**24.75**	**1.51**	**10.45**	**0.961**

naïve Bayes classifier to be adapted for detecting any anomaly with the best-performing baseline model or our proposed CBLM.

1) Performance Metrics for Evaluation: In this article, we adapted the following four common performance metrics to evaluate the accuracy of a model in predicting the operating and ambient conditions of the equipment: 1) the root-mean-squared error (RMSE); 2) the coefficient of variation (CV) of RMSE; 3) mean absolute error (MAE); and 4) R-Squared [56]. Among them, CV(RMSE) is the RMSE regularized by the average of the measured values

$$\mathrm{CV(RMSE)} = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{N}\left(y_i' - y_i\right)^2}{N}} \tag{6}$$

where y_i' is the predicted value, y_i is the real value, $\bar{y}$ is the mean of the real value, and N is the total number of data samples.

Fig. 8. This figure shows six kinds of ambient sensors and an electric device monitored by a smart energy meter that is deployed in our smart toilet, such as (a) odor sensor, (b) cubicle occupancy sensor, (c) a hand dryer monitored by a smart energy meter, (d) toilet tissue dispenser, (e) light intensity sensor, (f) people counter, and (g) soap dispenser.

MAE is the average value of the sum of the absolute differences between actual values and predicted values

$$\mathrm{MAE} = \sqrt{\frac{\sum_{i=1}^{N} |y_i' - y_i|}{N}}. \tag{7}$$

Models with larger error values are penalized by RMSE, which is given as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i' - y_i)^2}{N}}. \tag{8}$$

As a statistical measure of fit, R-Squared represents how much variation of y_i can be preserved in y_i'.

Finally, we adapted the following four common performance metrics to evaluate the accuracy of our naïve Bayes classifier in detecting the anomaly: 1) accuracy; 2) precision; 3) recall; and 4) F1 measure.

2) Results of the Evaluation: In this article, linear regression (LR), RIDGE, support vector regression (SVR), random forest, extra tree regressor, and extreme gradient boosting (XGBoost) [57] were selected to be the baseline models to be compared against CBLM in our benchmark [58]. To ensure a fair comparison, we optimized the parameters of each baseline model by conducting a grid search. For each set of parameters, the mean squared error of each baseline model was first minimized during the training process with the training data.

TABLE VIII
EXPERIMENTAL RESULTS OF DETECTING ANOMALY WITH THE OPERATING AND AMBIENT CONDITIONS PREDICTED BY CBLM AND XGBOOST UNDER VENTILATION FAN

	XGBoost+GaussianNB	CBLM+GaussianNB
Accuracy	0.97	0.98
Precision	0.66	0.80
Recall	1.00	1.00
F1	0.90	0.92

TABLE IX
EXPERIMENTAL RESULTS OF DETECTING ANOMALY WITH THE OPERATING AND AMBIENT CONDITIONS PREDICTED BY CBLM AND RIDGE UNDER LIGHTING DEVICE

	RIDGE+GaussianNB	CBLM+GaussianNB
Accuracy	0.97	0.98
Precision	0.63	0.88
Recall	1.00	1.00
F1	0.85	0.94

After that, each baseline model was evaluated with the testing set under the four performance metrics that were previously defined. The above process was repeated until the optimal set of parameters could be found.

TABLE X
OVERVIEW STATISTIC OF THE VENTILATION FAN DATA SET

	Operating Condition Variables					Ambient Condition Variables						
	Voltage (V)	Power (W)	Current (A)	Frequency (Hz)	Consumption (Degree)	Traffic of the day	Temperature (°C)	Humidity (%)	H_2S (mg/m^3)	Brightness (Lux)	Air quality	Ammonia ($\mu g/m^3$)
mean	227.7411	0.0226	0.1059	49.997	0.0005	85.3899	27.8345	64.6805	0.2051	277.5469	2.0899	74.8399
std	1.3336	0.0261	0.1225	0.0268	0.0023	120.4424	1.1505	5.0792	0.1687	107.7331	0.3617	61.5494
min	223.55	0	0	49.94	0	0	24.2094	50.6063	0.0137	8.3396	1.188	4.5226
25%	226.81	0	0	49.97	0	0.9412	27.5047	60.6739	0.068	207.8664	1.8107	25.1428
50%	227.77	0	0	50	0	6.3143	28.178	65.4875	0.1258	328.3071	2.0395	46.158
75%	228.71	0.053	0.247	50.02	0	161.9545	28.5687	68.5812	0.3548	361.8538	2.4553	128.2325
max	231.93	0.056	0.265	50.04	0.01	556.75	29.529	75.1768	0.5338	399.728	2.6292	197.512

TABLE XI
OVERVIEW STATISTIC OF THE LIGHTING DEVICE DATA SET

	Operating Condition Variables					Ambient Condition Variables						
	Voltage (V)	Power (W)	Current (A)	Frequency (Hz)	Consumption (Degree)	Traffic of the day	Temperature (°C)	Humidity (%)	H_2S (mg/m^3)	Brightness (Lux)	Air quality	Ammonia ($\mu g/m^3$)
mean	227.9243	0.0576	0.3334	49.9976	0.0014	85.3899	27.8345	64.6805	0.2051	277.5469	2.0899	74.8399
std	1.3106	0.0636	0.2638	0.0266	0.0035	120.4424	1.1505	5.0792	0.1687	107.7331	0.3617	61.5494
min	223.9200	0.0040	0.1100	49.9500	0.0000	0.0000	24.2094	50.6063	0.0137	8.3396	1.1880	4.5226
25%	227.0300	0.0040	0.1130	49.9700	0.0000	0.9412	27.5047	60.6739	0.0680	207.8664	1.8107	25.1428
50%	227.9600	0.0040	0.1130	50.0000	0.0000	6.3143	28.1780	65.4875	0.1258	328.3071	2.0395	46.1580
75%	228.8900	0.1070	0.5310	50.0200	0.0000	161.9545	28.5687	68.5812	0.3548	361.8538	2.4553	128.2325
max	231.8100	0.1960	0.9360	50.0500	0.0100	556.7500	29.5290	75.1768	0.5338	399.7280	2.6292	197.5120

Tables VI and VII list the results of CBLM and the other six baseline machine learning methods on the validation data sets of ventilation fans and lighting devices, respectively. In both Tables VI and VII, we observed that CBLM outperformed the other six baseline machine learning methods. This indicated that our proposed CBLM could make the best prediction on the operating and ambient conditions of the equipment being tested on.

Moreover, we observed that XGBoost and RIDGE were the best performers among the six baseline machine learning algorithms in the experiments with ventilation fans and lighting devices, respectively. Therefore, XGBoost and RIDGE were selected as the baseline models for performing our PoC demonstration along with our CBLM on applying our naïve Bayes classifier in detecting anomalies in the operating and ambient conditions of our ventilation fans and lighting devices, respectively.

The results of the anomaly detection experiments for XGBoost and our CBLM under the ventilation fan data set are shown in Table VIII. Meanwhile, the results of the anomaly detection experiments for RIDGE and our CBLM under the lighting device data set are shown in Table IX. Experimental results clearly indicated that our naïve Bayes classifier could accurately detect any abnormal operating and ambient conditions with either the baseline models (XGBoost and RIDGE) or the proposed CBLM. Therefore, our naïve Bayes classifier can act as a potential anomaly detector in real systems.

VI. CONCLUSION

In conclusion, we developed an integrated framework for forecasting the operating and ambient conditions of the equipment in a public toilet. Our system consists of an IoT and cloud-based monitoring framework for collecting and analyzing data. Moreover, we also present a hybrid learning model called CBLM for predicting the operating and ambient conditions. Through performing benchmarks with the data collected from a Hong Kong public toilet, we demonstrated that our proposed CBLM outperformed XGBoost, RIDGE, and four other traditional machine learning algorithms in forecasting the operating and ambient conditions of the equipment.

Meanwhile, we included a naïve Bayes classifier in our framework for detecting potential abnormal operating and ambient conditions and assisting management personnel to make decisions during their decision-making process. In our experiment, we successfully demonstrated our naïve Bayes classifier can be potentially applied to detect potential anomalies in the operating and ambient conditions.

We believe that this framework serves as a successful prototype of a generalized framework for solving the problem of proactive maintenance management of the equipment installed in commercial facilities and venues in the future.

APPENDIX

Tables X and XI list the operating and ambient conditions collected from 2020/4/28 8:15 to 2020/5/31 23:45 (totally

TABLE XII
ADDITIONAL INFORMATION REGARDING THE INSTALLATION OF THE AMBIENT SENSORS

	Power	Installation Method	Physical Dimension
a) Odour Sensor	12V DC	Ceiling Mount/ Wall mount	Diameter: 115mm Depth: 50mm
b) Cubicle Occupancy Sensor	3.7V DC	Wall mount	Height: 108mm Width: 160mm Depth: 44.5mm
d) Toilet Tissue Dispenser	5V DC	Wall mount	Height: 80mm Width: 125mm Depth: 32mm
e) Light Intensity Sensor	10 to 30V DC	Wall mount	Height: 85mm Width: 110mm Depth: 40mm
f) People Counter	12V DC	Ceiling mount	Diameter: 115mm Depth: 50mm
g) Soap Dispenser	4 C cell batteries	Wall mount	Height: 285mm Width: 160mm Depth: 120mm

807.5 h) while monitoring the status of the ventilation fans and the lighting devices. In Tables X and XI, columns 2 to 6 (i.e., voltage, power, current, frequency, and consumption) correspond to the operating condition variables and columns 7 to 13 (i.e., traffic of the day, temperature, humidity, brightness, air quality, and ammonia) correspond to the ambient condition variables.

Moreover, Tables X and XI also give the basic statistics of each condition. Actual photos of six kinds of ambient sensors and a hand dryer monitored by a smart energy meter that is deployed in our smart toilet are shown in Fig. 8. Table XII describes additional details regarding the installation of the ambient sensors. It is worth mentioning that odor sensors are deployed according to the manufacturer's installation recommendation, i.e., one sensor deployed per every 20 m^2 approximated to ventilation openings or odor sources. The people counters are also mounted according to the manufacturer's installation recommendation, i.e., 2.5–2.8 m above the floor.

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