ICIC Express Letters
Part B: Applications
Volume **9**, Number **11**, November **2018**

 ISSN 2185-2766
pp. 1161–1168

CLOUD-BASED PREDICTIVE MAINTENANCE FRAMEWORK FOR SENSOR DATA ANALYTICS

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Received April 2018; accepted July 2018

Abstract. *Machine maintenance is traditionally performed on a time schedule. At the scheduled time, a manufacturing company assigns technicians to check a machine's condition. This kind of approach, however, is not cost-effective as frequent visits will increase labor costs and lead to unnecessary maintenance as well. Predictive Maintenance (PdM) offers a cost-effective alternative maintenance scheme that predicts when repairs need to be performed. The rapid development of sensor technology has enabled manufacturing companies to utilize sensors to monitor machine condition and prevent performance degradation and/or breakdown thereby. This paper presents a cloud-based predictive maintenance framework for processing of huge amounts of machine sensor data to obtain useful insights related to machine maintenance.*
Keywords: Predictive maintenance, Predictive analytics, Machine maintenance

1. **Introduction.** High machine maintenance costs have become a considerable concern for manufacturing companies. Many companies have employed strategies for reduced machine maintenance costs and improved reliability. Moreover, application of a proper maintenance strategy enables more efficient and effective running of production processes. Manufacturing companies require an information system that has the capability of acquiring machine data that enables performance of efficient machine maintenance operations. As emphasized by Wang [8], a process of knowledge discovery that discerns particular data patterns is essential for any maintenance-decision support system. Candell et al. [1] outlined the broad applications of Information Communication and Technology (ICT) for data collection facilitation. Utilization of ICT enables the development of information systems for support of maintenance-decision-making. However, many readily available predictive maintenance software applications are of general scope, and as such did not

DOI: 10.24507/icicelb.09.11.1161

match our present case study's. The use of sensors, furthermore, incurs an additional challenge, which is the very large amounts of data to be processed. In this paper, therefore, we present a framework for support of machine maintenance decision-making processes. As adapted from [6], the knowledge discovery process incorporated into this framework entails, as illustrated in Figure 1, data acquisition, data preprocessing, data analysis, and information visualization.

In our case study, we stored voltage, current, frequency and other attributes to predict the reliability of a machine prior to its breakdown. To do so, our framework necessarily incorporates a feature for detection of false alarms. To support this feature, two essential functions were developed: first, a function to evaluate each sensor data value based on its threshold (lower and upper bounds) and to label it "alarm" when the threshold is exceeded; second, a function to calculate how long the particular sensor data value exceeds the threshold. Subsequently, the sensor data, as labeled, is assessed by the domain expert to determine whether it is a false or a true alarm; later, this data is used as a training dataset that will enable the machine-learning algorithm to detect false alarms automatically. Those two processes, sensor data evaluation and alarm duration calculation, are the data preprocessing steps. In the data analysis part, our application provides features that can help the domain expert to identify and analyze sensor data related to machine condition and machine maintenance. Since the application is still in the initial stages of development, the issue of predictive maintenance is beyond the scope of this paper. Table 1 describes the machine maintenance modules corresponding to the requirements thus far discussed.

FIGURE 1. Knowledge process discovery (adapted from [6])

TABLE 1. Machine maintenance modules

Module	Description
Monitoring	Provides proper data related to monitoring of machine-sensor data based on user's selected filter(s).
Predictive Analytics	Has three sub-modules to provide information related to: 1. Trend forecasting. Forecasts trends of certain sensor data. 2. False and true alarm detection. Detects false alarms based on certain rule(s). 3. Pattern detection. Detects certain patterns of sensor data in time-range period.
Predictive Maintenance	Has three sub-modules to provide information related to: 1. Remaining Useful Lifetime (RUL). Predicts life-span of components to minimize probability of catastrophic failure. 2. Failure prediction. Predicts occurrence of failure in future. 3. Anomaly detection. Detects unusual behavior based on sensor data analysis.

This paper is organized as follows. Section 2 discusses the related work, Section 3 outlines the cloud-based predictive maintenance framework and Section 4 presents the experimental results. Finally, Section 5 draws conclusions.

2. **Related Work.** There are three prominent maintenance strategies: reactive maintenance, preventive maintenance, and predictive maintenance. Predictive maintenance is considered to be a more efficient strategy since it monitors the machine state at a regular interval which allows for anticipation of potential breakdown or failure. Groba et al. [4] analyzed the requirements and introduced the initial predictive-maintenance-framework-related architecture. Their framework consists of four layers including data acquisition, layer-specific task execution, analytics-warehouse access, and model-framework access. Huang et al. [5] introduced the Intelligent Maintenance System (IMS) which integrates the factory floor with an enterprise system. Ming et al. developed a framework for practical predictive maintenance modeling of multi-state systems. From [4,5,7] we can conclude that the most common predictive maintenance framework consists of components responsible for data acquisition, detection of specific types of patterns, and input-target(s) modeling for prediction.

Many studies on predictive maintenance implementation have been conducted. Florea et al. [3] attempted to implement predictive maintenance for wind-farm operations optimization that requires efficient maintenance tasks. Optimization can be achieved through real-time noise monitoring for detection of behavior associated with system failures. This kind of detection is helpful for prevention of wind turbine breakdown and downtime minimization. Li et al. [2] implemented predictive maintenance to guarantee the safe and efficient operation of coal mining equipment. They acquired and analyzed machine parameters including vibration, temperature, air pressure and noise to identify potential safety threats. Based on [2,3], it is clear that any predictive maintenance framework architecture should consist of, at minimum, a data acquisition module, an analytics module, a monitoring module (i.e., an alarm system for machine faults), and a visualization module.

3. **Cloud-Based Predictive Maintenance Framework.** As noted in Section 1, the current framework incorporates specific features required by companies but that might not be provided by software currently on the market, such as false alarm detection (see Figure 5). In this section, we discuss the proposed cloud-based predictive maintenance architecture, its features, and the overall system environment.

3.1. **Architecture.** In general, the framework adopts a client-server architecture consisting of a server-side and client-side, as shown in Figure 2. The server-side has two layers, a storage layer and an application layer while the client-side has only one presentation layer.

3.1.1. *Storage layer.* The manufacturing company uses a third-party application that directly connects to one or more machines' sensor(s). It also performs data collection and periodically stores it in a database. Since we deal only with structured data, we prefer to use a relational database for storage of sensor data. The sensor data is saved in a table of the structure shown in Figure 3. Note that some columns (fields) are omitted for display convenience. The MC_ID field is for the machine ID, and the Dxx field is for sensor values.

Each machine has a configuration that indicates the number of recorded sensor values. This configuration is stored in a different table of the structure shown in Figure 4(a). As we can see in Figure 4(b), a machine with ID MC_0001 stores 13 sensor values while another machine might have a different number of sensor values.

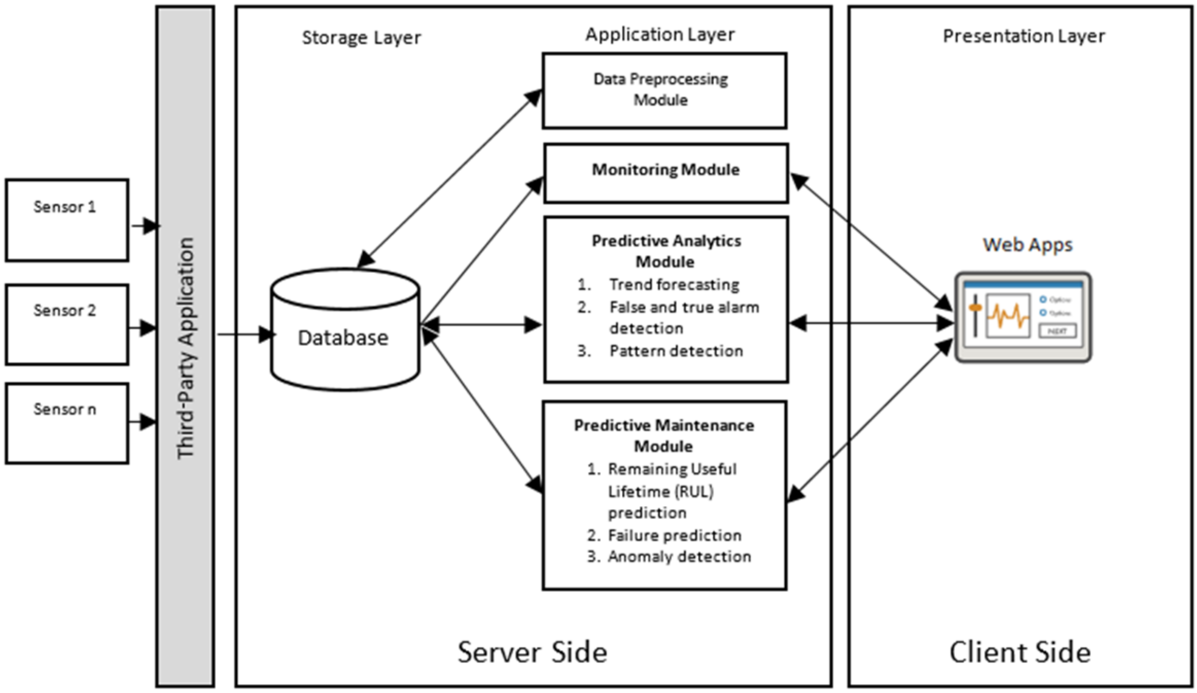

FIGURE 2. The architecture of cloud-based predictive maintenance

	#	Name	Datatype
	1	MC_ID	VARCHAR
	2	D00	DOUBLE
	3	D01	DOUBLE
	4	D02	DOUBLE
	5	D03	DOUBLE
	6	D04	DOUBLE
		...	

FIGURE 3. Table structure for storage of machine-sensor data (partial version)

3.1.2. *Application layer.* Figure 2 shows an application layer that has four modules: data preprocessing, monitoring, predictive analytics, and predictive maintenance. As explained in Section 1, there are two essential data preprocessing processes: sensor data evaluation, and alarm duration calculation. Those processes are performed by functions named *threshold evaluator* and *alarm duration calculator*, respectively (see Figures 5(a) and 5(b)).

The monitoring module is responsible for providing proper data visualization for specific machines according to the user's selection. The predictive analytics module has three sub-modules. The first is trend forecasting, which enables the user to see the future trend of a particular sensor. The second is false and true alarm detection, which provides automatic detection of false alarms by previously learning from labeled sensor data. The third sub-module is pattern detection, which supports the predictive maintenance module by providing a feature that can help the domain expert to identify unique patterns prior to the occurrence of failure and/or machine breakdown.

3.1.3. *Presentation layer.* Our application displays sensor data in two different forms: table and chart. No barrier is encountered in presenting sensor data in the table form; however, in the chart form, we need to find the proper chart library. We selected Dygraph

#	Name	Datatype
1	MC_ID	VARCHAR
2	CLM_IDX	INT
3	RATIO	DOUBLE
4	NM	VARCHAR
5	DESC	VARCHAR
6	DPUN	VARCHAR
7	ULIM	DOUBLE
8	UUSE	VARCHAR
9	UTM	INT
10	UULIM	DOUBLE
11	LLIM	DOUBLE
12	LUSE	VARCHAR
13	LTM	INT
14	LULIM	DOUBLE

(a)

MC_ID	CLM_IDX	RATIO	NM
MC_0001	0	1	Comm check
MC_0001	1	1	Setting Status
MC_0001	2	1	Current Status
MC_0001	3	1	Total Power(current)
MC_0001	4	1	Delata input Voltage
MC_0001	5	1	Star input voltage
MC_0001	6	1	Delta input current
MC_0001	7	1	Star input current
MC_0001	8	1	DC Voltage
MC_0001	9	1	Sequence number
MC_0001	10	1	Fault Number(current)
MC_0001	11	1	Inverter No.1 Power Command (SV)
MC_0001	12	1	Inverter No.2 Power Command (SV)
MC_0001	13	1	Converter Cooling water temp

(b)

FIGURE 4. (a) Table structure for machine configuration; (b) example of machine configuration

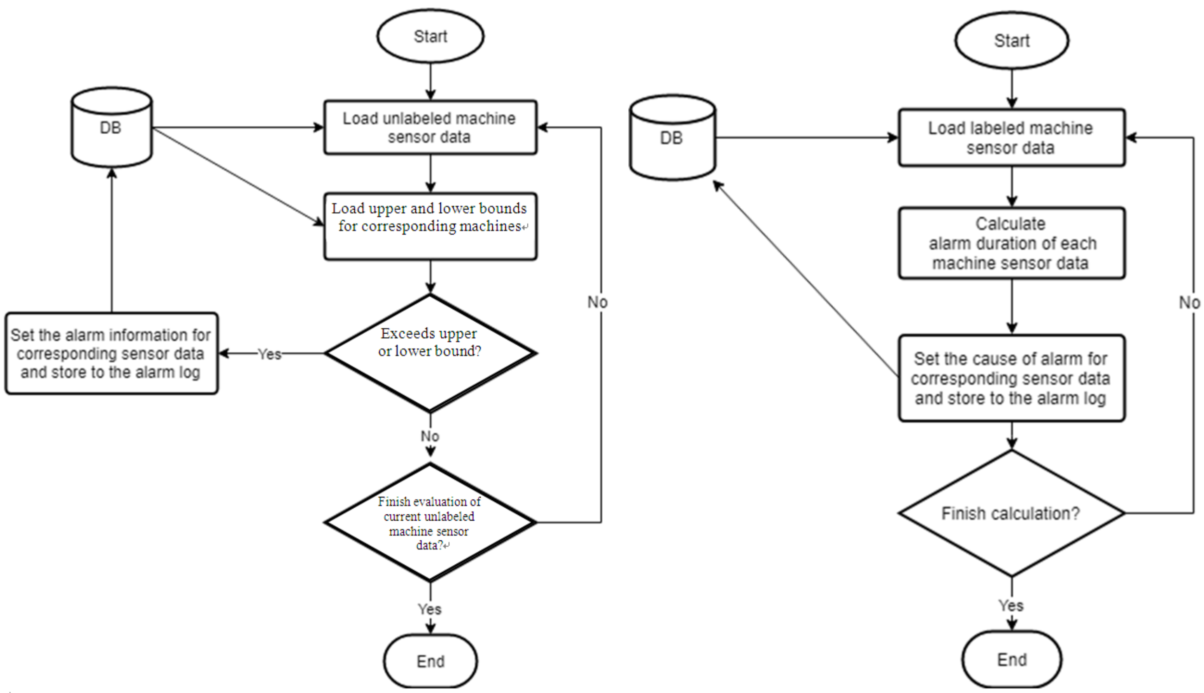

FIGURE 5. (a) Threshold evaluator; (b) alarm duration calculator

[10], because it has an excellent utility in rendering very large amounts of data either statically or dynamically in line-chart form, as shown in Figure 6.

3.2. **Features.** Table 2 provides the cloud-based predictive maintenance framework's application menu details.

The dashboard is the main page, since it is the first page that a user accesses. On the dashboard, the user can monitor one or more machines from different factories, as shown in Figure 7. The green color indicates that the machine is working well; the red color, meanwhile, warns of problems.

Operations Status provides for visualization of historical sensor data in the form of a line chart. The user can visualize such data based on his "machine" and "time period"

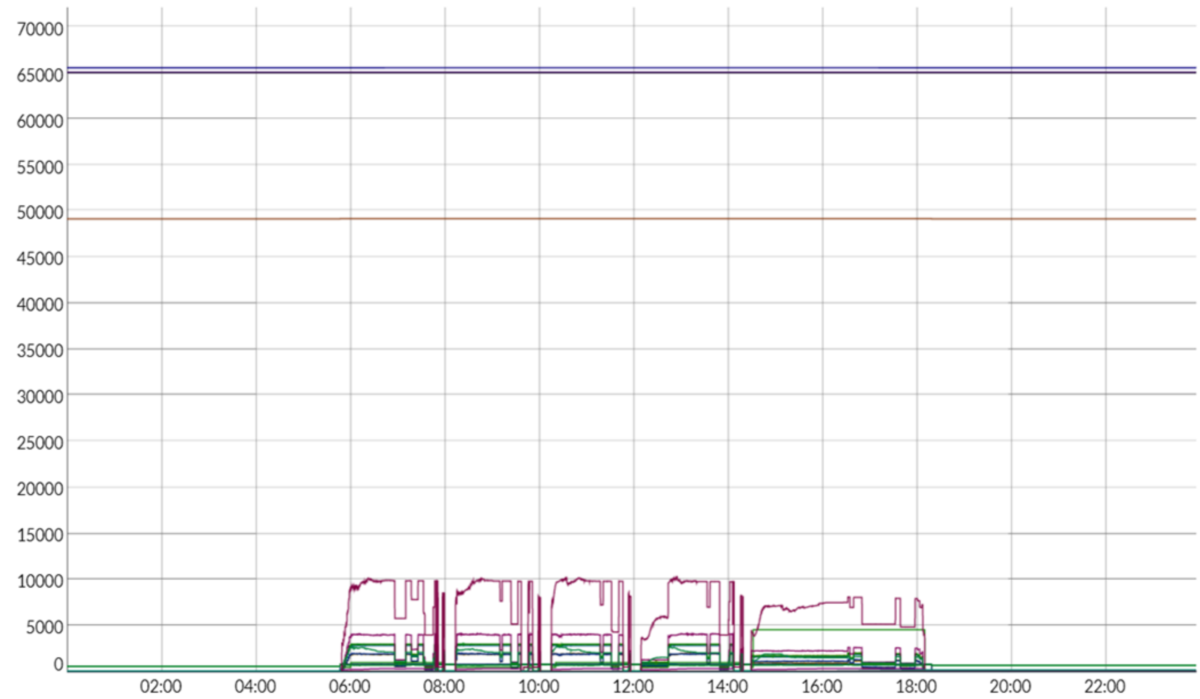

Figure 6. Line chart using Dygraph

Table 2. Cloud-based predictive maintenance framework's application menu

Application Main Menu	**Sub Menu**
Dashboard	
Operations Status	
Monitoring Item Status	
Setting	
Data Management	
	User Account
	Factory

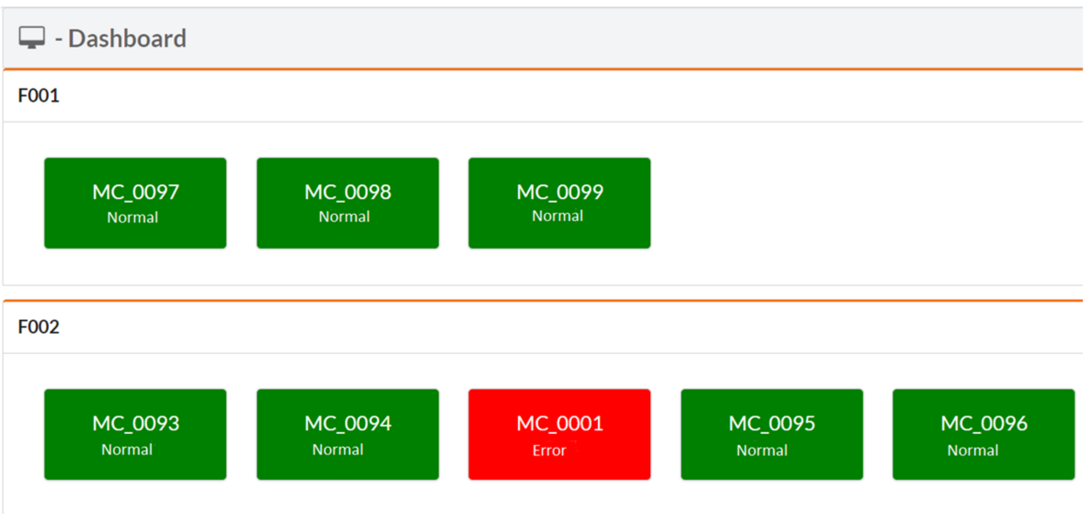

Figure 7. Machine monitoring from dashboard

Table 3. System environment of cloud-based predictive maintenance

Development Environment	
Web Server	Apache Web Server 2.4
Database	Maria DB 10.2
PHP Runtime	5.6.30
PHP Framework	Codeigniter 3.1.7
CSS UI Framework	Semantic UI 2.0
Javascript Library	Dygraphs, JQuery 3.2.1
Production Environment	
Operating System	Windows Server 2016 Datacenter
Web Server	IIS 7
PHP Manager Plugin	1.2
Database	Maria DB 10.2

selections. Monitoring Item Status enables the user to monitor the machine in a semi-real-time manner. This feature shows the previous 1 minute to 24 hours of sensor data dynamically. Our application also provides a functionality for ease of machine and factory data management.

3.3. **System environment.** The cloud-based predictive maintenance framework is being developed under the environment specified in detail in Table 3. For the server-side, we use PHP technology combined with the Codeigniter framework version 3.1.7. For the client-side, we use the Semantic-UI 2.0 framework and a Javascript library to provide for an interactive user interface.

4. **System Implementation.** In this section, we present the experimental results for the framework. We ran the application on a physical computer (specifications: Intel® Xeon® CPU E3-1220 V2 @ 3.10 GHz; 16GB RAM). The experiment was conducted using a real sensor dataset retrieved for the period 2017-10-01 to 2018-03-01 (no. of instances: approx. 1,400,000). The *threshold evaluator* and *alarm duration calculator* were executed every 10-15 minutes using Windows' Task Scheduler. Both functions check approximately 9,000 sensor data in a day to detect specific-machine problems and display the results on the dashboard page shown in Figure 7. The user can monitor the machine condition via the chart shown in Figure 6. The chart can show sensor data for a specific time period (hour/date range). Each color represents a different sensor data value. The PHP Script configurations related to the maximum execution time and memory limit should be set to 60 seconds and 123 MB, respectively, to guarantee that the Dygraph can render 100,000 data in chart form.

5. **Conclusions and Future Work.** This paper presents a cloud-based predictive maintenance framework that was developed to provide a solution for a specific case study on predictive maintenance. The web-based technology selected makes the application easy to access from anywhere regardless of platform. Certain specific features were developed to meet actual requirements. The current experimental results confirm that the application can, with proper configuration, handle a huge amount of data.

Acknowledgment. This work was supported by a National Research Foundation of Korea (NRF) grant funded by the Korean Government (MEST) (No. NRF-2015R1D1A1A09 061331).

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