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Cloud-based Data Analytics Framework for Real-time Lift Monitoring and Diagnostic System

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In this paper, we present an intelligent real-time lift safety monitoring system, incorporating Artificial Intelligence (AI) analytics for early fault detection and diagnosis, to improve labor productivity and benefit the society through digital transformation. We have analyzed historical data, find most frequent faults, select sensors that can give early signals that the fault can happen. To build the real time analysis, cloud architecture is used as the framework for implementation. To conduct the research, we collect data and build models in experiments of lift model and in real lift. Selected sensors are tested in lift model before being installed on site in real lift. Simulation data from lift model are collected to build initial model. Based on the functions of lift models, we simulated some experiments such as slow operation of lift, abnormal stops between floors, lift operation with weight in lift cabin. For data collected from real lift in operation, we build unsupervised machine learning model to detect slow moving and stoppage between two floors. In addition, from collected lift event data, we also can find outliers of door opening and closing behavior that can be early signal for abnormal door operation.

1. Introduction

With taller buildings dominating the modern urbanised cities, vertical transportation, which often taken for granted, is becoming more critical to serve people moving within these buildings. There is wide variations in industry practices and standards of lift maintenance companies. Current lift maintenance and inspection are on a periodic check basis, with a large percentage dependent on engineers and technicians' skill set. Monitor of vibration to analyze performance of lift operation has been the research attention in recent years. To collect data for vibration monitoring, quantity of sensors and placement of sensors are investigated to correctly determine how structure status of lift components is [1][2]. Lifts are constantly subject to changing operating parameters, the most dynamic of which is the lift load. The vibration characteristics of important components of the lift are studied deliberately before the sensors can be installed. In [3], anomaly detection algorithm to detect abnormal stops in lift operation due to faults in pressing of emergency stop button was presented. To detect abnormal door behaviour, frequency and pattern of door closing as well as door opening were analysed. Accelerometer and magnetic field sensor deployed on top of lift car were used to monitor health level of guide rails. Another feature was studied in this approach is the estimation of travel pattern. Abnormal or sudden stoppage of the lift is alarmed by detecting the abnormal status of deceleration. Vibration signal has been mainly the development focus of lift monitoring algorithms [4]-[6]. For example, in [4], the authors also explore the most optimal placement for vibration sensors to harvest rich data about the operation of the lift. However, the signals collected from electric components are not popular in the literature review. Recently, in [7], a framework for lift monitoring and diagnosis is described by using current sensor signals of electrical lift components. In the proposed monitoring framework, there is no need to install extra equipment or devices that change original system. Therefore, it makes flexible to install more sensors. Acoustic sensor is another sensor that studied in lift monitoring system [8][9]. The study in [8] shown that combination of using vibration and acoustics data is efficient in lift fault detection. Cloud-based approach for condition monitoring (CM) and predictive maintenance (PdM) has been more studied due to the popularity of cloud computing and there are more cloud service provides such as Amazon Web Service, Google Cloud etc. [10][11][12]. The main concept of cloud computing is that all IT resources including infrastructure and application for data storage, data processing, data analytics etc. are provided as services over the internet.

In this paper, we present an intelligent real-time lift safety monitoring system, incorporating Artificial Intelligence (AI) analytics for early fault detection and diagnosis, to improve labour productivity and benefit the society through digital transformation. We have analysed historical data, find most frequent faults, find sensors that can give early signals that the fault can happen. To build the real time analysis, cloud architecture based on AWS is used as the framework. Selected sensors are tested in lift model before being installed on site in real lift. Simulation data from lift model are collected to build initial model. We build unsupervised machine learning model to detect slow moving and stoppage between two floors. From collected lift event data, we also can find outliers of door opening and closing behaviour that can be early signal for abnormal operation.

2. Architecture of cloud-based lift monitoring system

In our research, an automated, consolidated data collection protocol towards a minimal-human-interference system using Amazon Web Service (AWS) is proposed as in Fig. 1. The advantage of cloud architecture is the competency to scale up the system easily for test-bedding of the advanced AI engines during the pilot trial, as well as to commercialize the fully developed system in larger numbers. The proposed cloud-based analytics framework for lift monitoring and diagnostic is to utilize the advantages of cloud computing platform such as scalability, pay per usage, built-in security feature, flexible fleet management and device configuration management. It has addressed the capacity issue to support up to thousands of devices online, publishing and subscribing message at same time. By tapping on the cloud services from AWS, it is able to build the data analytics pipeline from data collection, data processing, feature extraction, result prediction based on the model. The collected data can be used to further train the model by using the GPU computing power from the cloud provider.

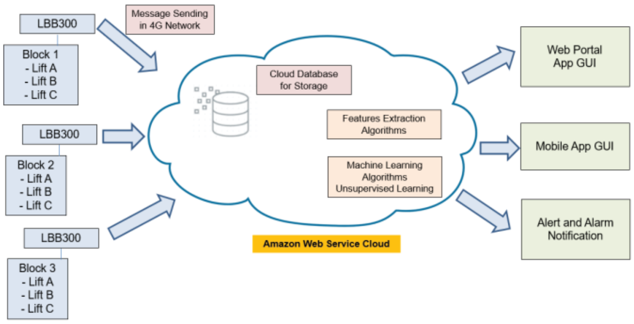

Fig. 1: Clouded-based framework architecture for real-time lift monitoring and diagnostic system

In proposed architecture of lift monitoring system, the core data acquiring, and processing device is designed by our project collaborator, SoftGrid company. It is called Lift Black Box 300 (LBB300), that is the third generation of LBB series. Two accelerometers are built-in and other sensors are connected externally via cables in order to meet the requirement of AI analysis for lift parts predictive diagnosis. Certain high-end laboratory level sensors needed, specifically, are two types of accelerometers. One kind is for acquiring moving parts velocity change from tri-dimensional, the other kind is to detect component vibration signal.

Each lift has been instrumented with a LBB300 that interfaces directly with the lift controller. The LBB300 senses and collects information, such as the lift door status (door opening/closing), movement direction (up and down), lift running or lift stationary. Type of sensors in LBB300 and their properties are presented in Table 1. Data collected in LBB 300 are then sent to AWS platform and stored in AWS database. Algorithms then process those stored data to detect anomaly. Fault alerts (after anomaly detection) are then sent to an alarm system that can automatically trigger the maintenance workflows, e.g., to inform the maintenance vendor (by generating the work orders) to examine the fault in a proactive manner to make sure the downtime of lift operation is minimized.

TABLE I – TYPES OF SENSORS USING IN THE FRAMEWORK

Type of sensor	**Where sensor is deployed**	**When data is captured**	**Format of collected data**
Accelerometer	Car lift roof	During a lift trip	.log
Accelerometer	Car door	When door open	.log
USB Microphone	Car lift roof	During a lift trip	.wav

3. Data collection and data pre-processing

Since installation of data collection embedded device in real lift need different parties to be involved, it is good to test the device in a lift model before onsite installation. The lift model used in this project is a 4-level, miniature lift as shown in Fig. 2. There are several controls that are possible in this lift model as followings:

- Two running speed modes: the lift can at normal speed or slow speed.
- Lift call pushbuttons for each floor. There are two options: moving up or moving down as real lift.
- Main lift controller

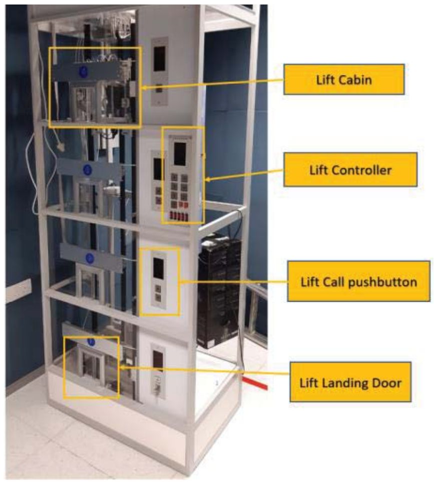

Fig. 2: Lift model for data collection test and fault simulation

The first purpose of using lift model is as a testbed to test data acquisition framework such as data template, data format, stored file name before deployment in live lifts. In other words, lift model is used to test the data capture framework for those sensors: accelerometers (csv or json format), acoustic sensor (wav format), levelling sensor, LBB300 operation function for data capture. Deploying the sensors on the lift model before deploying them on the real lifts enabled some amount of debugging of the installation process before the sensors are deployed. Changes to the sensor installation on actual lifts are more cumbersome due to the collaborative nature of the project; using the model as testbed in this way enabled a more concise deployment of the sensors in the live lifts.

The lift model is further open from the back, which enables easy deployment and access to the lift sensors. To further push the simulations in the lift model, the sensors were placed at the same places they would be placed in the actual lift (as described in Table I). Another hurdle in the deployment of this project is the absence of fault data in real lift operation since they have preventive maintenance frequently. One part of overcoming this hurdle is the usage of unsupervised learning elaborated later in this paper. However, even with the use of unsupervised learning, model validation requires some fault data to test the trained model. Given the rareness of detectable faults in live lifts, the lift model provided valuable fault simulation data which could be used to validate our machine learning model. And this is the second main purpose of using lift model in our proposed framework.

Fault simulation experiments in lift model are conducted to obtain sensor data for fault cases to enable machine learning model validation. Based on the functions of lift models, we simulated some experiments as followings. *Slow operation of lift:* Lift model was run at normal pace, followed by slow pace. Occasional slowing down of lifts is usually very hard to detect, and as such, often goes unnoticed. This data is helpful in detecting lift operation in cases of a faulty speed controller. *Abnormal stops between floors:* The lift model was interrupted halfway between trips to simulate abnormal stops of the lift car between floors. This data will enable to detect if the lift is stopping between floors. The detail of data analysis and machine learning model using those experimental data will be presented in Section IV.

After tested in lift model, sensors in LBB300 are deployed on site lift to collect data as shown in Fig. 3. All sensor data are collected in LBB300, then it is packed in Message. The Message is sent to AWS storage by 4G module in LBB300 each second for further clouded based processing. Real time GUI portal and real-time analytics algorithms access those stored Message in AWS by subscribing to corresponding AWS topic.

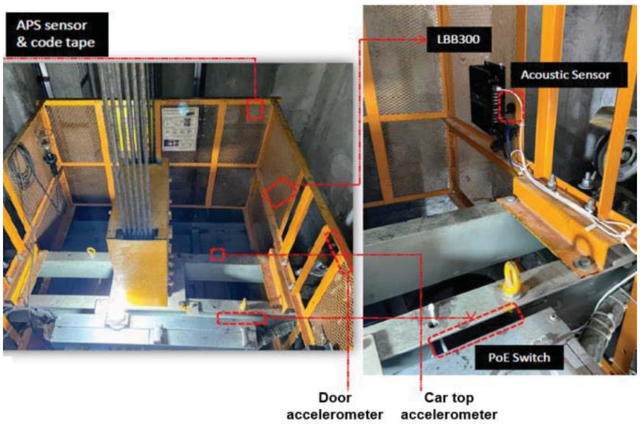

Fig. 3: Diagram of deployed sensors in onsite real operation lift

4.Feature extraction and machine learning models

After data is stored in AWS cloud, noise removal, data cleansing, feature extraction are processed in cloud backend. Unsupervised learning model is used in the framework as shown in Fig. 4.

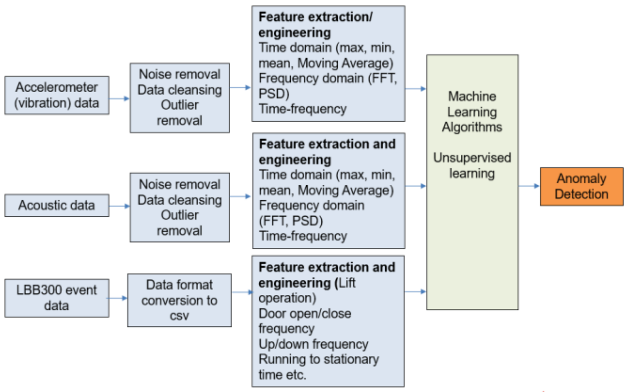

Fig. 4: Feature extraction and machine learning diagram for anomaly detection

For LBB300 lift event data, we extract some features etc.:

- Change of status from running to stationary, time taken: to determine how long the lift takes to come to a stop.
- Time taken to travel between each two floors.
- Time taken for door to open.
- Time taken for door to close.
- Door open/close frequency.

Example of histogram of Running to Stationary time in one day data is shown in Fig. 5. We can observe that, there are outlier points in the range around 4.75s. Those outliers may hint a signal for slow moving of the lift. From lift event data, we can extract time for door to open or close. This can give some signals to detect abnormal behavior of lift door operation. Frequency and pattern of door openings or closings at outlier values as shown in Fig. 6 can be hint for abnormal operation if those outliers are repeated. Normally, lift door systems are automatic during normal operation. The control system controls the torque, but it does not control the speed of the door motors. Therefore, the wear and tear as well as other defects of the door system due to heavy usage of the lift can cause the lift doors to move more slowly.

For vibration data, we extract features in time domain (statistical features) and in frequency domain (using Fast Fourier Transform to extract features)

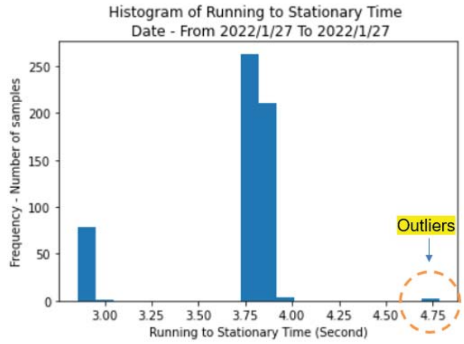

Fig. 5: Histogram of running to stationary time in one day lift operation.

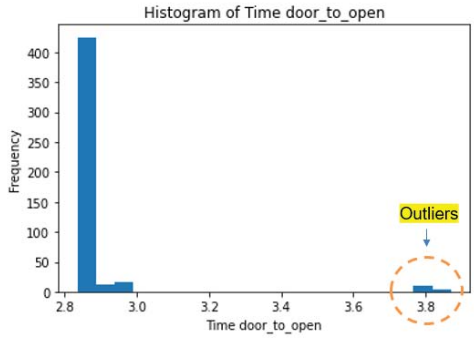

Fig. 6: Time of door_to_open histogram of one day lift operation

For acoustic data, we capture data by trip (when the lift moves only). Librora, a Python library for sound, music and audio analys is used for acoustic analysis. Time domain and frequency domain features are also extracted. Example of acoustics graph in time domain is shown in Fig. 7. To avoid distortion due to Nyquist sampling rate, we capture acoustic data at high quality frequency 44.1kHz. For acoustic analysis, the amplitude of the acoustic magnitude in time domain level can be converted into decibels. After conversion, the ranges of severe values are used for proactive maintenance decision making or anomaly detection. The standard design for acoustic signals in lifts can be referred as followings: maximum sound level of hoistway is 75dB. The limit sound level of the lift door is 65dB and the sound level from relay switching cannot surpass the value of 55dB [9]. Therefore, we can use those limits as indicators to detect anomaly.

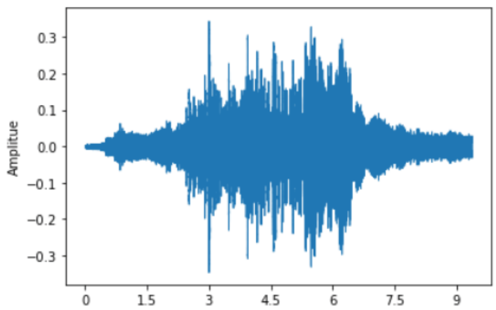

Fig. 7: Example of time domain plot of acoustic signal in one trip of the lift.

To detect anomaly in lift operation, we propose to use Isolation Forest unsupervised machine learning algorithm [13]. As in the name "Isolation" Forest, it identifies anomaly by isolating outliers within the data set. Isolation Forest model is built based on the fact that anomalies can be defined as data points that are "few" and "different". To train the model, the algorithm needs to construct a collection (or a profile) of data points so called "normal". Then, when new data points come, the algorithm can detect those new points that cannot considered "normal" and label them as "anomaly". The basis behind Isolation Forest algorithm is the popular Decision Tree algorithm. In Isolation Forest algorithm, based on features that are randomly selected, sub-sampled data is then processed in a tree structure. If samples travel deeper in the tree, they are highly considered as "normal" since they require more tree splits to isolate them. And those samples that are in shorter branches are likely "anomalies" as the split tree is easier to discriminate them from other samples [13]. To build the model, we collect data when the lift operates in normal condition. Example of "normal" floor time information is shown in Fig. 8. We can observe that the movement pattern in time domain in different trips are in similar shape. Statistical features are extracted from vibration data corresponding to the timestamps of these events and 75% of data set is used to train Isolation Forest model for anomaly detection.

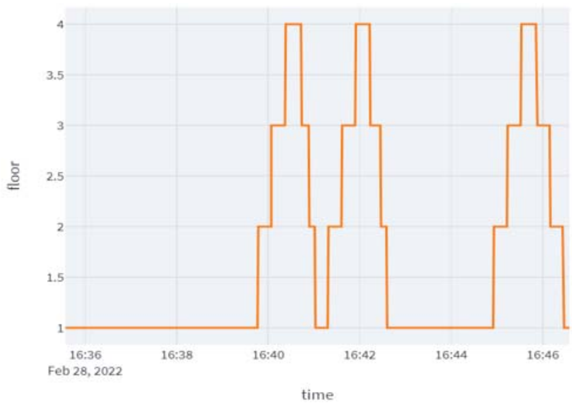

Fig. 8: Example of time in each floor when the lift operates normally

After the model is trained offline, it can be run online to detect anomaly in real time. To illustrate approach of our real time anomaly detection, we shown an example of sequence of lift operation events in a short period of time. As shown in Fig. 9, there are 6 events totally, and the first occurred event is in left side. The first three events are "normal" signal, as we can that the shape pattern is similar as in Fig. 8. when we train the model. In next coming 4th event and 5th event, the model can detect both are anomaly events. In the 4th event, we can observe that there is slow moving up from floor 1 to 2, 2 to 3, and 3 to 4. After reaching level 4, the lift starts to move down and we can see slow moving down from floor 4 to 3, 3 to 2, and 2 to 1. In the 5th event, the model can detect there is stoppage between floor 2 to 3, and 3 to 4. Moving down from floor 4 to 1 is normal condition. The 6th event the model does not detect any abnormal since it is in normal condition and normal pattern.

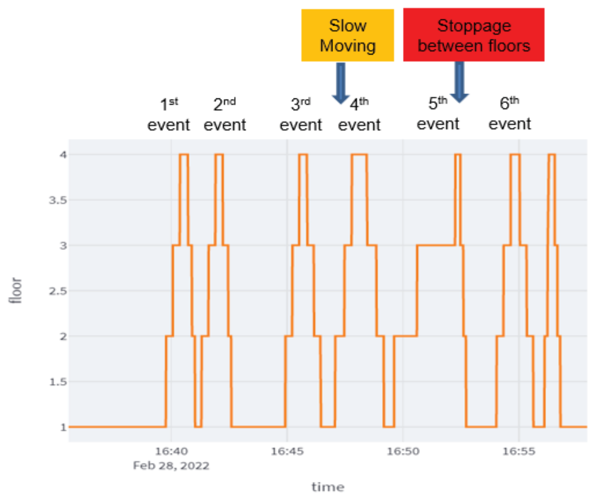

Fig. 9: Online real time model running to detect anomaly

5.Conclusion and future work

We present an intelligent real-time lift safety monitoring system, incorporating data-driven analytics for early fault detection and diagnosis using AWS cloud-based framework. Lift model is used as the experimental testbed to test selected sensors before being installed on site in real lift. Simulation data from lift model are collected to build initial model before the model is deployed for real-time onsite lift data. Unsupervised machine learning model to detect slow moving and stoppage between two floors is presented. Based on lift event data, outliers of door opening and closing behaviour can be early signal for abnormal door operation. In future work, when more data is being collected with more faults happening, the machine learning will be fine tuning for better accuracy. More machine learning models such as deep learning will be studied also in near future. There are not many studies to use energy anomaly patterns by power signals to identify lift faulty for diagnostics. Sudden unexpected changes in power consumption may hint at lift fault. In our approach, we installed equipment to collect onsite power meter data in real operation lifts and we will analyze this data in future work.

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