Condition-based and Predictive Maintenance Strategy for Lift Installations using Big Data Analytics

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Abstract. Safe and reliable lift services are essential for maintaining high accessibility and functional vertical transportation to help preserve the vitality of cities like Hong Kong which are renowned for its densely packed skyscrapers. This paper presents a proof-of-concept trial of a health monitoring platform for condition-based and predictive maintenance of lift installations using big data analytics. Implemented with various non-intrusive sensors, time series data of temperature, strain, acceleration, and displacement of lifts are collected and used to build predictive models with statistical and machine-learning techniques. The novel approach is capable of fault detection of brake malfunctions, lift car shaking, door malfunctions, and traction motor malfunctions and potentially enables prediction of the remaining useful life for the critical components.

1 INTRODUCTION

Lift installations play a crucial role in our daily lives, providing quick access to floors in buildings. However, lift systems are complex and require regular maintenance to upkeep their safe and reliable operation. Traditional maintenance approaches, such as time-based maintenance, can be inefficient and costly, leading to unnecessary downtime and repairs.

Condition-based and predictive maintenance strategies have emerged as promising alternatives to traditional approaches [1,2], leveraging big data analytics to monitor lifts and identify potential issues before they cause significant problems. These strategies rely on continuous monitoring of the lift installations. In recent years, they have been developed and implemented with various approaches. One approach is to monitor the traction sheave rope using computer vision [3]. Another approach is an automatic fault detection system using neural networks to monitor lift doors [4]. Besides, Li [5] proposed a vibration signal analysis to monitor the traction motor based on principal component analysis and Fourier methods. The exploration done in the field has enabled condition-based maintenance on specific critical components of lifts and advanced modern maintenance strategies.

In this paper, a condition-based and predictive maintenance strategy is implemented with non-intrusive sensors. Together with mathematical analysis and machine learning approaches, the detail of the methodology is established in Section 2. In Section 3, the results from four lifts at various locations in Hong Kong, namely Sir Ellis Kadoorie Secondary School Lift no.1, North Point Government Primary School Lift no.1, and Tai Po Government Office Lift no.1 and no.2 are discussed to evaluate the performance of this strategy. Finally, in Section 4, the findings are summarised, and the potential use in the future is discussed.

2 METHODOLOGY

To minimize any alteration of proprietary lift designs or interruption to the operation of different brands and models of lifts, non-intrusive electronic sensors were applied to monitor various physical parameters of interest. These sensors recorded the vibration of the traction motor, operation of the brake mechanism, and lift doors of the lift system. The sensor data is transferred to a cloud platform via a 4G LTE network periodically and analyzed to identify trends, anomalies, and potential failures.

In the following sessions, the lifts mentioned in Section 1 are mapped into Elevators 1, 2, 3, and 4 to enhance readability. Table 1 shows the name mapping of the lifts.

Table 1 Name mapping of lifts in the paper

Elevator 1	Tai Po Government Office Lift no.1
Elevator 2	Tai Po Government Office Lift no.2
Elevator 3	North Point Government Primary School Lift no.1
Elevator 4	Sir Ellis Kadoorie Secondary School Lift no.1

2.1 Traction Motor and Gear Box

Electrical accelerometers with a sampling rate of 1600 Hz installed on the outer edge of the lift car recorded its vibration signals. According to the industrial standards for lift safety in Hong Kong, the acceptable maximum peak-to-peak (P2P) lateral and vertical vibration is 0.25 m/s² for a lift speed of less than 6 m/s [6]. The measure is deployed as a shaking criterion, tagging any lift operation with P2P vibration above this level as a lift car shaking (LCS) incident. As the resonance frequencies of human body organs range from 2-50 Hz [7], a linear digital filter is applied to the vibration signals twice, once forward and once backwards, to preprocess the signals to [1, 50] Hz.

The same electrical accelerometers are installed on the traction motor to record its vibration signals. Assuming that the targeted components in the collected time series are sinusoidal, the Lomb method is suggested for the spectral analysis [8]. The Lomb-Scargle periodogram was first developed by Lomb [9] and formulated with a least-squares model fitting sinusoidal to data samples. It was proposed to analyze unequally spaced data of ground-based astronomical observation and further extended by Scargle [10] to search for periodic signals with low signal-to-noise ratios in unevenly sampled time series.

Given a set of n observations y_i, $i = 1,2,\ldots,n$ with zero mean and obtained at times t_i, the time series is described by

$$y_i + \varepsilon_i = acos(2\pi f t_i) + bsin(2\pi f t_i), \tag{1}$$

where ε_i is the independent random measurement error at different times t_i and f is the frequency. To identify the dominant frequencies of a time series, the periodogram is used to estimate the spectral density of a signal. The classical periodogram definition $P(f)$ [11] is given by

$$P(f) = \frac{1}{N}[(\sum_n g_n \, cos(2\pi f t_n))^2 + (\sum_n g_n \, sin(2\pi f t_n))^2]. \tag{2}$$

After modifications on the denominators and adding a parameter τ to ensure time-shift invariance, the Lomb-Scargle periodogram P_{LS} in terms of frequency-domain representation [9, 10] is given by

$$P_{LS}(f) = \frac{1}{2}\left[\frac{(\sum_n g_n \, cos(2\pi f[t_n-\tau]))^2}{\sum_n cos^2(2\pi f[t_n-\tau])} + \frac{(\sum_n g_n \, sin(2\pi f[t_n-\tau]))^2}{\sum_n sin^2(2\pi f[t_n-\tau])}\right], \tag{3}$$

where τ is given by

$$\tau = \frac{1}{4\pi f} tan^{-1}\left(\frac{\sum_n sin(4\pi f t_n)}{\sum_n cos(4\pi f t_n)}\right). \tag{4}$$

In this study, the Lomb-Scargle periodogram is used as an instantaneous frequency estimator to generate spectrograms and visualize the frequency components of motor vibration signals.

2.2 Brake System

Electrical strain sensors installed on the braking arms collected 50 Hz time series data on the braking arm movement and contact when the brake is engaged. The time series is processed into braking cycles, where each cycle is the period from which the brake disengaged, then engaged. Given the information from the current transformer logger installed on the controller board, unexpected brake-arm movements are searched for in the entire dataset.

2.3 Door System

Proximity sensors installed in the car doors of the lifts recorded the distance between the car doors at a sampling rate of 9.1 Hz. The collected time series is processed into door cycles, where each cycle is the period from which a door starts to open from a fully closed state to a fully opened state, and then returns to its fully closed state. The period can include regular partial door re-openings.

According to the maintenance records, door malfunction (DM) incidents are identified in the processed door cycles. During a DM incident, the door attempted to operate but became either “stuck” for a prolonged period or moved roughly. DM can occur anywhere within a door cycle and be classified into door not closing (DNC) and door not opening (DNO) types. Based on a case study on a DNC incident in Elevator 3, shown in Fig. 1, two methods are developed to search for DM in the closing and opening stages.

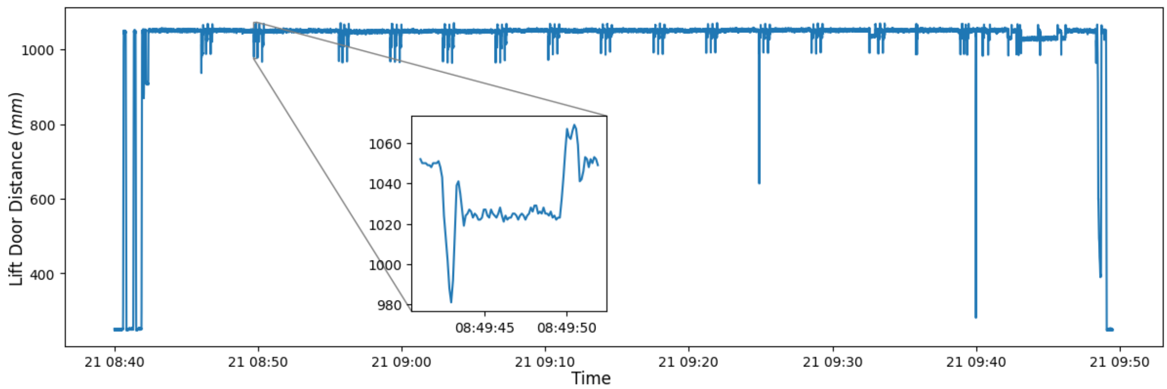


Figure 1 Lift door distance indicating a “door not closing” incident in Elevator 3, with zoom-in plot showing a door reopening waveform which is used in XGBoost training

Method 1: Threshold

In this method, door gap data is first normalized to [-1, 1] and abnormalities are detected using threshold(s). A door cycle is marked as suspected DM if the door gap stays within a prescribed high and low range for at least 4 seconds. The suspected DM is classified as DNC if found in the high gap and DNO if low. In Fig. 2, the DNC and DNO search areas are shaded in green and purple and correspond to the 0.75 to 0.9 and -0.75 to -0.9 levels. In the figure, a DNC spanned approximately 12 seconds was detected, highlighted in red. The method catches door movements indicating the door is “stuck” outside the fully opened and closed levels.

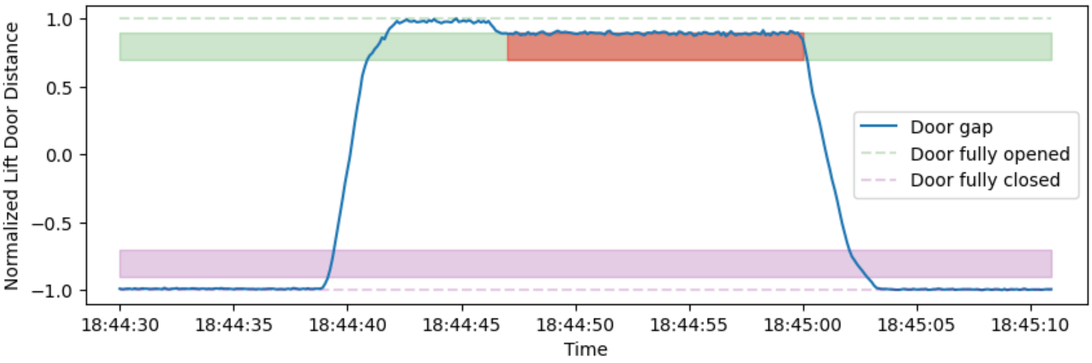


Figure 2 Door cycle with DNC failure (red region) found by threshold method

Method 2: XGBoost (eXtreme Gradient Boosting)

In this method, door gap data are sampled using a sliding window of 100 data points each, and a machine learning algorithm XGBoost [12] is trained to classify abnormal versus normal samples. The abnormal samples are taken from the "reopening" waveform in the DNC case illustrated in Fig.1, whereas the normal samples are taken from normal operating periods. An XGBoost classifier is trained and then applied to search for other unreported abnormalizes in the entire dataset.

2.4 Lift Levelling

Image sensors mounted on the lift car roof collected data on levelling deviation at each floor arrival by capturing the level code plate attached to each floor wall inside the lift shaft and computing the floor levelling. The daily spread of the levelling deviation of lift cars was studied by the standard deviation and interquartile range.

Given a set of n observations of levelling deviation y_i, $i = 1,2,\ldots,n$, obtained at each floor arrival in one day, the standard deviation σ is given by

$$\sigma = \sqrt{\frac{\sum_{i=0}^{n}(y_i-\mu)^2}{n}}, \tag{5}$$

where μ is the mean levelling deviation. The interquartile range IQR is given by

$$IQR = Q_3 - Q_1, \tag{6}$$

where Q_1 and Q_3 are the lower and upper quartiles of levelling deviation data in one day. To prevent the daily interquartile range and standard deviation from being highly biased to a few travels, the number of operations per day is computed and used for filtering out highly biased data. The interquartile range and standard deviation are only calculated for days where the daily travel count exceeds half of the mean daily travel count for the entire year. Furthermore, the data is organized into clusters based on the destination floor of the operation cycles.

3 RESULTS

3.1 Traction Motor and Gear Box

Vibration signals of the lift car body in the horizontal (Ax) and vertical (Az) directions in an operational cycle, or travel, were retrieved from the vibration sensor and shown in Fig. 3. In Fig. 4, the results for daily lift car shaking (LCS) count for the study period in Elevator 1 and Elevator 2 are visualized. On a typical weekday, LCS occurred in Elevator 1 throughout the year in large numbers (up to 800 instances), while LCS rarely occurred in Elevator 2 (up to 4 instances).

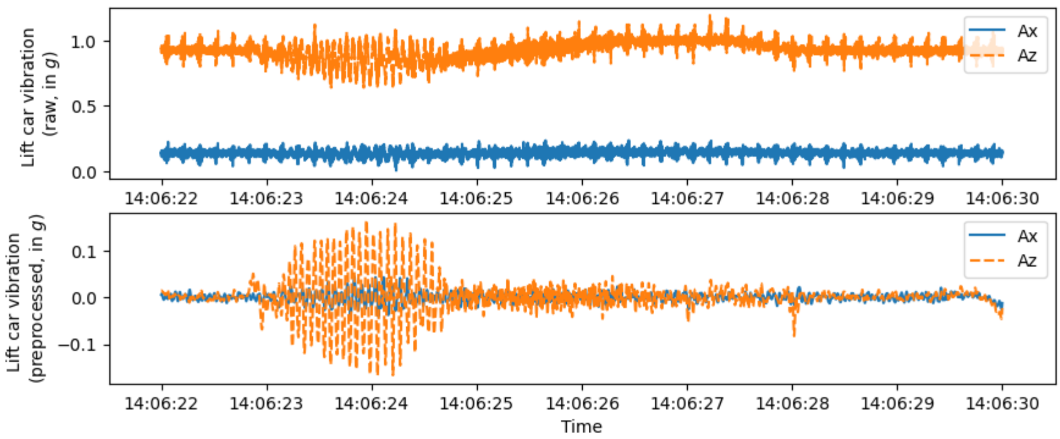


Figure 3 Time-domain signal of lift car vibration in an operational cycle

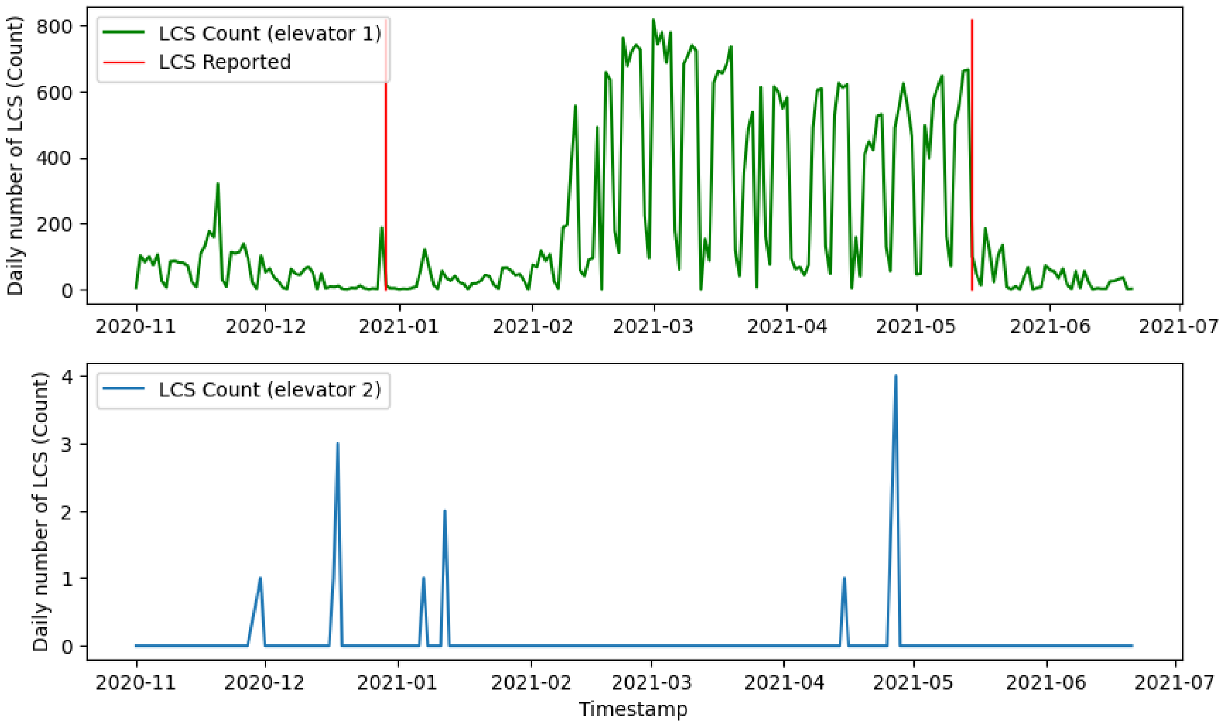
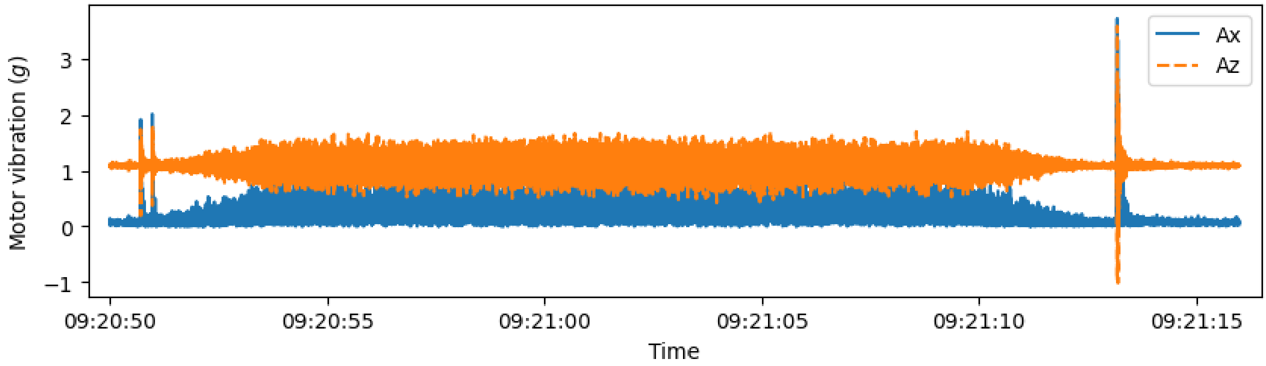


Figure 4 Number of lift car shaking found by our method (in green and blue) versus the actual lift car shaking events reported (the red lines) across the two lifts

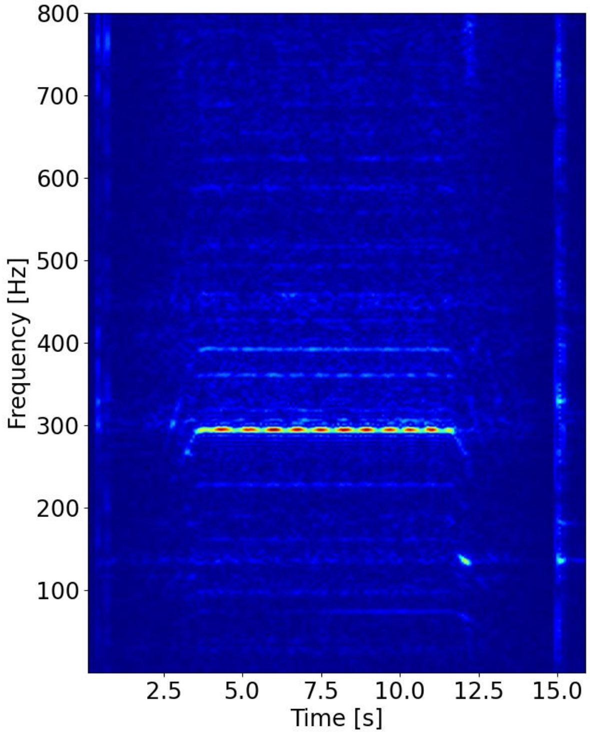
By analyzing the peak-to-peak (P2P) vibration amplitude exceeding a predefined threshold, our method suggests that Elevator 1 has a lot more potential LCS events compared to Elevator 2. This finding is consistent with the logbook records which logged two LCS incidents reported in Elevator 1, whereas Elevator 2 has none. So, we believe that P2P vibration amplitude is potentially a good metric for detecting lift car shaking events. However, due to the limited number of incidents, this hypothesis deserves further validation with more data in future studies.

In addition to lift car vibration, vibration signals of the traction motor in the Ax and Az directions in an operational cycle were retrieved from the vibration sensor and shown in Fig. 5. In Fig. 6, the typical signals of Elevator 1 and Elevator 4 are transformed into spectrograms computed with the Lomb method in Sec. 2.1. In Fig. 6(a) and 6(b), the time-frequency pattern is distinct throughout the lift journey for Elevator 4. The frequency, or motor rotation speed, gradually increased from the beginning of an operation cycle to a certain state and remained constant until near the end. It is consistent with Li's work [6]. However, the expected time-frequency pattern is insignificant in Elevator 1's signals in Fig. 6(c) and 6(d). The dispersed operational frequency pattern potentially relates to the deteriorating performance of the traction motor and gear box and causes the large LCS

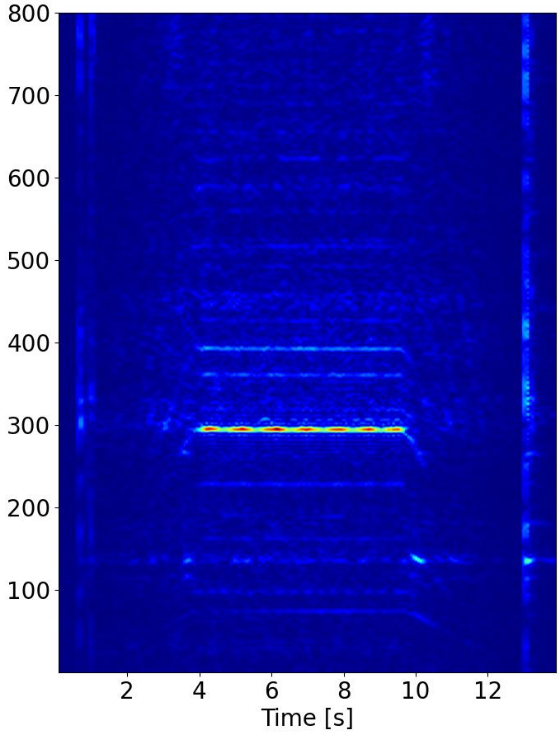


counts in Elevator 1 in Fig. 4.

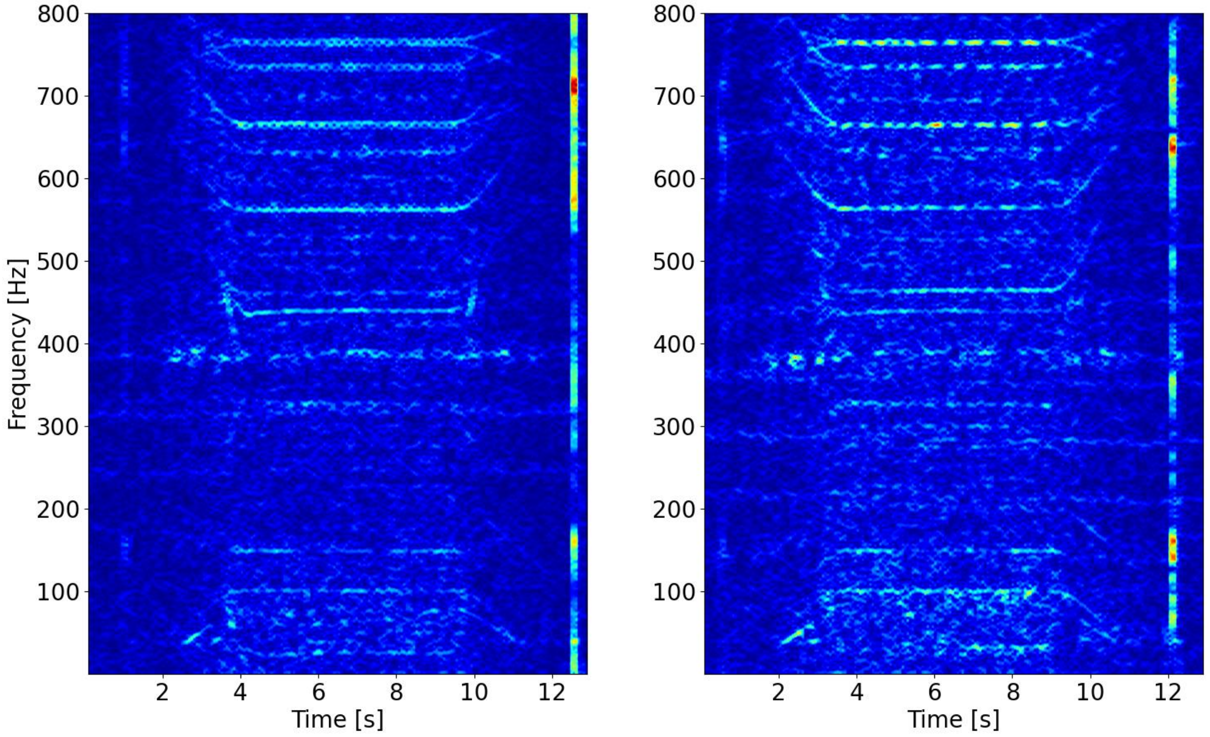
Figure 5 Time-domain signal of traction motor vibration in an operational cycle



(a) up-drive condition, Elevator 4



(b) down-drive condition, Elevator 4



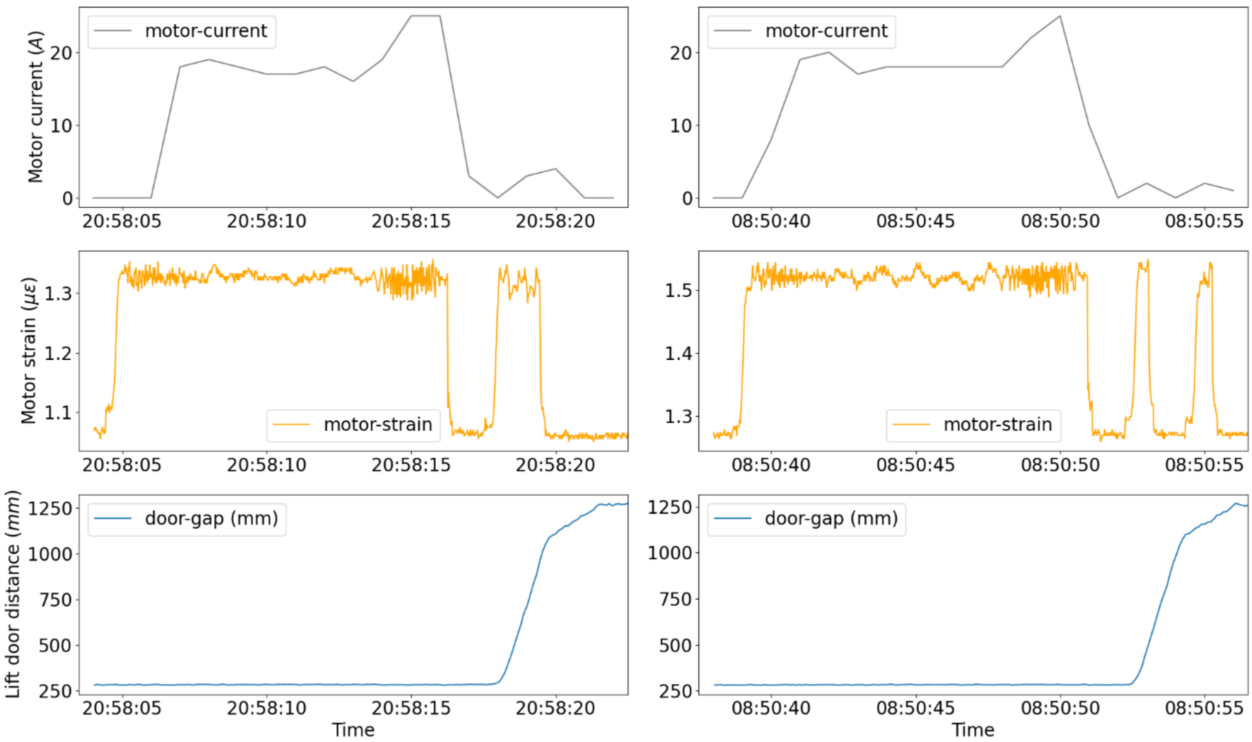
(c) up-drive condition, Elevator 1 **(d) down-drive condition, Elevator 1**

Figure 6 Spectrogram of traction motor vibration in different operating directions in lifts

3.2 Brake System

The strain sensor recorded the operation pattern of the brake system, in which the expected behaviour was to disengage once only when the lift car moved from one floor to another. However, in this study, unexpected behaviour of the brake system was discovered: multiple brake-arm engagements (MBE). In MBE incidents, the brake arm disengages and engages multiple times during and right after travel. In the study, the MBE incidents were classified into two groups: MBE-1 and MBE-2. In MBE-1, the extra brake cycle occurred just after the lift car travelled, while MBE-2 is within the lift car travelling period. There is no information regarding MBE incidents in the maintenance record.

MBE After Lift Travel (MBE-1) - In a typical MBE-1 travel visualized in Fig. 7(a), the additional brake cycle occurred as the lift car door opened. When the motor received the current supply, the brake arm disengaged, and the lift car moved to its destination floor. Once the lift car reached the designated floor, the brake arm engaged again, and the door opened. However, the brake arm operated again for about 1 to 2 seconds. Another typical type of MBE-1 travels, wherein the brake arm disengaged and engaged three times, has also been uncovered, comprising around 25% of all 20,000 MBE-1 in Elevator 1. A sample of this is illustrated in Fig. 7(b). MBE-1 is a potential risk for passengers and was not reported nor repaired. Furthermore, in Fig. 8, MBE-1 occurred in Elevator 1, Elevator 2, and Elevator 4 throughout the study period.



(a) MBE-1 (1 extra) **(b) MBE-1 (2 extra)**

Figure 7 Brake motor, brake arm, and car door operations during MBE-1 with extra brake operations (refer to the middle plot)

MBE During Lift Travel (MBE-2) - In Fig. 9, an MBE-2 travel is visualized. Brake engagements occurred during a lift operation. As seen in the middle subplot, the brake arm attempted to engage multiple times, which in turn caused large signal spikes highlighted by red points in motor vibration in Fig 9. Among the sites, 16 MBE-2 incidents were found in Elevator 2. The MBE-2 distribution throughout the study period is shown in Table 2.

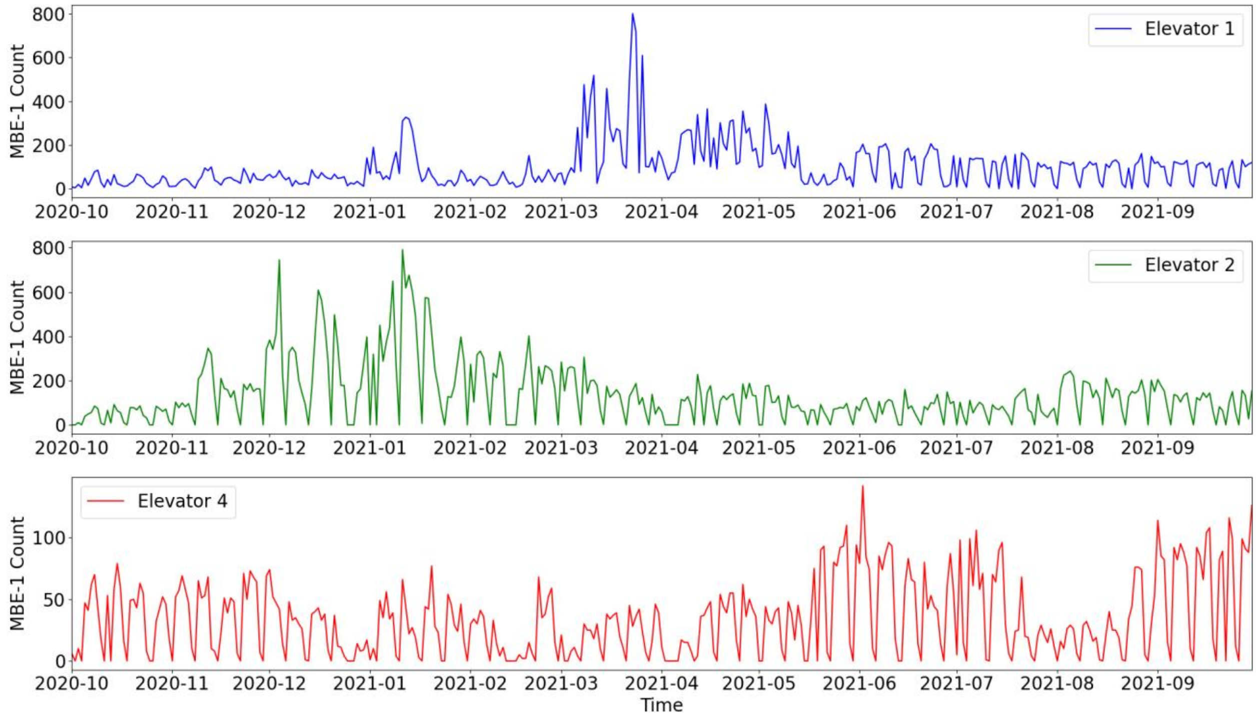


Figure 8 Daily count of MBE-1 in Elevators 1, 2, and 4

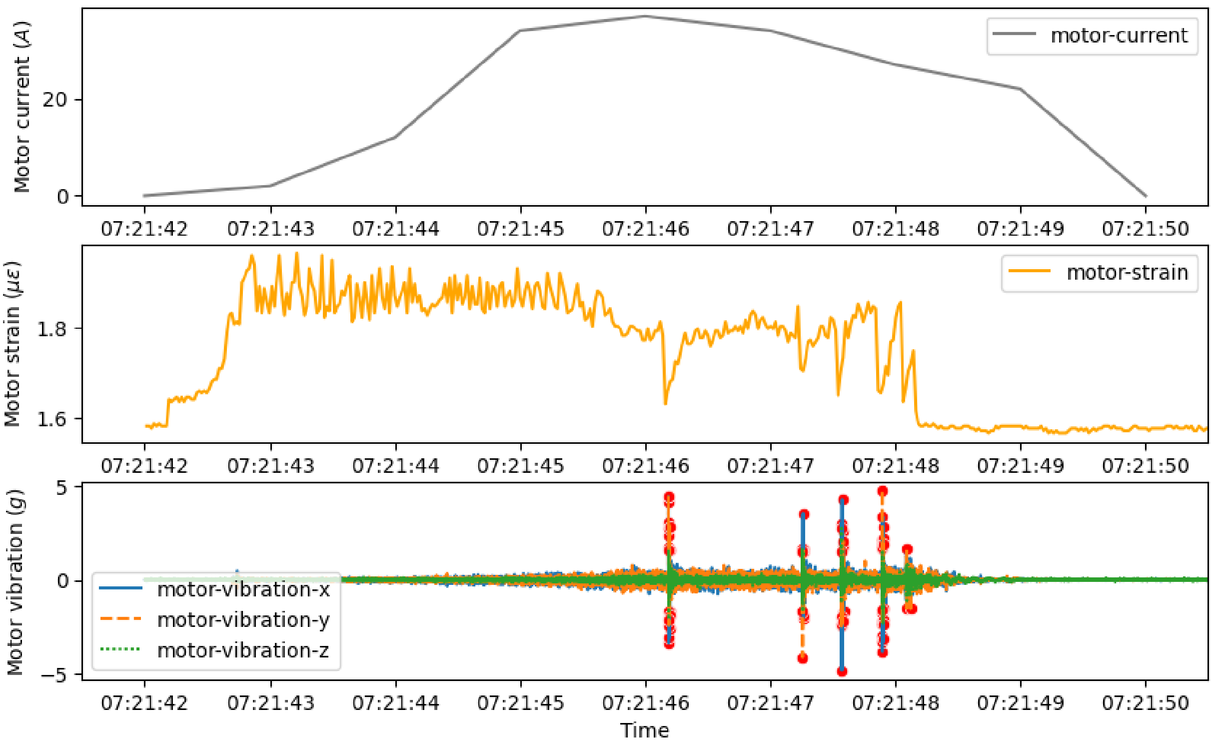


Figure 9 Motor current, brake strain, and motor vibration during MBE-2 incident. The red dots highlight the motor vibration spikes due to brake-arm engagement

Table 2 Distribution of Elevator 2 MBE-2 incidents in the study period

Month	Dec 2020	Jan 2021	Apr 2021
MBE-2 Count	2	1	13

3.3 Door System

In addition to the case study incident in Fig. 1, the methods captured other anomalous door movements. However, the DM discovered generally occurred within maintenance periods or post-incident repair works. A summary of DM incidents is given in Table 3. Plots of the three unrecorded failures found outside of maintenance and repair are included in Fig. 10 and Fig. 11 for the respective method. In Fig 10, the DM incident in the upper plot showed a door cycle where the door gap distance did not reach the fully opened door gap threshold, while the lower showed the door was moving roughly. In Fig. 11, the door gap distance largely fluctuated around the fully opened threshold.

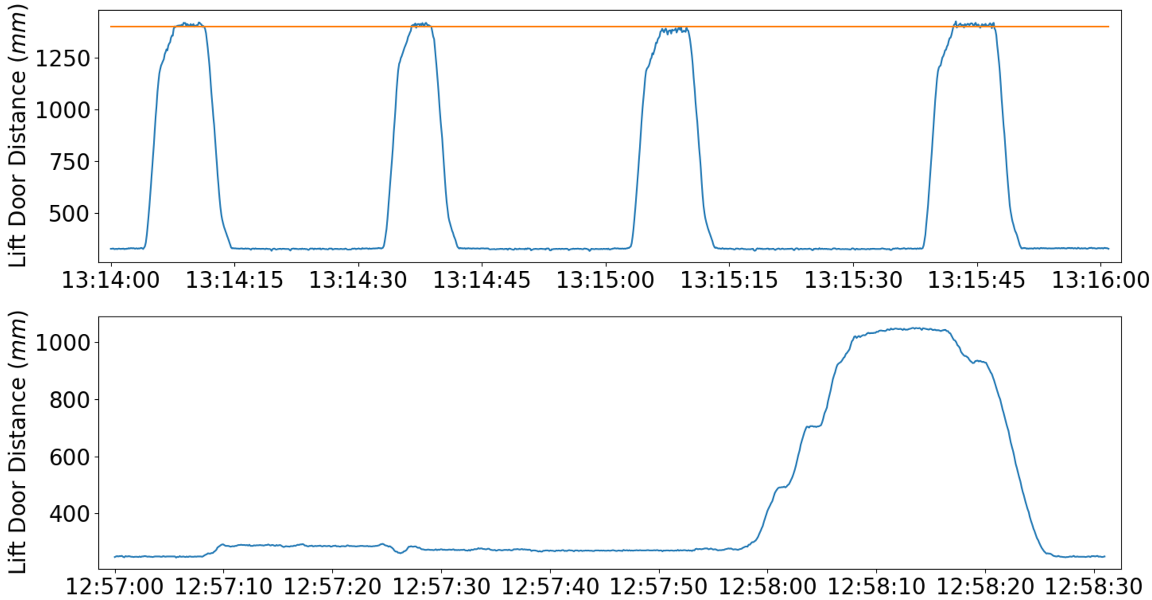


Figure 10 Unrecorded DM captured by the manual threshold method

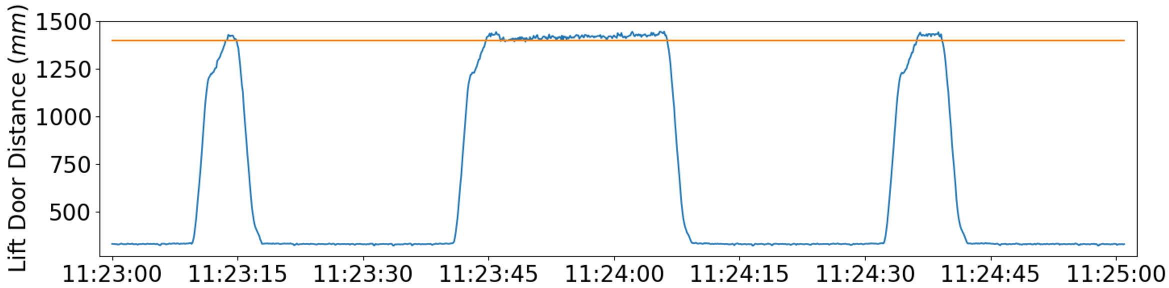


Figure 11 Unrecorded DM captured by XGBoost

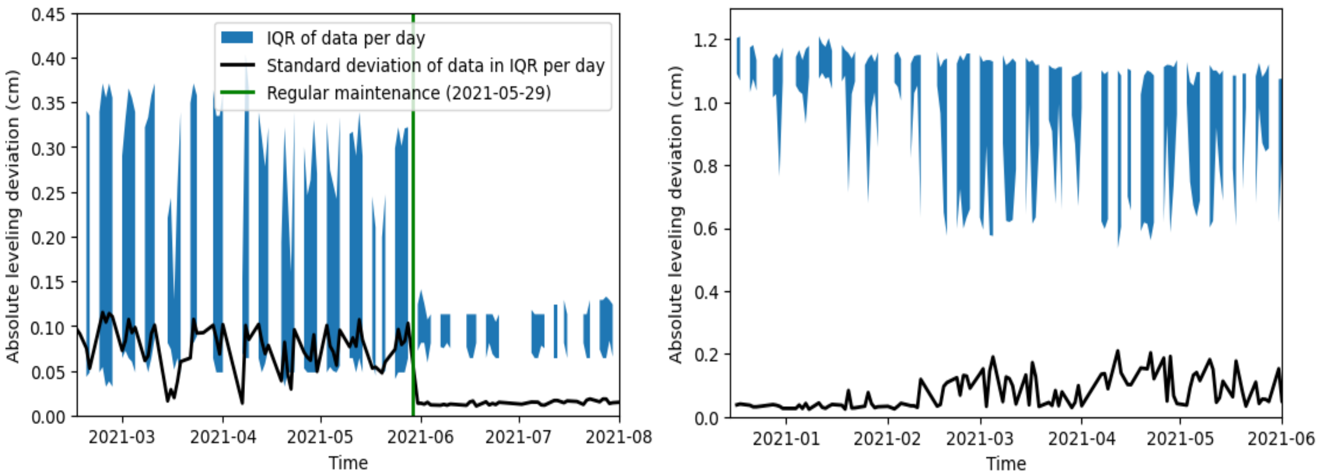
Table 3 Number of Days with DM by Threshold (Thr.) and XGBoost (XGB)

	Elevator 3		Elevator 4		Elevator 1		Elevator 2	
	Thr.	XGB	Thr.	XGB	Thr.	XGB	Thr.	XGB
Maintenance Period	1	1	2	0	6	1	5	0
Incident/Repair Period	2	1	0	0	1	0	1	0
Unrecorded Failure	1	0	0	2	0	0	0	0

Although the threshold method captured more failures than XGBoost due to its generic nature, it only checks the door gap when the door is moving, while the XGBoost method detects abnormalities at any point in the door cycle. The threshold method is confined to searching only a portion of the opening or closing phase, but this can be rectified by widening or adding more search ranges. In contrast, due to the high specificity of the XGBoost method, it captures only the waveform or very similar patterns. Besides, some false alarms are detected, which include partial door re-openings and strong fluctuations in readings while the door is at rest, but the amount is negligibly small.

3.4 Lift Levelling

In Fig. 12(a), the interquartile range and standard deviation of the levelling deviation of Elevator 1, 3/F were visualized. The accuracy and precision increased significantly after the regular maintenance on 29 May 2021. The daily upper quantile was about 0.4 cm and dropped to less than 0.15 cm. Furthermore, the highly fluctuated standard deviation became stable at about 0.02. It indicates an enhanced performance of levelling due to scheduled maintenance. In contrast, in Fig. 12(b), the interquartile range and standard deviation of Elevator 2, 1/F increased over time, which implies a deteriorating condition of the traction motor or the door clutch on 1/F.



(a) Elevator 1, 3/F **(b) Elevator 2, 1/F**

Figure 12 Interquartile range and standard deviation of levelling deviation per day.

4 CONCLUSION

This paper presents a proof-of-concept trial of a health monitoring platform for condition-based and predictive maintenance of lift installations using big data analytics. By using non-intrusive sensors, the critical components of the lift system are monitored and analyzed in various ways. The trial has been running for an entire year across four lifts and the data of all the sensors were collected and analyzed in order to construct various detection methods.

By using statistical methods and machine learning approaches, we developed methods that are capable of fault detection, brake malfunction, lift car shaking, door malfunction, and traction motor malfunction. And these methods can correctly identify the incidents reported by passengers during the study period. Additionally, these methods uncovered potentially unreported lift failures such as multiple brake arm engagements while the lift was moving, as well as unrecorded door malfunction incidents in two of the lifts.

Therefore, we believe that this health monitoring platform and the detection methods are useful tools for formulating condition-based and predictive maintenance strategy, could potentially be used to predict the remaining useful life for the critical components, and turns corrective maintenance into proactive maintenance.

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BIOGRAPHICAL DETAILS

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Mr. Calvin K.F. LEUNG is currently an experienced Building Services Engineer in the Electrical and Mechanical Services Department of the HKSAR Government. He has been active in various digital transformation projects in the Department, specifically on the safety enhancement and innovation technologies of lift and escalator installations. Mr. LEUNG is a Chartered Engineer with the Engineering Council (UK), a Member of the Chartered Institution of Building Services Engineers and a Corporate Member of the Hong Kong Institution of Engineers.

Mr. Wayne T.H. WONG is currently a Project Officer at EMSD. He has over 25 years of experience in the IT industry in Application and System Development. He has been actively participating in the promotion of IT applications to businesses and supporting innovative Startup companies. Mr. WONG is a Professional Member of the BCS.

Mr. Scotty C.H. KWOK is the founder and CTO of Sebit Company Limited, a technology startup based in Hong Kong. He has over 20 years of software development experience and is specialized in artificial intelligence, machine learning and computer vision. He and his team have been active in developing artificial intelligence and machine learning solutions for Lifts and Escalators. Mr. KWOK holds a Master of Science degree in computer science and is a frequent speaker at tech conferences.

Mr. Henry W. Y. WONG is currently a software engineer at Sebit Company Limited. He has three years of research and software development experience at university. He has been active in various projects of artificial intelligence and machine learning solutions for Lift and Escalators, and time series data analysis in physical science. Mr. Wong holds a Bachelor of Science degree in Physics.