Research │ Received 15 November 2024; Accepted 21 January 2025; Published 13 February 2025
https://doi.org/10.55092/aias20250001

Enhanced safety and efficiency in traction elevators: A real-time monitoring system with anomaly detection

Safa Ozdemir [1], Osamah N. Neamah [1] and Raif Bayir [2,*]

[1] Department of Mechatronics Engineering, Graduate Institute of Karabuk University, Karabuk, Turkey
[2] Department of Mechatronics Engineering, Faculty of Engineering, Karabuk University, Karabuk, Turkey

* Correspondence author; E-mail: rbayir@karabuk.edu.tr.

Highlights:

- Real-time system monitors elevator vibration and speed with sensor data.
- Anomaly detection with Isolation Forest, SVM, and Z-score boosts safety.
- Study lays groundwork for digital twin systems in elevator maintenance.

Abstract: This study presents the design and implementation of a real-time monitoring system for traction elevators, leveraging piezoelectric sensors for vibration measurement and speed sensors for velocity data acquisition. The system is powered by a LattePanda dashboard equipped with an integrated Real-Time Clock (RTC), ensuring precise data collection and timestamping. Vibration data is captured through piezoelectric sensors, while velocity data from speed sensors is used to calculate acceleration. The collected data is stored locally and can also be transmitted remotely. Aimed at improving elevator safety and efficiency, the system detects potential issues such as misalignments and mechanical wear. Given the increasing number of elevator accidents, this study focuses on enhancing monitoring capabilities using advanced technologies. Data from an electric elevator was analyzed with three anomaly detection algorithms: Isolation Forest, Support Vector Machine (SVM), and Z-score. The results revealed that Isolation Forest identified 15 anomalies (1.06% of the data), SVM detected 25 anomalies (1.77% of the data), and Z-score identified 86 anomalies (6.08% of the data). This research not only enhances elevator condition monitoring but also lays the groundwork for future digital twin systems in passenger elevator applications.

Keywords: condition monitoring; passenger elevator; anomaly detection; predictive maintenance

1. Introduction

In recent years, problems related to vertical transportation systems, commonly referred to as passenger elevators, have seen a notable increase, particularly in the context of the growing prevalence of high-rise buildings exceeding 900 meters in height. Current research indicates that there are plans to construct structures reaching up to 1,584 meters [1]. This trend towards ultra-tall buildings has coincided with a rise in fatal accidents associated with elevator systems. For instance, since 2019, the United States has recorded over 10 incidents resulting in approximately 30 fatalities and around 17,000 injuries [2]. This situation underscores the urgent necessity for advanced condition monitoring systems and predictive maintenance strategies within the field of elevator technology.

Passenger elevators are subject to stringent safety regulations as outlined in the ISO 4190 series and ISO 8100 series [3,4]. These standards mandate that elevators not only prioritize safety but also optimize for the fastest travel times and minimal energy consumption. Additionally, there is a need to balance costs and the spatial footprint of elevators within buildings. This balance is often achieved by reducing the number of elevators and minimizing waiting time [5]. The emerging trend towards two-dimensional (2D) passenger elevators in high-rise or ultra-tall buildings further underscores the importance of these considerations [6].

Passenger elevators are typically divided into four main types: traction, hydraulic, machine-room-less, and pneumatic. Traction elevators are most used in high-rise buildings because they can travel long distances at high speeds, making them ideal for structures requiring high performance. However, they are complex and expensive to maintain. Hydraulic elevators are often used in mid-rise buildings as they offer a good balance of cost-effectiveness and reliable performance, though they are less efficient and more prone to issues than traction elevators. Pneumatic elevators are cost-effective and appropriate for low-rise buildings, but they frequently suffer from operational failures and have a limited range [7–9].

Anomaly detection is a fundamental pillar of predictive maintenance and safety in numerous transportation applications. This area involves a variety of strategies, including statistical methods and intelligent approaches, such as unsupervised machine-learning techniques [10]. Over the past decade, researchers have made substantial progress in developing and enhancing these strategies, underscoring their importance in improving transportation safety and reliability [11].

Recent studies have demonstrated significant advancements in the application of deep learning for anomaly detection across various datasets related to passenger elevators. Video classification techniques, applied to datasets such as UCF24, UCF101, HMDB51, and the Something-Something-v1 dataset, have shown substantial improvements in anomaly detection accuracy compared to traditional methods. Notably, deep learning approaches have achieved an accuracy increase of approximately 10%, reaching a total accuracy of 95% compared to the PPTSM model [12]. Graph Neural Networks (GNNs) have also been explored for anomaly detection in CAN Bus data related to elevators, yielding a high accuracy of approximately 98.4% [13]. Furthermore, the development of digital twin technology for passenger elevators has integrated the PCA-DNN model for effective classification [14]. In the domain of object detection, a modified YOLOv8 model has been introduced, achieving a mean Average Precision (mAP) of about 92% [15]. Condition monitoring systems have benefited from deep learning approaches, such as the GNN-LSTM-BDANN model, which predicts Remaining Useful Life (RUL) based on historical data for passenger elevators [16,17]. Moreover, some researchers have employed machine learning techniques with feature extraction for fault classification, achieving an impressive accuracy of 99%. However, this approach may present challenges for real-time systems due to delays associated with the feature extraction stage [18]. The contributions of following paper as following:

- Development of an embedded system for detecting anomalies in electric passenger elevators.
- Integration of LattePanda dashboard, speed and vibration sensors, and Real-Time Clock (RTC) technology for real-time monitoring.

- Implementation of unsupervised machine learning algorithms, including Isolation Forest, Support Vector Machines (SVM), and Z-score normalization, for anomaly detection.

2. Methodology

This section delineates the methodologies employed to accomplish the study's objective of condition monitoring in electric elevators. It encompasses the use of embedded systems for data acquisition, the processes involved in data collection, and the techniques applied for anomaly detection.

2.1. Embedded system

The implementation of a condition monitoring system is centered on several key functions, including fault prediction, diagnosis, predictive and proactive maintenance strategies, the application of digital twin technology, and the intelligent analysis of expert systems [19]. However, a significant challenge within the transportation sector is the design of a cost-effective system that can adequately perform these functions. This challenge is compounded by the expense associated with highly sensitive sensors, as well as the complexities involved in integrating these sensors into a unified system. Such integration can lead to issues such as noise and disturbances, which may adversely impact the precision of the measurements [20,21].

This system employed a LattePanda dashboard connected to the RTC, piezoelectric sensors for measuring vibrations, and a speed sensor, along with an LCD to display the measurements. Additionally, acceleration was calculated by estimating it from the speed sensor data using differentiation, as described in Equation (1).

$$a(t) = \frac{dv(t)}{dt} \tag{1}$$

Where: $a(t)$ represents the acceleration at time (t), $v(t)$ is the velocity at time (t), and $\frac{dv(t)}{dt}$ represents the rate of change of the elevator's velocity with respect to time, which gives the acceleration. Figure 1. illustrates the embedded system designed to execute the data collection function.

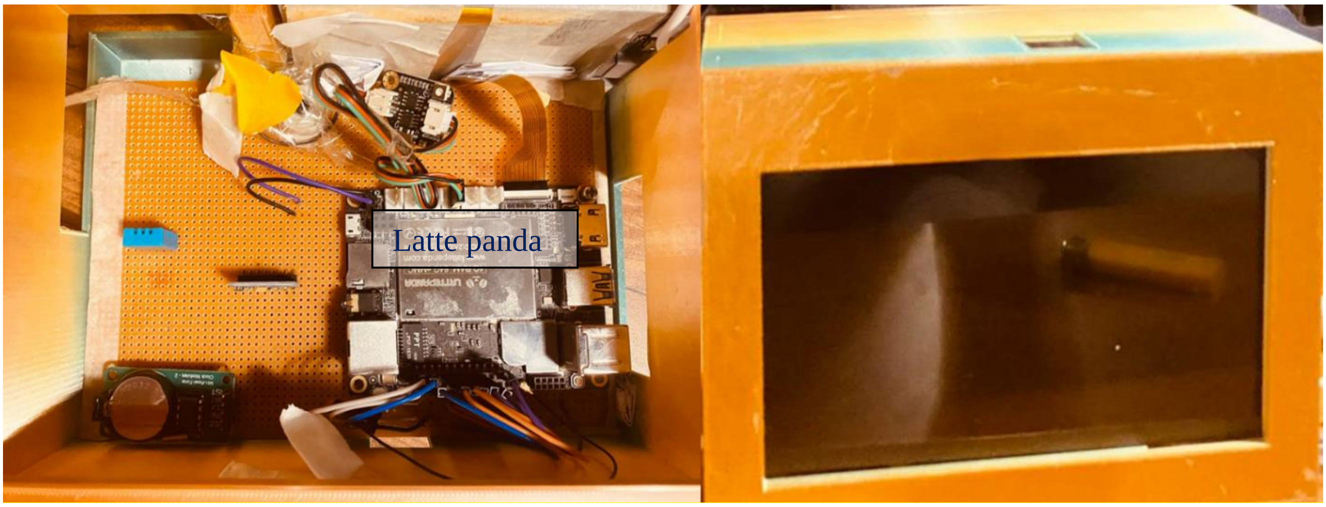


Figure 1. Proposed embedded system for condition monitoring of passenger elevator.

Several elevator monitoring systems have been proposed and implemented by previous researchers, each offering unique advantages and limitations. One system was developed using a power-efficient STM32 microcontroller paired with a CAN Bus for data transmission. This system is noted for its speed and robust design; however, it does not incorporate intelligent predictive models and is associated with a moderate cost [22]. In another study, a traditional LED-based system was designed using an STM32 microcontroller. While this system is valued for its simplicity, it lacks additional complementary features [23]. Moreover, a remote monitoring system was developed, emphasizing the transmission of remote faults for comprehensive monitoring, also utilizing an STM32 microcontroller. This system is particularly significant for digital twin applications, yet it is limited by its sole focus on fault transmission [24]. Nevertheless, our elevator monitoring system provides notable benefits, such as being both cost-effective, efficient, and learning-based. However, it faces challenges due to the high sensitivity of the signals it measures. This heightened sensitivity requires signal filtering to address inaccuracies, but the filtering process introduces delays because of the computational workload it adds.

2.2. Data collection

There are several datasets related to passenger elevators, including video and image datasets such as the UCF101, UCF24, HMDB51, and Something-Something-v1 datasets [12]. These datasets are primarily used for video analysis and activity recognition. Moreover, there are digital datasets focused on predictive maintenance, including the Elevator Predictive Maintenance Dataset in Kaggle, Predictive Condition-Based Maintenance for Vertical Lift Vehicles, Phase I dataset from NASA, and the Predictive Maintenance Dataset in Kaggle.

Our system's measurements tend to be noisy because the sensors are highly sensitive. To deal with this, we applied zero-phase filtering, especially when working with vibration data. For this study, we collected condition monitoring data from a passenger traction elevator. The dataset includes 1416 real-time samples of time, speed, acceleration, and vibration, all captured using the LattePande Dashboard Kit across different scenarios. This time-series data is particularly useful for detecting anomalies and can also be applied to unsupervised machine learning projects. The data collection was completed on April 21, 2024.

Figure 2 illustrates the dynamic behavior of a passenger elevator over a specific time interval, captured through three key metrics: acceleration, speed, and vibration. These parameters provide insights into the elevator's operational characteristics and mechanical responses.

The first plot depicts acceleration, with oscillations around zero indicating frequent changes in speed and direction. Sharp increases and decreases correspond to the elevator's start and stop movements, reflecting its cyclic operation.

The second plot shows speed, with alternating positive and negative values representing upward and downward travel. Rapid acceleration followed by gradual deceleration aligns with typical elevator motion, ensuring efficient movement and smooth stops.

The third plot presents vibration data, where peaks coincide with moments of increased mechanical stress, such as starting, stopping, or changing direction. The correlation between spikes in vibration and shifts in speed and acceleration highlights the mechanical forces acting on the system. Understanding these relationships helps in assessing performance, detecting anomalies, and ensuring smooth operation.

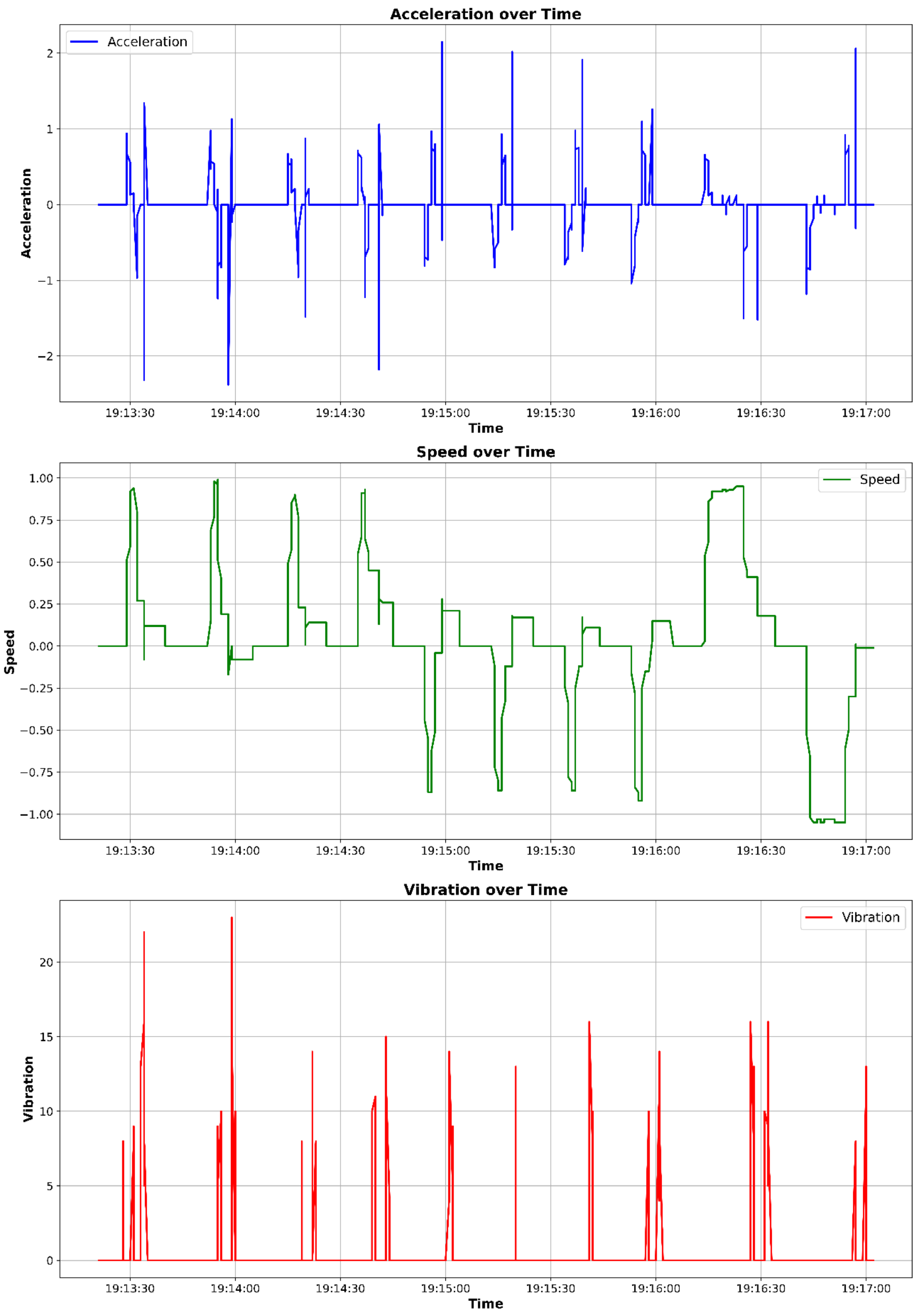


Figure 2. The real-time data measurements for electric elevators.

2.3. Anomaly detection

Anomaly detection is a critical area within the broader field of machine learning, particularly in identifying outliers. It is commonly classified under unsupervised learning methodologies, encompassing algorithms such as Support Vector Machine (SVM) OneClass, Z-Score, and Isolation Forest, among others [25,26]. The SVM OneClass algorithm is another prominent technique in anomaly detection. It functions based on the principle of hyperplane separation, where the majority of data points cluster within a defined region, while outlier points are positioned at a distance from this cluster. This algorithm is recognized for its strong capability in managing high-dimensional data, though it requires meticulous tuning and is associated with a high computational cost [30,31]. Optimization problem for One-Class SVM can be expressed in Equation (2):

$$\min_{W,\rho,\xi} \frac{1}{2}||W||^2 + \frac{1}{vn}\sum_{i=1}^{n} \xi_i - \rho \tag{2}$$

Subjected to:

$$\left(W \,.\, \phi(x_i)\right) \geq \rho - \xi_i, \qquad \xi_i \geq 0, \qquad i = 1, 2, \dots, n$$

Where: W represents the normal vector of the hyperplane or hypersphere. $\phi(x_i)$ is the kernel function used to map the data into a higher-dimensional space. ξ_i denotes the slack variables that allow for margin violations. ρ is the offset of the decision boundary, and v is the regularization parameter that controls the trade-off between the margin size and the proportion of outliers. Decision rule of One-Class SVM in Equation (3)

$$\left(W \,.\, \phi(x_i)\right) \geq \rho \tag{3}$$

The Isolation Forest algorithm, which operates on the principle of random trees to isolate anomalies, is notably effective when applied to high-dimensional datasets. This algorithm demonstrates robustness in handling large-scale data and exhibits reduced sensitivity to data distribution. However, its performance can be influenced by the choice of hyperparameters, and it may be less effective with smaller datasets [27]–[29]. The anomaly score for a data point x of Isolation Forest algorithm in Equation (4)

$$s(x, n) = 2^{-\frac{\mathbb{E}|h(x)|}{c(n)}} \tag{4}$$

Where: $h(x)$ represents the path length of x in the isolation tree. n is the total number of data points. $c(n)$ denotes the average path length of an unsuccessful search in a binary tree as in Equation (5).

$$c(n) = 2H(n-1)\,\frac{2(n-1)}{n} \tag{5}$$

Where:

$$H(n){:}\ Harmonic\ number{:}\ H(n) = \sum_{i=1}^{n} \frac{1}{i}$$

The decision rule for Isolation Forest states that a score close to 1 indicates an anomaly, while a score close to 0 suggests the data point is normal. The Z-Score algorithm, in contrast, relies on the standard deviations of data points from their mean, using a defined threshold to identify anomalies. While this approach is straightforward, it is less effective when applied to multi-dimensional datasets [32,33]. This study applies the aforementioned algorithms to the context of passenger elevator systems, with a focus on implementation, analysis, and discussion of the resulting data. However, for a data point of Z-scores algorithm x_i, and calculated as in Equation (6)

$$Z(x_i) = \frac{x_i - \mu}{\sigma} \tag{6}$$

Where μ is the mean of the dataset, and σ is the standard deviation of the dataset. the decision rule of Z-score

$$|Z(x_i)| > Threshold$$

The threshold is typically set to 2 or 3, depending on the desired sensitivity.

3. Experimental results

In a study focused on anomaly detection in passenger elevator systems, three distinct algorithms—Isolation Forest, SVM, and Z-score—were employed to identify irregular data points indicative of potential issues. Each algorithm was applied to the same dataset consisting of 1,415 data points. The results revealed varying effectiveness across the methods. Isolation Forest detected 15 anomalies, representing 1.06% of the dataset, while SVM identified 25 anomalies, corresponding to 1.77%. The Z-score method, however, marked a significantly higher number of anomalies, with 86 identified, accounting for 6.08% of the total data points as in Table 1.

Table 1. Summary of anomaly detection algorithms for passenger elevator.

Algorithm	Number of Anomalies Detected	Total Data Points	Proportion of Anomalies Detected
Isolation Forest	15	1415	1.06%
SVM	25	1415	1.77%
Z-score	86	1415	6.08%

The statistical analysis of the Isolation Forest algorithm's results for the passenger elevator data provides insights into the characteristics of normal and anomalous data across three key parameters: acceleration (Acc), speed, and vibration (Vib). For the 1,400 normal data points, the mean values for acceleration, speed, and vibration are 0.022764, -0.005096, and -0.035358, respectively, indicating that these parameters typically exhibit minimal deviation around their central tendencies. The standard deviations for these parameters are relatively low, particularly for acceleration (0.909477) and vibration (0.883566), suggesting a consistent pattern in the normal operational data. In contrast, the 15 data points identified as anomalous by the Isolation Forest algorithm show marked differences. The mean acceleration in anomalous data is significantly lower at -2.124606, indicating a substantial deviation from normal operating conditions. Similarly, the mean speed is higher at 0.475605, and the mean vibration is notably elevated at 3.300102, suggesting abnormal operational behavior. The standard deviations for these anomalous points are also much larger, particularly in acceleration (3.677975) and vibration (3.356281), highlighting greater variability and instability in these parameters when anomalies occur as in Table 2.

Table 2. Summary of isolation forest statistical results.

Statistic	Acc (Normal)	Speed (Normal)	Vib (Normal)	Acc (Anomalous)	Speed (Anomalous)	Vib (Anomalous)
Count	1400.000000	1400.000000	1400.000000	15.000000	15.000000	15.000000
Mean	0.022764	-0.005096	-0.035358	-2.124606	0.475605	3.300102
Std	0.909477	0.998781	0.883566	3.677975	1.068394	3.356281
Min	-7.508016	-2.705406	-0.223244	-8.194968	-1.986207	-0.223244
25%	-0.020244	-0.101408	-0.223244	-4.244997	-0.237808	-0.223244
50%	-0.020244	-0.101408	-0.223244	-2.596313	0.568191	3.004249
75%	-0.020244	0.320191	-0.223244	-0.020244	1.324591	6.030024
Max	7.364485	2.353790	6.231742	4.582331	1.857790	9.055799

The statistical summary of the SVM algorithm's results offers a comparative analysis of normal and anomalous data across three key parameters: acceleration (Acc), speed, and vibration (Vib). Out of a total dataset of 1415 data points, the SVM algorithm classified 1390 as normal and 25 as anomalous. For the normal data points, the mean values of acceleration, speed, and vibration are 0.003305, -0.003814, and -0.015431, respectively, indicating a stable operational state with minimal deviations from expected behavior. The standard deviations for these normal data points 0.868062 for acceleration, 0.987282 for speed, and 0.978992 for vibration suggest moderate variability within a typical range of operation. In contrast, the 25 anomalous data points exhibit distinct statistical characteristics. The mean acceleration for these points is -0.183739, reflecting a deviation from the normal mean, while the mean speed and vibration are 0.212064 and 0.857966, respectively, indicating significant differences from normal operational conditions. The standard deviations for the anomalous data 3.913040 for acceleration, 1.580628 for speed, and 1.645870 for vibration are notably higher than those for the normal data, suggesting greater variability and instability in these parameters when anomalies occur as in Table 3.

Table 3. Summary of SVM statistical results.

Statistic	Acc (Normal)	Speed (Normal)	Vib (Normal)	Acc (Anomalous)	Speed (Anomalous)	Vib (Anomalous)
Count	1390.000000	1390.000000	1390.000000	25.000000	25.000000	25.000000
Mean	0.003305	-0.003814	-0.015431	-0.183739	0.212064	0.857966
Std	0.868062	0.987282	0.978992	3.913040	1.580628	1.645870
Min	-8.194968	-2.705406	-0.223244	-7.988883	-2.655806	-0.223244
25%	-0.020244	-0.101408	-0.223244	-2.871093	-0.547808	-0.223244
50%	-0.020244	-0.101408	-0.223244	-0.020244	0.196192	-0.223244
75%	-0.020244	0.320191	-0.223244	1.868872	1.684190	1.793939
Max	6.917966	2.353790	9.055799	7.364485	2.254590	4.617995

The statistical analysis of the Z-score algorithm's results provides a detailed examination of the differences between normal and anomalous data points in the elevator system, focusing on three key parameters: acceleration (Acc), speed, and vibration (Vib). The Z-score method identified 86 anomalous data points out of a total of 1,415, leaving 1,329 data points classified as normal. For the normal data points, the mean values of acceleration, speed, and vibration are 0.006117, -0.018014, and -0.194406, respectively. These values suggest that the normal operation of the elevator typically involves slight fluctuations around expected levels. The standard deviations 0.718227 for acceleration, 1.007927 for speed, and 0.253954 for vibration indicate relatively low variability in the normal dataset, with vibration showing the least variability. In contrast, the 86 anomalous data points display significantly different statistical characteristics. The mean acceleration for these points is -0.094531, which is a departure from the normal mean, while the mean speed is higher at 0.278378. The mean vibration for anomalous data is notably higher at 3.004249, indicating a substantial deviation from normal operating conditions. The standard deviations for the anomalous data are also larger 2.928830 for acceleration, 0.831493 for speed, and 2.432457 for vibration reflecting greater variability and instability in these parameters when anomalies are present as in Table 4.

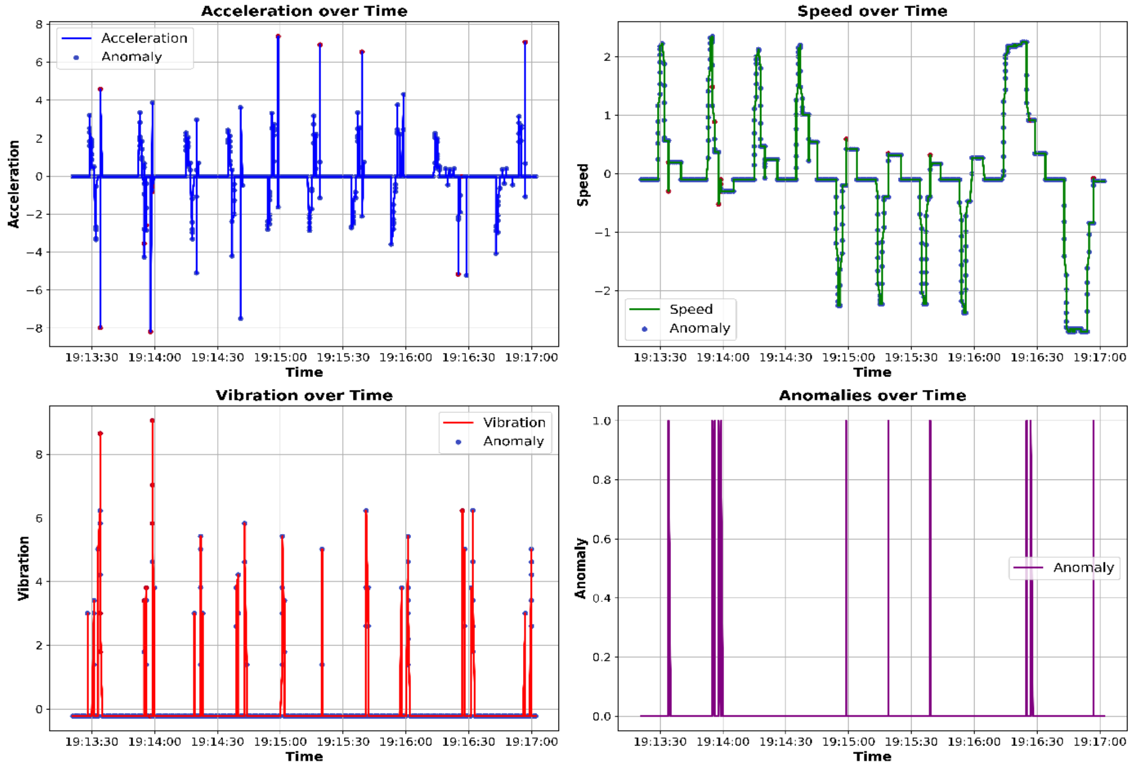
The detection of anomalies in an elevator system, as analyzed using three algorithms Isolation Forest, SVM, and Z-score provides valuable insights into their behavior when applied to time-series data for acceleration, speed, and vibration. In the Isolation Forest results, anomalies are depicted as distinct red points in the plots. The acceleration data shows anomalies detected at extreme positive and negative deviations, indicating the algorithm's effectiveness in identifying significant outliers. The speed data, however, contains fewer anomalies, suggesting that deviations in speed are less frequent or pronounced. For vibration data, Isolation Forest identifies a higher density of anomalies, reflecting its sensitivity to irregular patterns. The cumulative anomaly plot further confirms this with sharp spikes, corresponding to the detected anomalies over time.

Table 4. Summary of Z-score statistical results.

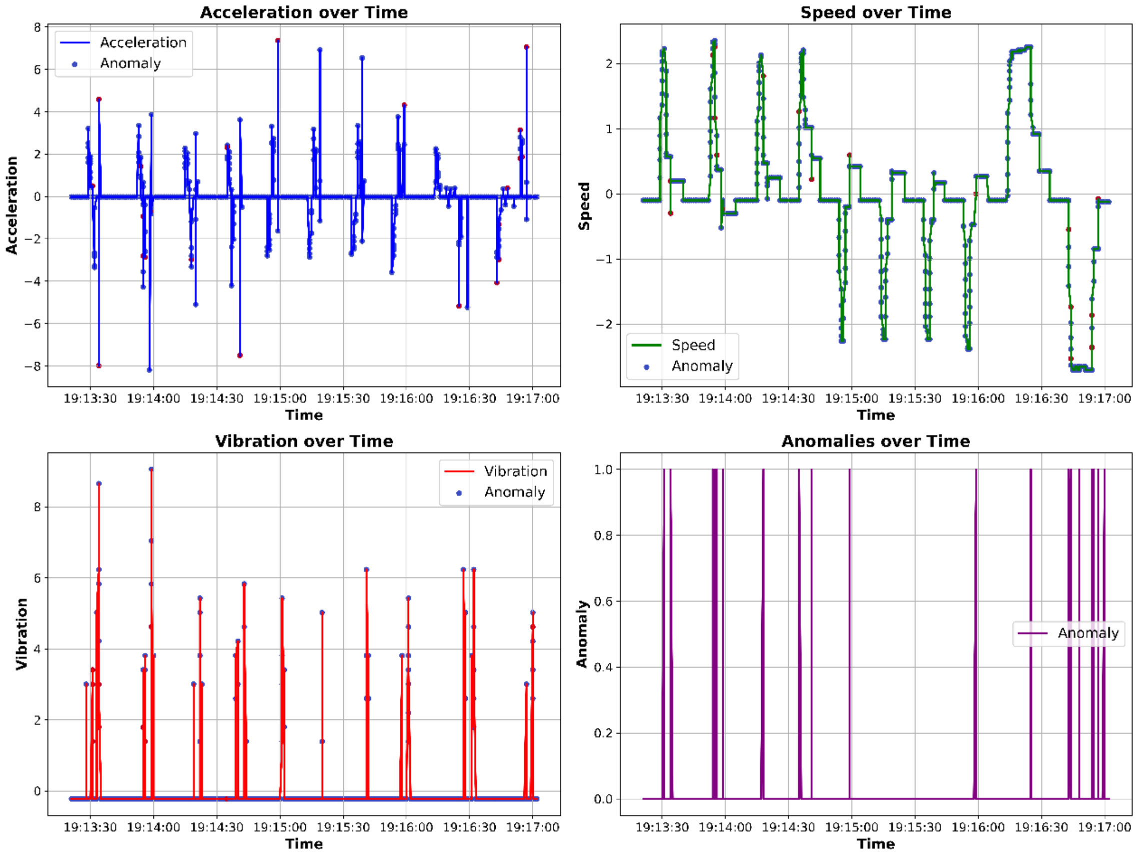
Statistic	Acc (Normal)	Speed (Normal)	Vib (Normal)	Acc (Anomalous)	Speed (Anomalous)	Vib (Anomalous)
Count	1329.000000	1329.000000	1329.000000	86.000000	86.000000	86.000000
Mean	0.006117	-0.018014	-0.194406	-0.094531	0.278378	3.004249
Std	0.718227	1.007927	0.253954	2.928830	0.831493	2.432457
Min	-2.974136	-2.705406	-0.223244	-8.194968	-2.358207	-0.223244
25%	-0.020244	-0.101408	-0.223244	-0.020244	-0.101408	-0.223244
50%	-0.020244	-0.101408	-0.223244	-0.020244	0.320191	3.407685
75%	-0.020244	0.270591	-0.223244	-0.020244	0.568191	4.617995
Max	2.967995	2.353790	2.600812	7.364485	2.229790	9.055799

The SVM-based detection also marks anomalies as red points but demonstrates a slightly different detection pattern compared to Isolation Forest. In the acceleration data, SVM identifies many of the same anomalies but with slight variations due to its unique classification criteria. The speed plot under SVM reveals a more scattered pattern of anomalies, indicating a higher sensitivity to smaller deviations in speed. For vibration data, the algorithm detects numerous anomalies, although the pattern differs from Isolation Forest's results. The cumulative anomaly plot for SVM shows a smoother, more continuous pattern, suggesting that SVM tends to classify a broader range of outliers as anomalies.

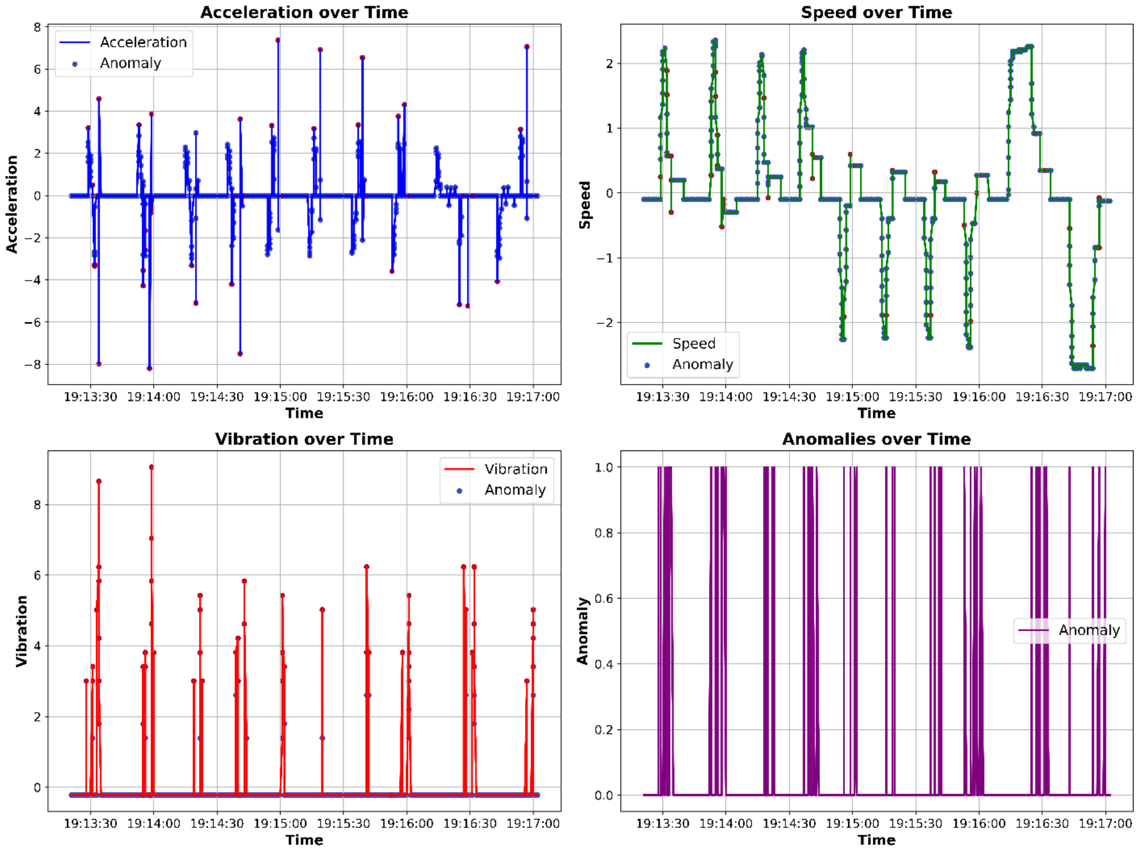
The Z-score algorithm takes a different approach, with its detection focusing on statistical deviations from the norm. In the acceleration plot, anomalies are flagged primarily at points of sharp changes, though Z-score tends to classify more points as anomalous than the other two methods. For speed, the algorithm consistently detects anomalies at various steps, highlighting its sensitivity to deviations from expected values. The vibration data shows a dense concentration of anomalies, reflecting Z-score's threshold-based method of identifying outliers. The cumulative anomaly plot reveals periods of frequent anomaly detection, suggesting that Z-score is the most aggressive of the three methods in classifying deviations as anomalies. This detailed comparison highlights the strengths and trade-offs of each algorithm, providing valuable context for their application in monitoring elevator systems. These observations are visually summarized in Figure 3.



(a) Isolation forest.



(b) SVM.



(c) Z-score.

Figure 3. Tracking of anomaly detection results. **(a)** Isolation forest. **(b)** SVM. **(c)** Z-score.

The comparison of three anomaly detection algorithms Z-Score, Isolation Forest, and One-Class SVM applied to the operational metrics of acceleration, speed, and vibration in a traction elevator system highlights their strengths and limitations. The Z-Score algorithm is highly sensitive to deviations, identifying many anomalies across all metrics. This sensitivity is due to its reliance on statistical thresholds to flag outliers. However, its simple approach, which treats each metric separately without accounting for their relationships, can lead to a higher number of false positives, particularly in multi-dimensional datasets where interactions between variables are more complex.

The Isolation Forest algorithm takes a more focused approach by isolating outliers from most of the data. It detects fewer anomalies, concentrating on substantial deviations from normal operations. This makes it ideal for applications that prioritize identifying critical anomalies over capturing every minor deviation. However, its conservative nature may cause smaller, yet still relevant, anomalies to go undetected. Meanwhile, the One-Class SVM algorithm offers a middle ground between the broad detection of Z-Score and the targeted detection of Isolation Forest. It captures a moderate range of anomalies by modeling the normal system behavior in a multi-dimensional feature space. This ability allows it to detect a wider variety of deviations while avoiding excessive false positives. However, this approach requires higher computational resources, which may limit its use in real-time or resource-constrained environments. This comparison is presented in Figure 4, which provides a detailed breakdown of the performance of these algorithms across the operational metrics.

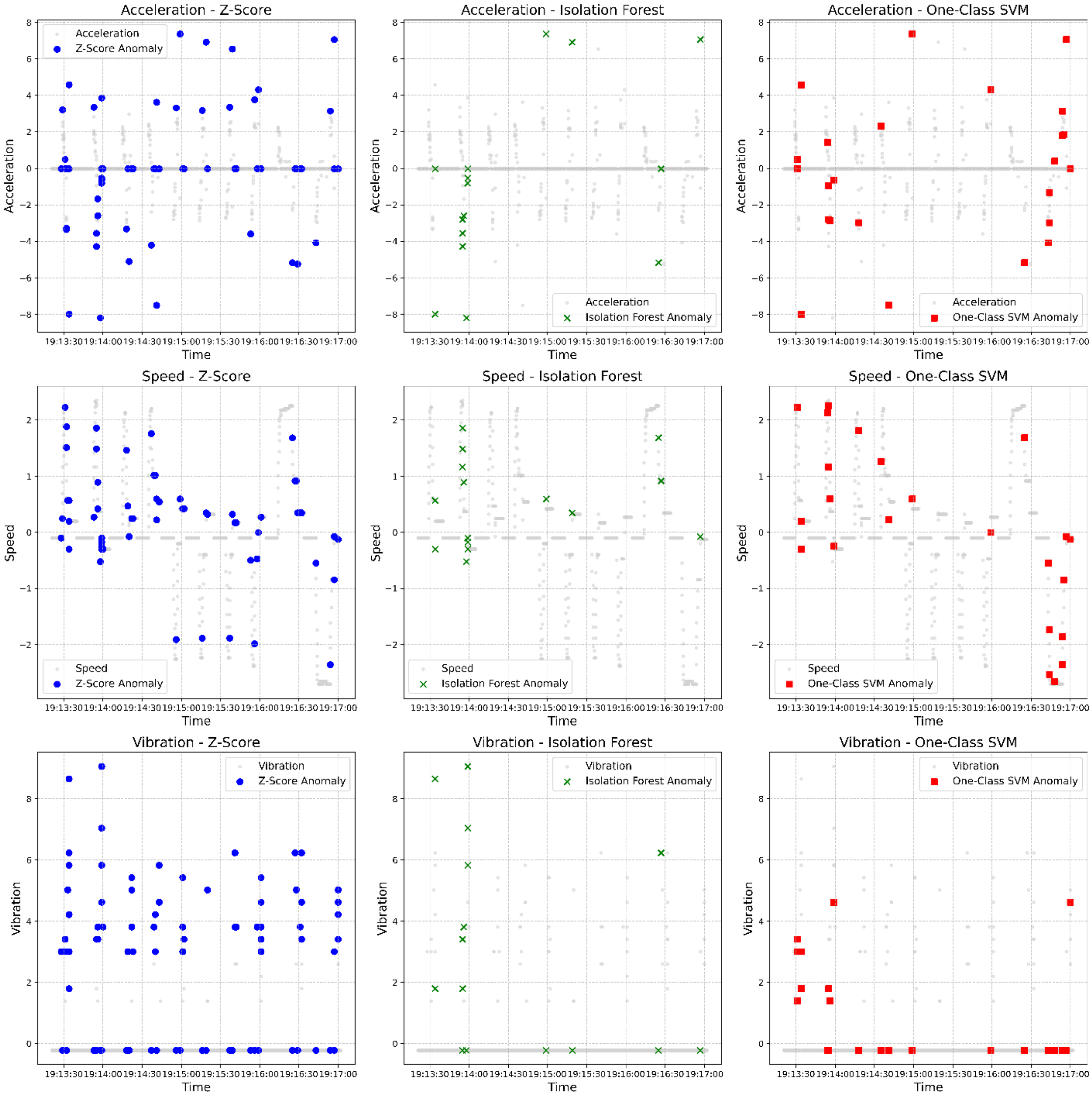


Figure 4. Anomaly detection results comparisons.

These findings indicate that selecting an anomaly detection algorithm should depend on the dataset's characteristics and the application's specific requirements. For datasets where minimizing false positives is critical, the Isolation Forest algorithm is a favorable choice. Conversely, SVM OneClass is better suited for scenarios requiring nuanced detection of diverse anomalies, assuming adequate computational resources are available. Although less effective in multi-dimensional settings, the Z-Score method remains useful in applications that demand higher sensitivity to outliers and involve lower-dimensional data. Real-time systems face several limitations, including susceptibility to noise and disturbances that can compromise measurement accuracy, as well as the risk of sudden failure due to increased load. Furthermore, the constrained availability of memory and processing resources poses challenges for effective implementation. When integrating anomaly detection algorithms in real-time systems, additional limitations arise. Some algorithms exhibit high sensitivity to outliers, leading to instability and necessitating frequent maintenance, which increases operational costs. Moreover, the scarcity of labeled data reduces the accuracy of these algorithms, resulting in potential incompatibility with critical standards such as the ISO 4190 and ISO 8100 series.

4. Conclusion

This study presents a cost-effective, integrated system for monitoring the condition of electric elevators, utilizing acceleration estimates from a speed sensor and piezoelectric sensors for vibration measurement. Unsupervised machine learning algorithms, including Isolation Forest, SVM, and Z-score, were implemented for anomaly detection. The Isolation Forest algorithm identified 15 anomalies (1.06% of the data), the SVM algorithm detected 25 anomalies (1.77% of the data), and the Z-score method identified 86 anomalies (6.08% of the data). This research represents a significant advancement in condition monitoring and serves as a foundational step toward the development of a digital twin system for passenger elevators**.**

Supplementary data

Data Availability Statement: https://figshare.com/s/becf1d59ea38b0eff1d9.

Authors' contribution

Resources, S.O., O.N., and R.B.; Data Curation, S.O., O.N., and R.B.; Formal analysis, S. O., O.N, and R.B.; Writing—Original Draft, O.N. and S.O.; Writing—Review & Editing, R.B. All authors have read and agreed to the published version of the manuscript.

Conflicts of interests

The authors declare no conflict of interest.

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