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LIFT ENGINEERING EQUIPMENT EVENT LOG DATA ANALYSIS

Petrashenko A., Liu Yang. Lift Engineering Equipment Event Log Data Analysis. This paper is devoted to the collection and analysis of log files of lift engineering equipment, considering their technical complexity and significant impact on the safety of their use. The usage of log analysis can quickly identify and resolve problems, keeping elevators functional, extending service life, and increasing passenger safety. Using a log file of a real IoT monitoring system, the study provides baseline statistics, revealing information about event distribution and hardware status. The analysis focuses on the "Elevator Power On/Off" event type, focusing on the average time for the equipment to transition from an emergency state to a normal state, as well as calculating the probability of remaining in an operating state for 1, 12, or 24 hours. The results highlight the different transition times between the equipment under consideration, providing valuable information for maintenance planning and resource optimization.
Keywords: Internet of Things, monitoring system, log files analysis, survival function, Kaplan-Meier estimator

Петрашенко А.В., Лю Янг. Аналіз даних журналу подій ліфтового інженерного обладнання. У даній роботі розглядаються питання збору та аналізу файлів журналів інженерного обладнання ліфтів, враховуючи їх технічну складність і значний вплив на безпеку користування ними. Використання аналізу журналів дозволяє оперативно виявляти та оброблювати аварійні ситуації, забезпечуючи функціональність ліфтів, продовжуючи термін служби та підвищуючи безпеку пасажирів. Використовуючи файл журналу реальної системи моніторингу в галузі «Інтернету речей», дослідження надає базову статистику, розкриваючи інформацію про розподіл подій і стан обладнання. Аналіз зосереджується на типі події «Ввімкнення/вимкнення живлення ліфта», акцентуючи увагу на середньому часі переходу обладнання з аварійного до нормального стану, а також на розрахунку імовірності залишитись у справному стані протягом 1, 12 або 24 годин. Результати підкреслюють різний час переходу між обладнанням, що розглядається, надаючи цінну інформацію для планування технічного обслуговування та оптимізації ресурсів.
Ключові слова: інтернет речей, система моніторингу, аналіз файлів журналів, функція виживання, оцінка Каплана-Майєра

Introduction. Among the other crucial components of the modern lift-oriented technical infrastructure, the monitoring system of lift engineering equipment is important for several critical reasons. Firstly, it plays a pivotal role in ensuring the optimal and safe performance of elevators by providing real-time monitoring of key parameters such as power usage, door operations, and motor performance [1]. This constant surveillance allows for the early detection of anomalies or irregularities in elevator components, triggering timely alerts for investigation and preventive measures. Another significant aspect is the system's ability to swiftly identify faults within the elevator system and offer detailed diagnostics. This facilitates quick problem resolution and contributes to predictive maintenance, wherein the system analyzes performance data to predict potential failures or maintenance needs. This proactive approach minimizes unexpected downtime, enhances reliability, and extends the overall lifespan of the elevator. Capturing and logging a wealth of data related to elevator operations, the monitoring system serves as a valuable resource for performance analysis, trend identification, and decision-making. Many systems offer remote access capabilities, allowing for monitoring and control from a central location, facilitating quicker response times and reducing the need for on-site interventions.

The urgency of solving the problems of collecting and analyzing information obtained from elevator engineering equipment in the form of log files is important due to the high degree of technical complexity and significant impact on the safety and convenience of building operation. This technique allows not only to promptly detect and solve problems in the operation of elevators, ensuring their uninterrupted work and extending their service life, but also contributes to increasing the level of safety for users [2]. In addition, the possibilities opened up by log analysis, such as automated control and efficiency optimization, are becoming key to modern infrastructure management and maintaining high standards of functionality of elevator systems in modern buildings. This approach is critical in the context of fast-paced urban development and the construction industry, where the reliability and safety of elevators are important aspects of comfort and safety for their users.

Related works. The general architecture of a lift-oriented monitoring system consists of sensors, central or distributed processing unit, communication modules, data storage and monitoring core software. The sensors capture real-time data on motion, door status, weight, and other relevant parameters. The

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processing unit allows to handle, process and aggregate the data, received from the sensors. Data storage allows to store and access the data efficiently using modern SQL/NoSQL database engines. Monitoring software provides the user interface allowing to interact with an end user giving him a sophisticated dashboard, visualization means etc.

The logs play a crucial role for recording and storing a comprehensive history of events, activities and performance metrics related to the lift operations. In the work [3] authors highlight Run-to-Failure, Preventive Maintenance and Predictive Maintenance (PdM) techniques of technical management. They state that Machine Learning methods have been emerged as a promising tool in PdM applications to prevent failures in equipment. The authors of [4] proposed obtaining patterns from log records, and set corresponding rules to deal with logs in certain patterns which significantly improve the efficiency of distributed and cloud-based log analysis. J.Horalek and others in [5] proposed a log collection and analysis using the hybrid Elastic based and Kubernetes technologies. Nevertheless, previous work with an emphasis on data analysis of elevator events indicates the need for further improvement of methods and tools.

Problem statement. The purpose of this publication is to explore the capabilities of collecting and analyzing basic statistics obtained from the elevator equipment event log [6]. In particular, it is intended to investigate the relationships between various events by the types, their characteristics and time indicators like a timestamp. The main emphasis is on understanding the operational state of the equipment (functioning or failure) and its identification in the context of the occurrence of specific events. With the help of this analysis, we aim to improve maintenance strategies, predict possible malfunctions and ensure more efficient management of elevator equipment.

The description of the research. In this paper the authors have analyzed a log file gathered from the real IoT monitoring system during approximately 1-year of 24/7 monitoring of engineering equipment. The dataset, derived from lift engineering equipment event logs, contains a comprehensive record of events spanning a considerable timeframe. The first few rows of the dataset provide a snapshot of the data (see fig.1), revealing details such as the timestamp of events (date_time), the type of event (event_type), a description of the event (event_text), the unique identifier of the equipment (equipment_id), and the corresponding equipment state (equipment_state).

date_time	event_type	event_text	equipment_id	equipment_state
31.10.2022 10:34	4	Elevator power is on	9	1
31.10.2022 10:35	4	Elevator power is on	13	1
31.10.2022 10:36	6	The cabin door is open	136	0
31.10.2022 10:36	6	The cabin door is open	242	0
31.10.2022 10:36	6	The cabin door is open	8	0
31.10.2022 10:36	6	The cabin door is open	362	0
31.10.2022 10:39	4	Elevator power is on	317	1
31.10.2022 10:39	4	Elevator power is on	318	1
31.10.2022 10:39	4	Elevator power is on	257	1
31.10.2022 10:39	5	The doors of MP are open	428	0

Fig. 1. A snapshot of the dataset

Upon conducting basic statistical analyses, several noteworthy insights emerge. The dataset comprises a total of 306,915 entries, with a diverse range of event types, spanning from 4 to 10 (see Table 1). The event_type distribution indicates that certain events, such as event type 4, are more frequent than others, shedding light on the prevalence of specific activities within the lift engineering context.

Table 1. Distribution of Event Types

Event Type	Event Text	Total Count	Failure Count
4	Elevator power is on/off	106365	55300
5	The engine room door is open/close	21491	10575
6	The cabin door is open/close	16610	16610

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8	Exists/No phase A electrical supply	52025	39896
9	Exists/No phase B electrical supply	57910	31574
10	Exists/No phase C electrical supply	52514	25427

In terms of equipment states, the dataset showcases a balance between operational states (equipment_state equals to 1) and states indicating a malfunction or failure (equipment_state equals to 0). Approximately 127,533 entries indicate the equipment is in working order, while 179,382 entries suggest equipment failure.

Examining the numerical features, the dataset's temporal span ranges from October 31, 2022, to October 9, 2023. The mean event_type is approximately 6.83, with a standard deviation of 2.43, indicating a moderate level of variability in event types. The equipment_id values range from 1 to 476, and the equipment_state reveals an average operational state of around 41.55%.

No missing values are observed in any of the columns, ensuring the dataset's completeness and reliability for analysis. Additionally, the distribution of unique values in each column provides an overview of the dataset's diversity, with 132,001 unique timestamps, six distinct event types, 12 unique event descriptions, and 476 unique equipment identifiers.

Elevator power on/off analysis

This algorithm is designed to analyze and compare the average transition times of state changes in engineering equipment, focusing on events with event_type=4 (Elevator power on/off). By identifying the equipment with the quickest, longest, and middle-range state transitions, it provides insights into potential performance issues, operational efficiency, and overall reliability of the equipment. This information can be valuable for maintenance planning, resource optimization, and proactive decision-making, ultimately contributing to enhanced operational effectiveness and reduced downtime in lift engineering systems.

The algorithm begins by loading data from a CSV file containing timestamped events with relevant information such as event type, equipment state, and equipment ID. It specifically focuses on events with event_type=4. The data is then filtered, sorted chronologically by equipment and time, and time differences between consecutive transitions are calculated.

To facilitate analysis, the time differences are converted to seconds. The algorithm proceeds to calculate the average transition times for each equipment by grouping data based on equipment ID. The resulting average times are sorted, and the top 3 equipment with the quickest transitions and the top 3 with the longest transitions are identified.

Additionally, the algorithm selects a set of 3 equipments in the middle in terms of average transition times. These three sets of equipment (quickest, longest, and middle 3) are then formatted into human-readable timespans and presented in tabular form.

The results

The results which are presented in the table 2 shows that the time it takes for equipment to switch from one state to another can differ a lot. Some equipment does it really quick, like in a few seconds, while others take much longer, sometimes hours. It's important to find out why some equipment takes so much time, maybe because of maintenance or specific ways they work or they are maintained. This information helps technical managers organize the equipment work and maintenance better and more efficiently.

Table 2. Quickest, Longest and Middle 3 Transitions

	Quickest Transitions		Longest Transitions		Middle 3 Transitions	
Number	Equipment ID	Average Transition Time	Equipment ID	Average Transition Time	Equipment ID	Average Transition Time
1	461	00:00:07	166	43:55:57	141	05:11:16
2	369	00:00:08	385	36:08:42	8	05:13:05
3	207	00:00:10	364	35:14:38	126	05:15:28

The subsequent focus of our research delves into the challenging yet crucial task of predicting when the next failure event will transpire within the elevator system. This problem inherently falls under the domain of time-to-event or survival analysis [7], a statistical methodology widely employed to forecast the

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duration until a specific event of interest unfolds. In our specific context, the event of interest revolves around the prediction of when the next failure event will occur for a designated equipment, which entails assessing the time until the equipment_state transitions to 0, indicative of an impending failure.

To tackle this predictive challenge, we leveraged the 'lifelines' library [8], a powerful survival analysis toolkit designed for implementation in the Python programming language. Survival analysis, particularly employing the Kaplan-Meier estimator, serves as the cornerstone of our predictive modeling approach. This estimator is employed to calculate the survival function, offering insights into the probability of an equipment surviving (not experiencing failure) beyond a specific point in time.

The 'lifelines' library's robust capabilities enable us to construct survival curves, visualize the probability distribution of failure events over time, and extract valuable insights into the reliability and resilience of individual equipment units. By considering the temporal dimension and the probability of equipment failure, our approach enhances our ability to implement proactive maintenance strategies, allocate resources judiciously, and ultimately contribute to the overarching goal of minimizing downtime and optimizing the overall performance of elevator systems. Through this predictive analysis, we aim to provide stakeholders with actionable information that empowers them to implement targeted interventions, thereby fostering a more resilient and dependable elevator infrastructure.

Table 3. The survival analysis of the Elevator power on/off event

Equipment ID	Survival Probability		
	Survive in 1 hour	Survive in 12 hours	Survive in 24 hours
461	0.70	0.64	0.58
369	0.83	0.83	0.83
207	0.77	0.63	0.59
166	0.96	0.84	0.24
385	0.93	0.51	0.34
364	0.92	0.76	0.60
141	0.89	0.44	0.24
8	0.84	0.75	0.71
126	0.91	0.56	0.39

The results provided in the table 3 indicate the varying survival probabilities for different equipment IDs at different time intervals, reflecting the reliability and resilience of each piece of equipment. Some equipment demonstrates consistent high survival probabilities, suggesting robust performance, while others experience rapid declines, highlighting potential vulnerabilities.

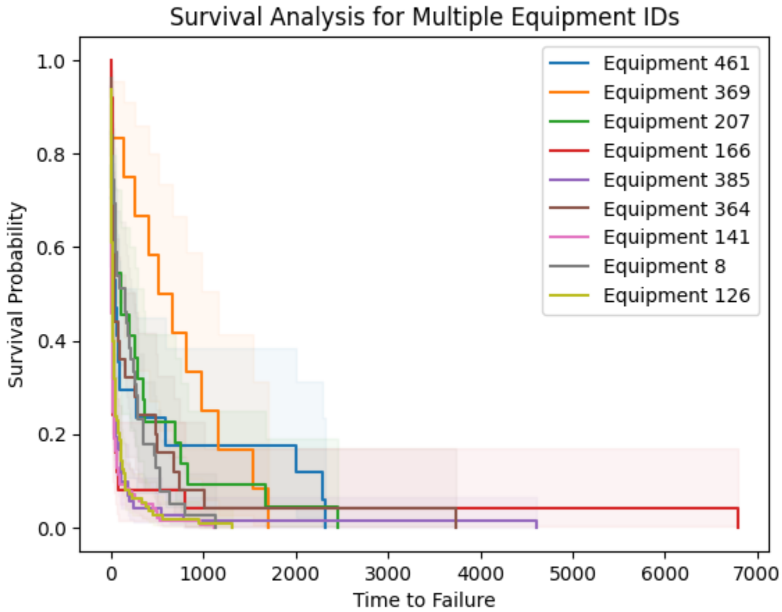

Fig.2. Survival Analysis for Multiple Equipment

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The survival analysis for equipment with quickest, lowest and middle transition time are shown in the fig.2. The results support the idea that in first hour the equipments form all groups show quite high survival rate (>70%) while later in 12 hours there are worse results indicating the reveal of some equipment failures (>44%). Having such kind of information about the survivance of lifts the engineers along with managers can predict the upcoming problems with equipment and to plan the maintenance procedures.

Conclusions

This study focused on collecting and analyzing log files from elevator engineering equipment, considering its technical characteristics. Log analysis proved instrumental in swiftly identifying and resolving issues, ensuring elevator functionality, prolonging service life, and enhancing user safety. The research aimed to enhance maintenance practices by exploring relationships among events, their characteristics, and timestamps. Utilizing a log file from a real IoT monitoring system, the study presented baseline statistics, highlighting the event distribution and equipment status. Specifically, focused on the "Elevator Power On/Off" event type, the analysis concentrated on average transition times, aiming for more efficient control and improved equipment performance. The results underscored varied transition times across equipment, offering valuable insights for maintenance planning and resource optimization.

Prospects for further research

Having the access to diverse datasets and practical insights, there are a lot of area for the further research. Firstly, we can delve into more advanced predictive modeling techniques, exploring beyond the Kaplan-Meier estimator to leverage the capabilities of deep learning models for enhanced failure event predictions. A dynamic maintenance scheduling algorithm could be developed, adapting interventions based on real-time equipment health, optimizing resource allocation, and minimizing downtime. Additionally, a comprehensive cost-benefit analysis considering factors like downtime, maintenance costs, and overall impact on building operations could guide the formulation of cost-effective maintenance approaches.

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