Data-Driven Short Circuit Detection in Energy Storage Systems: A Low-Resource Strategy for Logistics Scenarios

Christoph Schrade[1], Theo Zschörnig[2], Leonard Kropkowski[3] and Bogdan Franczyk[1,2,4]

[1]Information Systems Institute, Leipzig University, Grimmaische Str. 12, 04109 Leipzig, Germany
[2]Institute for Applied Informatics (InfAI), Goerdelerring 9, 04109 Leipzig, Germany
[3]Fraunhofer-Institut für Nachrichtentechnik, Heinrich-Hertz-Institut HHI, Einsteinufer 37, 10587 Berlin, Germany
[4]Business Informatics Institute, Wrocław University of Economics, ul. Komandorska 118-120, 53-345 Wrocław, Poland
`schrade@wifa.uni-leipzig.de`, `zschoernig@infai.org`, `leonard.kropkowski@hhi.fraunhofer.de`, `franczyk@wifa.uni-leipzig.de`

Abstract. The increasing adoption of energy storage systems driven by national and international regulations highlights their critical role in reducing greenhouse gas emissions and stabilizing power grids during the global shift to renewable energy. Energy storage system applications span from battery electric vehicles to stationary storage in residential and commercial settings. As deployment scales up, a growing number of these systems will eventually return from the field, creating new challenges in logistics and safety. While operational battery systems are typically monitored via integrated battery management systems, standardized methods for monitoring during transportation and storage are lacking. This article presents a low-resource approach for externally monitoring batteries during logistics processes. A data-driven algorithm, adapted from existing literature, is employed to detect internal short circuits (a key precursors to thermal runaway) and detection times are compared to other approaches. The study further examines how varying data transmission frequencies from external monitoring devices impact detection performance, with the aim of optimizing resource usage without compromising safety.

Keywords: Internal Short Circuit, Energy Storage System, Battery Electric Vehicle, Battery Energy Storage System, Data Driven Early Detection

1 Introduction

Against the backdrop of international frameworks and guidelines, such as the European Green Deal or the Renewable Energy Directive of the European Union, the importance and utilization of energy storage systems (ESS) in different areas of everyday life has steadily increased. These systems are pivotal in driving the global shift toward the overarching usage of sustainable energy. This transition aims not only to curb overall energy use and cut greenhouse gas emissions but also to significantly boost the adoption and integration of renewable energy sources. ESS make it possible to capture and store renewable energy, which is typically produced intermittently. By doing so, they enhance the reliability and adaptability of the power supply and grid therefore supporting a more resilient and sustainable energy system. Two important application areas of ESS are found in battery electric vehicles (BEVs) as well as in battery energy storage systems (BESS) for residential and commercial applications. Their importance in the energy transition is clearly reflected in increasing sales figures in both areas over the last years. For example, while only less than 140 thousand BEV were registered in Germany in 2020, as of October 2024 there are already more than 1.5 million; an increase by more than a factor of 10 in less than five years [30]. The increase of sales figures for residential BESS is in the same order of magnitude: In January of 2020 less than 110 000 storage systems were implemented in Germany with a total capacity of around 850 MWh; today there are more than 1.5 million running systems providing a total capacity of more than 13 GWh [6]. Despite their benefits, the use of ESS involves complex logistics, including transportation to installation or manufacturing sites, return at end of life for recycling or reuse, and storage throughout various lifecycle stages. During these periods, continuous monitoring of ESS is necessary due to the sensitivity of the integrated batteries, the resulting safety risks and for ongoing quality assurance. In this context, one of the most critical safety threats arises from internal short circuits (ISCs) in battery cells, which can lead to hazardous failures and severe operational risks. Current research has introduced promising Artificial Intelligence (AI)-driven methods for detecting ISCs. However, these solutions rely heavily on the continuous operation of the integrated battery management system (BMS); a condition that cannot be guaranteed throughout the transportation or storage of ESS. Furthermore, the effect of reducing the frequency of monitoring on the performance of these approaches has not been investigated. Against this background, we proposed an approach to enable the early detection of battery short circuits remotely, even during ESS transportation and storage scenarios (cf. [26]) therefore addressing the aforementioned problems.

In our previous work, kernel principal component analysis (KPCA), a data-driven method, was utilized as the algorithmic backbone of the detection approach. In the present paper, two additional algorithms for ISC detection are presented and experimentally compared with the KPCA approach to further investigate the suitability of the previously proposed approach.

The rest of this paper is organized as follows: Section 2 outlines the motivation and background of our study, along with the key challenges our approach aims to tackle. Section 3 provides an overview of related work in this domain. In Section 4, we introduce our proposed solution, followed by Section 5, which details experiments exploring the detection times for ISCs in various settings of different monitoring frequencies and short circuit resistances. In particular, two new data-driven ISC detection methods are presented in Section 5 and their performance is compared with the KPCA method. Section 6 presents a discussion of our experimental results. Finally, in Section 7, we conclude by summarizing our key findings and outlining potential directions for future research in this area.

2 Background

As the number of deployed ESS in everyday life increases, so does the demand for their safety. Lithium-ion batteries have become the standard technology for ESS in both BEV and stationary systems used in homes and commercial facilities [7, 15]. Typical features of those Lithium-based batteries are high power and energy density, no memory effect, a long cycle life, and fast charging capabilities [3]. Lithium-ion batteries, while generally safe, can become hazardous if exposed to conditions like excessive charging, high temperatures, or physical impact. In such cases, a sudden and uncontrolled energy discharge may occur, potentially leading to fire or explosion. This dangerous reaction is known as thermal runaway, a chain reaction where the battery's internal temperature increases possibly exponentially. These thermal overreactions are difficult to control from the outside of a battery. If thermal runaway occurs, the cells inside the battery are heated further, which accelerates the chemical reactions in the battery and generates even more heat. This leads to a positive feedback loop, possibly resulting in serious accidents [4, 31]. In terms of BEVs and residential or commercial BESS, charged battery systems can contain large amounts of energy, e.g., more than 120kWh for the traction battery of the VinFast VF 9 Extended Range [5], or more than 17kWh for the SENEC.Home P4 AC 17.75 home storage [19], thus highlighting the potential danger of thermal runaway. Following [28], there are three major reasons for thermal runaway to start:

- **Mechanical abuse (R1)** of batteries is principally caused by deformation, displacement or penetration. This damages or destroys the separator between the cathode and the anode of the battery, resulting in an ISC.
- **Electrical abuse (R2)** is primarily triggered by external short circuits (ESCs), which is caused either by exposure to water, contamination of the conductor, electric shock or deformation of the battery under mechanical stress. Another reason for electrical abuse is overcharging the battery. In both scenarios, thermal runaway can occur.
- **Temperature abuse (R3)** may occur because of overheating due to mechanical or electrical stress as well as faulty battery connectors. It causes rising internal and external temperatures, which in turn may damage or destroy the separator between the cathode and the anode of the battery, resulting in an ISC.

The main reasons for thermal runaways are ISCs [13, 28, 39]. The speed of progression of an ISC, however varies greatly depending on the type and severity of the mishandling [31]. In many cases, the rate of progress is slow enough to allow sufficient time for safety measures to be taken and thus prevent a catastrophic thermal runaway.

For this reason, early detection of an ISC is a particularly important aspect of battery safety and a vivid research topic.

Previous studies have introduced several promising AI-driven methods capable of identifying ISCs in their earliest phase. Some of these are also already in use by practitioners [27]. However, these approaches expect the constant availability of the BMS so that the data needed for the detection can be queried in real time. While this is possible if ESS are embedded inside a BEV or respectively installed in a private or commercial property, steady access to the BMS cannot be guaranteed away from their place of operation. Moreover, there is no standardized way of checking a battery's condition apart from their first life, especially during logistical processes such as transporting or storing [18]. Safely managing ESS in logistics becomes thus far more challenging, as stakeholders like freight forwarders and logistics providers lack practical means to assess the condition or risk level of individual batteries during handling. In this regard, various accidents have already occurred in the past during the transportation of lithium-based batteries, e.g. [36].

A possible solution to this problem involves the deployment of an external device capable of retrieving data from the BMS while the ESS remains offline. Furthermore, this device records environmental influences in the vicinity of the ESS. The recorded data can subsequently be used to detect potential abuse as soon as it occurs and to identify the resulting ISCs at an early stage.

While previous studies have explored the design and deployment of such devices, their focus has been limited to monitoring ESS during their operational phase. In contrast, our previous article [26] addresses this critical gap identified in recent research (e.g. [18]) by introducing a comprehensive approach for tracking ESS not only in BEVs and BESS but also throughout non-operational phases, particularly during transportation and storage.

A key challenge when using an external device to record the BMS and environmental data of an ESS is its power supply. Especially in logistics scenarios, there are often no fixed power sources. Additionally, the direct use of the batteries of the monitored ESS to power the external device would decrease the utility of it due to the necessary voltage conversions and additional connection interfaces. Moreover, the continuous operation even when an ESS is damaged, could not be guaranteed. For these reasons, the external device needs to provide its own power using batteries. This led to additional framework conditions which have to be observed when designing the external device and must be considered when solving the overall problem (cf. [26]):

- **High energy usage for data transmission (FC1):** Sending data via wireless networks such as Wi-Fi, Bluetooth or mobile radio consumes significantly more energy than the actual data collection, which greatly reduces battery life [9].
- **High energy usage for complex computations (FC2):** Complex computations such as the training of machine learning algorithms greatly increase the load on the processor thus reducing battery life [33].
- **Continuous operational readiness (FC3):** The device needs to be operational continuously, energy-saving options such as shutdown or sleep mode cannot always be

used [2]. Even standby modes, which would normally save energy, can only be used to a limited extent since continuous sensor readings and communication are required.

- **Compact design and limited battery capacity (FC4):** An external device and its battery power supply bring their own weight and, above all, require space [2, 9]. However, especially in logistics scenarios, space is scarce, therefore the device needs to be as small as possible. This limits the amount of energy available and makes it difficult to supply power in the long term.
- **Longevity and low maintenance (FC5):** The device must last for long periods without maintenance, maybe several years [2, 9].

Given these conditions, a concept must be developed that strikes a balance between the need for close monitoring and the limitations of the required battery operation. Ideally, this will enable the earliest possible detection of hazards by ESS while still providing a monitoring solution with a long lifecycle.

Against this backdrop, our previous research introduced a method for enhancing the early detection of ISCs in ESS by integrating an external device that records battery cell voltages and environmental conditions during transport and storage [26]. In this regard, the core research question addressed was whether ISC detection remains viable when monitoring data is collected at low frequencies. To explore this, a detection strategy established in prior work [21], [22], [23], [24], that utilizes cell level voltages and is based on KPCA, was implemented and its reported detection times were validated through a series of experiments. Furthermore, the method was compared with related approaches and systematically evaluated in terms of how varying data sampling rates impact detection performance. Apart from the KPCA approach, the literature research provided only two other detection strategies that are based solely on the individual cell voltages of a battery. For this reason, the KPCA approach was only compared with these two strategies in our previous work. In order to further investigate the performance of KPCA and enhance our previous work, the present article introduces two new cell voltage-based techniques for ISC detection and compares their detection times in several different experimental settings and for different monitoring frequencies to those of the KPCA method. These new approaches are based on existing methods that have been specially adapted and further developed for the present application.

3 State of the Art

Three different classes of data analysis methods for the detection of battery errors can be found in scientific literature [23, 29]: The first category are threshold-based methods in which an attempt is made to define critical values for directly measurable features which, if exceeded or undercut, indicate a faulty function of the battery. Secondly, model-based approaches attempt to estimate features that cannot be measured directly (e.g. state of charge or state of health resp. capacity) and then use them for error detection. These estimates are based on mathematical equations and formulas derived from physical and chemical laws that describe the internal processes of a battery cell.

Thirdly, data-driven methods employ statistical and machine learning techniques to uncover patterns and correlations within the measured battery data.

In addition to the distinction between measurable features and characteristics that have to be estimated, features can also be assigned to different levels of an ESS, for instance to the level of single cells, modules or the whole battery system.

Early-stage ISCs with high resistance ("soft" ISCs) produce only minor changes in battery behavior. Because these subtle deviations are hard to distinguish from normal fluctuations in the data, detecting such faults using threshold-based methods is highly impractical [12], [21]. This renders fixed-limit approaches largely unsuitable for identifying ISCs in their early phases. For example, cell level voltages are well-suited variables for ISC detection as they are directly influenced by a short circuit. Nevertheless, the small drop in voltage at an early stage of an ISC is difficult to distinguish from normal small fluctuations during regular operation of an ESS [21]. To avoid false alarms, the threshold would have to be decreased, which would result in a longer detection time.

The review [29] gives a thorough treatment of the most recent research literature concerning the other two classes of detection methods, namely model-based and data-driven approaches. As noted in [22], model-based approaches mostly suffer from the drawback that the reliability of feature estimations cannot really be secured, making fault detection itself only reliable up to a certain degree of uncertainty. Therefore, the present work focuses on data driven methods.

Data driven methods for battery fault detection that are present in recent research work include: Isolation Forest [10], Support Vector Machines [14, 37], various neural network architectures, for example LSTM and Radial Basis Function neural networks [17, 35] and Local Outlier Factors [32] can all be found as employed detection methods.

Since, as described above, the change in the individual battery features is still small at the early stages of a developing ISC, a major challenge in the early detection of ISC is the robustness against noise in the sensor data [21, 23, 29]. This makes principal component analysis (PCA) a good detection approach: It is a well-known fact that the way dimension reduction is performed in a PCA can result in a large part of the noise being projected away. The authors of [23] describe this robustness against sensor noise as one of their main motivations to use a PCA approach.

But since non-linear variations of the cell voltages are to be expected, especially at a low state of charge (SoC), purely linear methods like the PCA are not optimal for fault detection [21, 22, 24]. As a relatively low SoC is to be expected in logistics scenarios involving an ESS, it can be assumed that a PCA is not the correct approach for the present work.

In [21], [24] and [22] the non-linearity problem is tackled by using a non-linear extension of PCA, the kernel PCA (KPCA) originally introduced in [25]. Solving both the non-linearity and the sensor noise issue makes the KPCA model from [21], [24] and [22] a very promising approach for early ISC detection in our use case scenario. Furthermore, the data frequency during the monitoring phase does not have to be the same as during the training phase in the KPCA approach. This makes it possible to train with high frequency, thereby injecting a lot of information from data ranging over a relatively short time period and monitor with a low frequency later.

The reasons mentioned were the rationale behind the decision to employ KPCA for early ISC detection at low transmission frequency in our previous work, in which we investigated the extent to which this is possible [26]. For this we compared the KPCA approach with the other two cell voltage based detection methods from the literature (namely, plain PCA [23] and a simple approach that compares the differences of the individual cell voltages with each other [12]) for several low monitoring frequencies. KPCA outperformed the other tested approaches and delivered promising detection times even when transmitting only one point every 15 minutes.

4 Solution Proposal

This section recalls the dedicated strategy from [26] for supervising ESS within logistical operations, including both transportation and warehousing phases. The proposed solution directly responds to the contextual demands and constraints (FC1-5) previously detailed in the second section. Following [8], these are the rationale behind all architectural decisions and regarding [34] also the goals to be solved by the overall approach.

The core premise underlying the solution design is that both BMS and environmental data must be gathered using an independent external device powered by its own battery. The primary objective of this approach is to facilitate continuous early detection of ISCs within ESS, with a particular focus on logistics applications. Within this framework, the framework conditions outlined in Section 2 give rise to a set of specific requirements (REs):

- RE1 (derived from FC1, 4 and 5): The approach should be able to early detect ISCs using only low frequency BMS data, because of energy constraints and the direct correlation between data frequency and energy demand of the external device.
- RE2 (FC2): Computations should be offloaded from the external device as much as possible to save energy.
- RE3 (FC3): The approach should allow continuous monitoring (while still considering FC4 and 5), since ISCs can happen at any stage of the lifecycle of an ESS.

To address the fundamental causes of thermal runaways, it is recognized that any type of battery abuse significantly raises the likelihood of an ISC. Therefore, the chosen approach must account for this risk, allowing for the development of additional safety requirements:

- RE4: The approach should be able to detect mechanical (R1), electrical (R2) and thermal (R3) abuse.
- RE5: The approach should be able to change data collection frequency according to predefined conditions.

These requirements serve as a starting point for the design of the solution approach and result in several design decisions. In this regard, RE1 is most important for the feasibility of the proposed approach. Because wireless transmission of BMS data is energy-intensive, minimizing how often data is sent is essential. This must be set as low as possible without impairing the monitoring of the ESS. In this context, in our previous work it was decided to choose a KPCA-based detection approach (cf. Section 3).

- RE2 is addressed in the presented approach by introducing 2 different layers for data processing:The edge layer that comprises the external device and enables the collection of BMS and environmental data.
- The cloud layer, which receives and processes the collected data from the edge layer.

In this context, we suggest that the data collection frequency in the edge layer is variable, therefore addressing RE3 and RE5. This means that the detection frequency, and thus also the power consumption due to processor load and data transmission, has a basic setting that is always executed in the absence of other external conditions (baseline frequency). As soon as external influences such as movement, vibrations or temperature changes are observed by the external device, the detection frequency is adjusted. For example, strong vibrations might lead to an increased frequency. For this purpose, the external device must be equipped with appropriate sensors that measure various environmental variables such as speed, rotational movements or temperature. By implementing rule-based logics, this also allows the detection of various potential abuses, therefore addressing RE4. In the event that abuse of any kind is detected, the detection frequency can also be adjusted to suit the situation. In any case, the detection frequency must be selected so that the trade-off between detection time and power consumption is appropriate for the current conditions of the ESS, while considering the battery life of the external device.

The cloud layer is designed in such a way that the ingestion and processing of the recorded data as well as the distribution of derived information can be scaled up horizontally. The main reason for this is the current already high amount of ESS in circulation, which is set to increase in the future. This is made possible by the use of established IoT and big data technologies. Data exchange between the edge and the cloud layer takes place at the network level via mobile phone standards such as GSM, LTE or 5G and is enabled at the application level by lightweight protocols such as MQTT, CoAP or AMQP [1]. Data processing is divided into 2 parts: On the one hand the model training and on the other hand the model inference. In order to be able to monitor a battery throughout its entire life cycle, the normal behavior of a battery over the entire cycle must also be reflected in the training data. Since this data is not or only partially available from laboratory tests when new battery types are introduced, it can be assumed that the training of the models will be repeated continuously in order to increase the quality of the prediction. The inference must be carried out in real time so that critical batteries are recognized in good time and the stakeholders involved can be informed. In the context of data processing, this leads to the use of a lambda architecture in which model training takes place periodically in the batch layer and inference in the streaming layer. Example technologies to implement this are Apache Kafka[1], Hadoop[2],

---

[1] https://kafka.apache.org/

[2] https://hadoop.apache.org/

Apache Spark[3] or Apache Storm[4]. Further processing of the information obtained takes place via the provision of various interfaces. These include APIs, message brokers, but also dashboards, for example. This allows the relevant stakeholders, such as logistics service providers, battery manufacturers or freight forwarders, to either access the information directly or integrate it into their own systems and trigger automated processes.

5 Experiments

In our previous work, several experiments were carried out which showed that the chosen data-based KPCA approach (cf. Section 3) is suitable for detecting ISCs at low monitoring frequencies (more precisely, frequencies between 1Hz and $\frac{1}{900}$Hz were tested) [26]. In order to obtain the experimental data, batteries consisting of 6 cells connected in series were short-circuited in several laboratory tests. The short circuit was caused in each case in one of the six cells by an externally attached resistor, whereby several different resistances were tested (10Ω, 1kΩ, 10kΩ). In each experiment, there was an initial phase during which the cells, which were not yet short-circuited, were cycled over several hours to generate training data for the KPCA. A cycling protocol based on the “Worldwide harmonized Light vehicles Test Procedure” (WLTP) has been applied for this initial cyclization in order to generate data similar to this used in [21] and [22]. After the initial phase, the resistor was then implemented to trigger an external short circuit (ESC) in one of the battery cells and the time until the KPCA approach detected the short circuit was measured. Recall that in the case of an experiment for early ISC detection, it is valid to trigger ESCs (instead of actual ISCs), as the battery behavior of an early stage ISC is similar to that of an ESC [38]. As a result, ESCs were chosen for the experiments as they are easier to trigger than real ISCs.

For the different monitoring frequencies between 1Hz and $\frac{1}{900}$Hz in our previous experiments the detection times for the KPCA approach were measured and compared with the corresponding performance of the other two purely cell voltage-based detection methods from the literature (cf. Section 3).

Similar to [21], [24] and [22] the line of attack for fault detection with the KPCA approach was to check how close a given cell’s voltages vector lies, after a transformation, to the principal component space that was computed using training data. More precisely the so called T^2- and Q-test statistics values of the vector of cell voltages were computed while monitoring. The general principle is here that low T^2- and Q-values correspond to data which is similar to the training data while high values display anomalous behavior.

As the KPCA strategy for ISC detection was only compared to two additional purely cell voltage-based approaches for ISC detection in our previous work, the aim of the present work’s experiments was to introduce two new related detection strategies and compare detection times. Instead of carrying out the battery experiments again we used

---

[3] https://spark.apache.org/

[4] https://storm.apache.org/

the voltage measurements data from our last experiments to have a reference for comparison.

As far as the two new detection methods are concerned, one neural network-based detection strategy is introduced and one in which the voltage difference technique from [12] is improved.

The first method underlies one of the most widely used neural network architectures for unsupervised anomaly detection, namely autoencoders (AE) (cf. [16], [11], [20]). AEs are neural networks that firstly project the data into a lower dimensional latent space and then learn how to reconstruct the input data from that lower dimensional representation. The main idea behind utilizing AEs for anomaly detection is that anomalous data points resp. data points that look significantly different from the data used for training are harder to reconstruct so that larger reconstruction errors indicate anomaly points. Since deep neural networks with several high dimensional layers not only imply computational expensive training but also inference phases, we used a relatively shallow AE with a 4-dimensional latent space and one 32-dimensional layer inside the encoder and decoder respectively. This architecture for the AE is also justified by the low dimension of the input data, which is equal to the number of battery cells, i.e. 6.

The second method is inspired by the voltage difference approach from [12] where a maximal voltage difference of 0.5V between the single cells was defined to indicate a short circuit. We tried to improve upon this method by making it independent from setting an explicit threshold by hand. Instead of using a fixed bound of 0.5V we used the 0.999 quantile of maximal cell voltage differences from the initial training phase.

5.1 Experimental Setup

This section recalls the setup for the experiments that were carried out for our previous article and which still form the basis of the data used for the present work.

The batteries utilized in the experiments were Samsung INR18650-32E cells, each with a nominal capacity of 3.2Ah. These cells feature a lithium-nickel-cobalt-aluminum oxide cathode paired with a graphite anode. The cells were arranged in a series configuration using 3D-printed cell holders, as illustrated in Figure 1. Individual monitoring of the cell voltage has been implemented using a Gantner Q.bloxx XL A107[5]. The cycling of the cells was managed using an EA-PSB 10080-120 power supply in conjunction with custom software tailored to administer the dynamic cycling protocol. To minimize the impact of external temperature fluctuations on short circuit detection, the entire experimental setup was housed within a thermal chamber maintained at 35°C.

---

[5] https://www.gantner-instruments.com/de/produkte/bloxx/

Fig. 1. Experimental setup that was used to generate the training and inference data.

5.2 Training and Inference

To assess the performance of the detection algorithms, time series datasets were collected from ESC experiments involving artificially induced short circuits using resistors of varying values: 10Ω (R_1), 1kΩ (R_2), and 10kΩ (R_3). While the 10Ω and 1kΩ resistors generated detectable fault signatures, the 10kΩ configuration resulted in an exceptionally gradual fault evolution. This slow progression led to the termination of the experiment after several hours, during which none of the algorithms identified any anomalies. Due to the absence of meaningful detection outcomes, the 10kΩ dataset was excluded from subsequent analysis. In our previous work [26] the detection time for the resistor values R_1 and R_2 was evaluated for different inference data frequencies of 1Hz (F_1), $\frac{1}{60}$ Hz (F_2), $\frac{1}{300}$Hz (F_3), $\frac{1}{600}$Hz (F_4) and $\frac{1}{900}$Hz (F_5).

We compared the detection performance of the KPCA (A_1) approach with the plain PCA from [23] (A_2) and the method that just tracks the maximal voltage difference between the cells and checks if the threshold of 0.5V is exceeded [12] (A_3). Since all approaches (A_1-A_3) were evaluated using the data sets from two different resistor settings (R_1 and R_2) while applying five different monitoring frequencies (F_1-F_5) 30 different experimental settings were studied.

In addition, in the present work 20 more configurations are examined in which the AE approach (A_4) and the optimized voltage difference technique (A_5) are tested for the resistors R_1 and R_2 and frequencies F_1-F_5 and compared to the previous detection times.

After sampling down the recorded training data time series from 10Hz to 1Hz by averaging in a very first cleaning step, 1000 points were extracted across the entire training phase, evenly spaced in time. This was done to build a compact yet representative training dataset that fully captures the initial cycling phase. These 1000 points were used exclusively for training, with no overlap with the data used for inference. Furthermore, we used the same 1000 points for training all 5 different methods A_1-A_5.

As is standard practice in machine learning and data analysis, the training data underwent a standardization process during preprocessing. For the KPCA approach employed in this study, a refined preprocessing strategy was applied. Specifically, consider the training dataset represented by a 1000×6 matrix, where each row corresponds to a sample of the time series data and each column corresponds to the voltage measurement

of one of six battery cells. The preprocessing consisted of two steps: 1. Outlier robust row wise standardization: Each 6-dimensional row vector was first transformed using an outlier-robust variant of sample standardization (cf. [23]). This step enhances robustness to outliers in the individual cell voltage measurements, thereby mitigating their influence on the model.
2. Column wise standardization: Subsequently, each of the six columns (i.e., each cell's voltage across all samples) was standardized such that the resulting distribution has zero mean and unit variance. This ensures comparability across features and aligns with the assumptions of KPCA. The resulting standardized matrix is then used for training the KPCA model. During the monitoring or inference phase, incoming voltage data is preprocessed using the same procedure to ensure consistency with the training data.

The starting data point of the data series for the inference (T_0) was selected for R_1 and R_2 approximately 30 minutes before the short circuit was induced.

Initially the 0.999 quantile of the training T^2- and Q-values was set as the detection threshold in the KPCA method. But since the experiments revealed fluctuations in those statistical values, particularly at higher monitoring frequencies, the detection mechanism was made more robust. To prevent false detection behavior caused by these variations, the system now triggers an alert only if elevated T^2 and Q-values persist for at least 10 minutes (cf. Table 1). To enhance robustness against fluctuations at the two highest frequencies (1Hz and 1/60Hz), we required that at least 20% of all values within the past 10 minutes must be critical in order to indicate a short circuit. For the lower frequencies, a similar consideration is omitted, as only one point is transmitted every 5, 10 or 15 minutes.

Table 1. The detection logic for all utilized monitoring frequencies.

Monitoring Frequency	**Detection Logic**
1Hz	>20% of last 600 points of smoothened (moving average of) T^2- and Q-values above threshold
$\frac{1}{60}$ **Hz**	>20% of last 10 points of T^2- and Q-values above threshold
$\frac{1}{300}$**Hz**	last two points of T^2- and Q-values above threshold
$\frac{1}{600}$**Hz**	last point of T^2- and Q-values above threshold
$\frac{1}{900}$**Hz**	last point of T^2- and Q-values above threshold

5.3 Results

With the aforementioned detection logic implemented, the following detection times shown in Table 2 were achieved using the KPCA approach. In this context, Figure 2 shows the exemplary detection curves using the T^2- and Q-values for experimental settings $A_1R_1F_1$ and $A_1R_1F_3$ to illustrate the experimental procedure. The red line marks the start of the short circuit and the green line the time at which it was detected.

Table 2. Detection times of the KPCA approach using different monitoring frequencies and ESC resistors (experimental settings $A_1R_{1,2}F_{1\text{-}5}$); cf. Table 1 in [26].

	1Hz	$\frac{1}{60}$Hz	$\frac{1}{300}$Hz	$\frac{1}{600}$Hz	$\frac{1}{900}$Hz
10Ω	2min 7sec	1min	6min	1min	1min
1kΩ	151 min	97 min	133 min	103 min	253 min

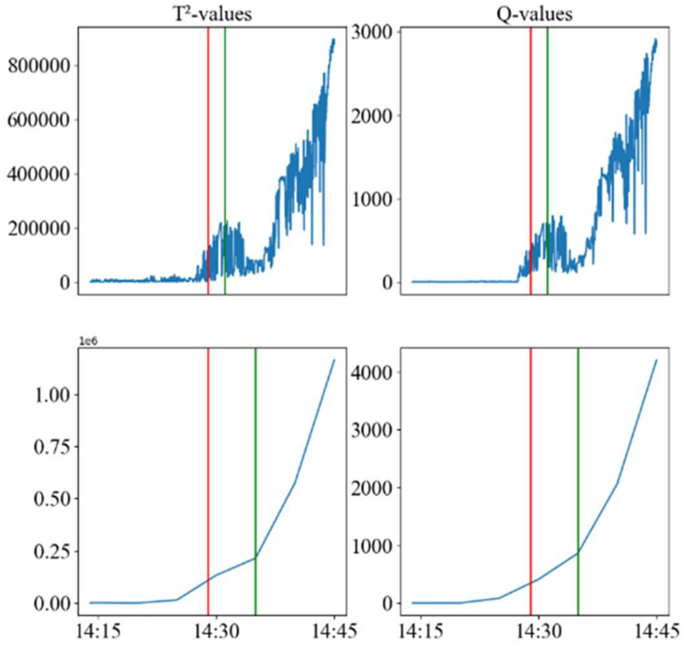

Fig. 2. Exemplary detection curves for experimental settings $A_1R_1F_1$ (top) and $A_1R_1F_3$ (bottom).

The experiments were repeated using the same short circuit trigger logic, this time based on a PCA-driven algorithm. For the 10Ω resistor, detection times matched the previous KPCA results. However, the PCA approach was ineffective for the 1kΩ resistor, failing to detect a short circuit at any monitoring frequency [26].
An alternative method, inspired by [12], defined a short circuit event as occurring when the voltage difference between individual cells exceeded 0.5V. This approach successfully detected a short circuit only in the 10Ω case. No detection was achieved for higher short circuit resistances and even for 10Ω the detections times were from 3 times to 20 times higher than for the KPCA approach [26]

For the AE approach, the neural network was trained for 100 epochs with an Adam optimizer. The mean squared error was selected as loss function and the 0.999 quantile of the training losses was selected as threshold for detection. However, in analogy to the KPCA approach, a somewhat refined trigger logic was selected (cf. Table 1) that is almost completely identical to this, with the only difference that for the two highest frequencies it is only assumed that 10% (and not 20%) of all points in the last 10 minutes are critical. In all cases, the detection times were slower than with the KPCA approach and for very low frequencies the AE was unable to detect the short circuit in the 1kΩ case (cf. Table 3).

Table 3. Detection times for the AE approach using different monitoring frequencies and ESC resistors (experimental settings $A_4R_{1,2}F_{1\text{-}5}$).

	1Hz	$\frac{1}{60}$**Hz**	$\frac{1}{300}$**Hz**	$\frac{1}{600}$**Hz**	$\frac{1}{900}$**Hz**
10Ω	9min 1sec	11 min	16 min	11 min	16 min
1kΩ	287 min	287 min	-	-	-

What should also be mentioned for the 10Ω case is that monitoring with the AE approach with high frequency led to false positive alarms, as the reconstruction errors were already high 15 to 5 minutes before the short circuit resistor was implemented. This is illustrated in Figure 3 on the left. Again, the red line indicates the start of the short circuit and the green line the time at which it was detected.

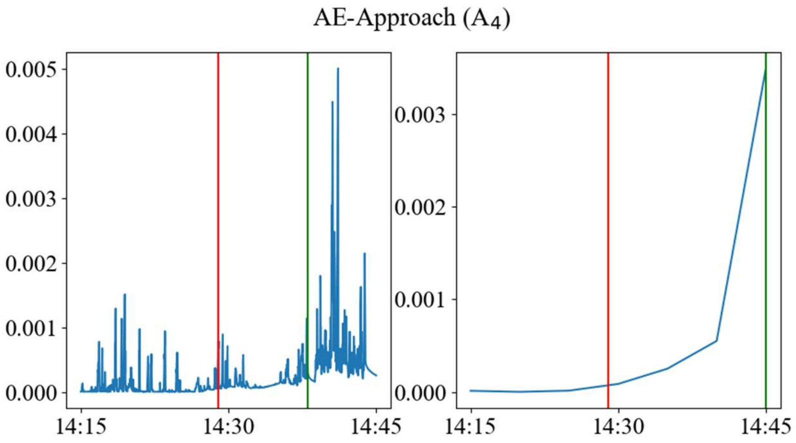

Fig. 3. Detection curves for experimental settings $A_4R_1F_1$ (left) and $A_4R_1F_3$ (right).

In the optimized voltage differences method, the 0.999 quantile of the maximum voltage differences from the training data was used as detection threshold (as opposed to a fixed threshold of 0.5V). Again, the same detection logic as in the KPCA case was used; this time the exact same logic (cf. Table 1). The method performed well for the 10Ω resistor, even outperforming the KPCA approach in the case of a 1Hz monitoring frequency (cf. Figure 4). In this case the method detected the ESC as fast as possible after only 1 second. For a 1kΩ resistor the detection times were on average slightly slower than for the KPCA with the only exception being the 1Hz case. However, nothing could be detected for some low frequencies, whereas the KPCA detected the short circuit for all different frequencies (cf. Table 4).

Table 4. Detection times for the optimized voltage difference approach using different monitoring frequencies and ESC resistors (experimental settings $A_5R_{1,2}F_{1\text{-}5}$).

	1Hz	$\frac{1}{60}$**Hz**	$\frac{1}{300}$**Hz**	$\frac{1}{600}$**Hz**	$\frac{1}{900}$**Hz**
10Ω	1 sec	1 min	6 min	1 min	1 min
1kΩ	125 min	185 min	-	243 min	-

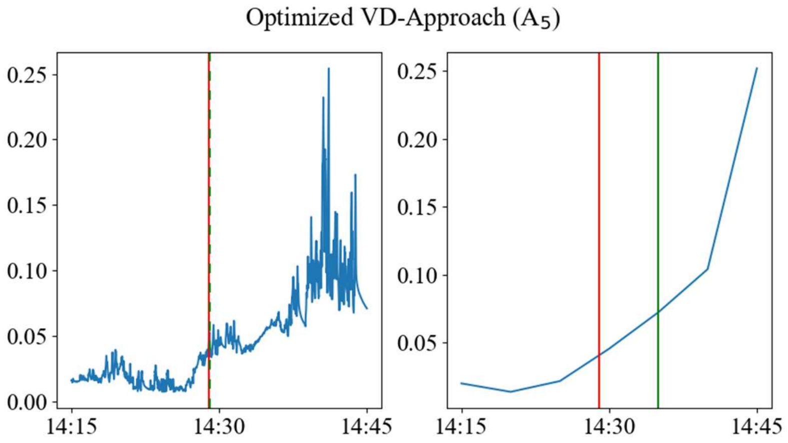

Fig. 4. Detection curves for experimental settings $A_5R_1F_1$ (left) and $A_5R_1F_3$ (right). On the left, detection happened almost instantly.

6 Discussion

The results of the experiments confirm that the KPCA approach (A_1) is most suitable for detecting ISCs at an early stage at low data transmission frequency. KPCA performed better than the pure PCA approach (A_2) as well as the simple voltage difference method (A_3) and the AE (A_4). Additionally, the results of detection times for the experimental settings $A_1R_{1,2}F_{1\text{-}5}$ are of the same order of magnitude as those in [21] and [22], which supports the validity of our results regarding the detection times. As already previously noted by Schmid et al. [22], the PCA-based method (A_2) proves ineffective for detecting high-resistance short circuits (R_2). Similarly, the voltage-difference method (A_3) fails to deliver reliable detection under these conditions.

However, it is striking that the optimized voltage difference approach (A_5), which is still much simpler than KPCA and PCA, performed surprisingly well. At a high transmission frequency, the detection time of (A_5) was faster for both resistances (R_1F_1, R_2F_1) and in the 10Ω case it performed at least as good as the KPCA approach for all frequencies. The KPCA was only superior for lower transmission frequencies and high short circuit resistance. Nevertheless, this also means that in settings where a higher data transfer rate is possible, the optimized voltage difference method is a good alternative to the KPCA approach for ISC detection. In this regard we recall that the monitoring solution for ESS proposed in Chapter 4 incorporates not only the core requirements for ISC detection (RE1–RE3), but also additional security measures. These include, on one hand, the detection of common misuse patterns that elevate the risk of ISCs (RE4), and on the other hand, the potential adjustment of the data transfer rate when such misuse is identified (RE5). The results of the experiments show that, in the case of such an adjustment, it may be advisable to switch from the KPCA approach to the optimized voltage difference approach.

The findings furthermore reveal no consistent linear correlation between monitoring frequency and detection time across the experimental setups. This indicates that detection times are highly sensitive to the specific distribution of sampled data points and may vary significantly with different data selections. In order to reinforce this assumption, the experimental settings $A_1R_{1,2}F_{1-5}$ were used again for detection with an initial time offset of T_0+7 minutes. The results show that detection times for lower frequencies (<= $\frac{1}{300}$Hz) increase up to 13 times, which further highlights that detection latency for low frequencies is highly influenced by the reception time of the data points. Additionally, the results indicate that detection times are inherently limited by the interval between successive voltage measurements.

Analysis of the experimental results reveals that higher monitoring frequencies did not consistently lead to quicker detection of ISCs. This challenges the intuitive expectation that increased sampling rates result in faster detection. Moreover, the detection logic seems to be a deciding factor - at higher frequencies, statistical value (T^2- and Q-values) fluctuations are more pronounced, whereas these fluctuations are less pronounced at lower frequencies. In this context, it can be seen in Figure 2 that the 'deflections' of the statistical variables decrease as the data frequency is reduced. Consequently, the effectiveness of a given detection logic is highly dependent on the monitoring frequency. In this study, a uniform detection logic was applied across all frequencies to ensure result comparability. However, for real-world applications, this implies that frequency-specific, optimized detection strategies should be employed.

In conclusion, by comparing the KPCA approach to two new promising data-driven detection strategies, our experiments further underline that KPCA is an important part to implement our solution proposal for low-frequency monitoring, energy-efficient, scalable battery monitoring. In addition, the experiments have shown that in a situation where higher data transfer rates are possible, the optimized voltage difference method can be a good alternative.

7 Conclusion & Outlook

In this paper, we propose an approach enabling remote early battery short circuit detection for ESS in logistics scenarios. In this regard, we provide background information about the research area as well as the rationale behind conducting our own research. Furthermore, an overview of similar works in existing scientific literature is given. Current ISC detection approaches using BMS data are effective in controlled settings, but lack support during transport and storage, where risks remain high. Key requirements identified in this paper include low-frequency data collection to conserve battery life, offloading computations to the cloud, and continuous monitoring that adjusts frequency based on external factors, like temperature or movement, which might indicate abuse. Against this background, this research proposes a battery-powered external device to monitor ESS remotely by collecting battery and environmental data. Furthermore, a data processing architecture is presented that comprises two layers: an edge layer for data collection through IoT technologies and a cloud layer for scalable analysis and distribution, enabling real-time ISC alerts to stakeholders and a lambda architecture for model training and inference. In our previous work [26] experiments were conducted using a 6-cell battery setup, where cells were artificially short-circuited with resistors of 10Ω, 1kΩ, and 10kΩ. The short circuits were induced to simulate an early ISC phase, and voltage data at various frequencies were analyzed using a simple voltage difference method, PCA and KPCA for anomaly detection. In the present article KPCA was further compared to two new data-driven detection methods, one AE based and one that improved upon the voltage difference method. KPCA proved to be the most reliable method overall, especially at low frequencies and high short-circuit resistance. These findings suggest KPCA's robustness for low-frequency ISC detection, further confirming its suitability for logistics applications and the overall soundness of the monitoring approach presented.

Another important result was that the optimized voltage difference method, which is much simpler than KPCA, proved to be very effective at high transmission frequencies and could be a good alternative in those cases.

Future research needs to investigate how analyzing data across the entire lifecycle of a battery could refine detection logic and improve accuracy. Additionally, federated learning methods that aggregate data from many batteries of the same type can further enhance detection precision. Finally, evaluating how data frequency impacts the lifespan of the external device is also important. While offloading data to the cloud is generally efficient, it may be feasible to perform inference directly on the device. Once the KPCA algorithm is trained, real-time data monitoring becomes computationally light, suggesting that the monitoring algorithm could operate locally on the device. This would enable efficient ISC detection without significantly impacting the device's battery life.

A surprising result of the experiments was the relatively low performance of the AE, although AE methods are a standard approach for anomaly detection in various applications. In future work, rigorous hyperparameter tuning would have to be performed to verify whether the approach is generally not suitable for ISC detection or whether only the optimal hyperparameter constellation was not found in the present work.

Acknowledgements. The work presented in this paper is co-funded by the German Federal Ministry for Economic Affairs and Climate Action (BMWK 16TNW0016D), the German Federal Ministry of Education and Research (BMBF 02J21E022) as well as by the European Union and from tax revenues on the basis of the budget adopted by the Saxon State Parliament.

REFERENCES

1. Al-Masri, E., Kalyanam, K. R., Batts, J., Kim, J., Singh, S., Vo, T., et al. (2020). Investigating Messaging Protocols for the Internet of Things (IoT). *IEEE Access,* 8, 94880–94911. doi:10.1109/ACCESS.2020.2993363.
2. Callebaut, G., Leenders, G., van Mulders, J., Ottoy, G., Strycker, L. de, & van der Perre, L. (2021). The Art of Designing Remote IoT Devices-Technologies and Strategies for a Long Battery Life. *Sensors (Basel, Switzerland),* 21(3). doi:10.3390/s21030913.

3. Colombo, C. G., Longo, M., & Zaninelli, D. (2024). Batteries: Advantages and Importance in the Energy Transition. In S. Passerini, L. Barelli, M. Baumann, J. Peters, & M. Weil (Eds.), *Emerging Battery Technologies to Boost the Clean Energy Transition* (pp. 69–82, The Materials Research Society Series). Cham: Springer International Publishing.
4. Electric Power Research Institute (2024). BESS Failure Incident Database.
5. EV Database (2024). Useable battery capacity of full electric vehicles.
6. Figgener, J., Hecht, C., Haberschusz, D., Bors, J., Spreuer, K. G., Kairies, K.-P., et al. (2022). *The development of battery storage systems in Germany: A market review (status 2023)* : arXiv.
7. IEA (2022). Global Supply Chains of EV Batteries.
8. Jansen, A., & Bosch, J. (2005). Software Architecture as a Set of Architectural Design Decisions. In *5th Working IEEE/IFIP Conference on Software Architecture (WICSA'05), Pittsburgh, PA, USA, 06-10 Nov. 2005* (pp. 109–120): IEEE. doi:10.1109/WICSA.2005.61.
9. Jayakumar, H., Lee, K., Lee, W. S., Raha, A., Kim, Y., & Raghunathan, V. (2014). Powering the internet of things. In Y. Xie, T. Karnik, M. M. Khellah, & R. Mehra (Eds.), *ISLPED'14: International Symposium on Low Power Electronics and Design, La Jolla California USA, 11 08 2014 13 08 2014* (pp. 375–380). [Erscheinungsort nicht ermittelbar]: ACM. doi:10.1145/2627369.2631644.
10. Jiang, J., Li, T., Chang, C., Yang, C., & Liao, L. (2022). Fault diagnosis method for lithium-ion batteries in electric vehicles based on isolated forest algorithm. *Journal of Energy Storage,* 50, 104177. doi:10.1016/j.est.2022.104177.
11. Kamat, P., & Sugandhi, R. Anomaly Detection for Predictive Maintenance in Industry 4.0- A survey. In Sanap, S. B. et al. (Ed.) (Vol. 170, p. 2007). doi:10.1051/e3sconf/202017002007.
12. Lai, X., Yi, W., Kong, X., Han, X., Zhou, L., Sun, T., et al. (2020). Online detection of early stage internal short circuits in series-connected lithium-ion battery packs based on state-of-charge correlation. *Journal of Energy Storage,* 30, 101514. doi:10.1016/j.est.2020.101514.
13. Liu, H., Zhang, L., & Li, L. (2024). Progress on the Fault Diagnosis Approach for Lithium-ion Battery Systems: Advances, Challenges, and Prospects. *Protection and Control of Modern Power Systems,* 9(5), 16–41. doi:10.23919/PCMP.2023.000213.
14. Lskaafi, M. A. (2015). *Fault Diagnosis and Failure Prognostics of Lithium-ion Battery based on Least Squares Support Vector Machine and Memory Particle Filter Framework*. Doctoral Dissertation. University of Tennessee, Knoxville. https://trace.tennessee.edu/utk_graddiss/3594/. Accessed 18 November 2024.
15. Marsh, J. (2023). Comparing lithium-ion battery chemistries.
16. Neloy, A. A., & Turgeon, M. A comprehensive study of auto-encoders for anomaly detection: Efficiency and trade-offs. *Machine Learning with Applications*, p. 100572.
17. Ojo, O., Lang, H., Kim, Y., Hu, X., Mu, B., & Lin, X. (2021). A Neural Network Based Method for Thermal Fault Detection in Lithium-Ion Batteries.

IEEE Transactions on Industrial Electronics, 68(5), 4068–4078. doi:10.1109/TIE.2020.2984980.

18. Plotnikov, M., Schreynemackers, P., Joachimsthaler, C., Jarmer, J.-P., Kuhlmann, G., Karlstedt, F., et al. (2023). *Batterie-Logistik. Whitepaper* : Fraunhofer-Gesellschaft.
19. pv magazine group (2023). Produktdatenbank Batteriespeichersysteme für Photovoltaikanlagen 2023.
20. Said Elsayed, M., Le-Khac, N.-A., Dev, S., & Jurcut, A. D. (2020). Network Anomaly Detection Using LSTM Based Autoencoder. In C. Li (Ed.) (pp. 37–45, ACM Digital Library). New York,NY,United States: Association for Computing Machinery. doi:10.1145/3416013.3426457.
21. Schmid, M., & Endisch, C. (2022). Online diagnosis of soft internal short circuits in series-connected battery packs using modified kernel principal component analysis. *Journal of Energy Storage,* 53, 104815. doi:10.1016/j.est.2022.104815.
22. Schmid, M., Kleiner, J., & Endisch, C. (2022). Early detection of Internal Short Circuits in series-connected battery packs based on nonlinear process monitoring. *Journal of Energy Storage,* 48, 103732. doi:10.1016/j.est.2021.103732.
23. Schmid, M., Kneidinger, H.-G., & Endisch, C. (2021). Data-Driven Fault Diagnosis in Battery Systems Through Cross-Cell Monitoring. *IEEE Sensors Journal,* 21(2), 1829–1837. doi:10.1109/JSEN.2020.3017812.
24. Schmid, M., Liebhart, B., Kleiner, J., Endisch, C., & Kennel, R. (2021). Online Detection of Soft Internal Short Circuits in Lithium-Ion Battery Packs by Data-Driven Cell Voltage Monitoring. In *2021 IEEE 12th Energy Conversion Congress & Exposition - Asia (ECCE-Asia), Singapore, Singapore, 24.05.2021 - 27.05.2021* (pp. 1711–1718): IEEE. doi:10.1109/ECCE-Asia49820.2021.9479175.
25. Schölkopf, B., Smola, A., & Müller, K.-R. (1997). Kernel principal component analysis. In G. Goos, J. Hartmanis, J. van Leeuwen, W. Gerstner, A. Germond, M. Hasler, et al. (Eds.), *Artificial Neural Networks — ICANN'97* (Vol. 1327, pp. 583–588, Lecture Notes in Computer Science). Berlin, Heidelberg: Springer Berlin Heidelberg.
26. Schrade, C., Zschörnig, T., Kropkowski, L., & Franczyk, B. (2025). Resource-Efficient Monitoring of Energy Storage Systems During Transport and Storage: A Data-Driven Approach to Early Short Circuit Detection. In *27th International Conference on Enterprise Information Systems, Porto, Portugal, 04.04.2025 - 06.04.2025* (pp. 781–788): SCITEPRESS - Science and Technology Publications. doi:10.5220/0013291900003929.
27. SENEC (2024). Batteriemanagementsysteme und Smartguard.
28. Shahid, S., & Agelin-Chaab, M. (2022). A review of thermal runaway prevention and mitigation strategies for lithium-ion batteries. *Energy Conversion and Management: X,* 16, 100310. doi:10.1016/j.ecmx.2022.100310.
29. Shang, Y., Wang, S., Tang, N., Fu, Y., & Wang, K. (2024). Research progress in fault detection of battery systems: A review. *Journal of Energy Storage,* 98, 113079. doi:10.1016/j.est.2024.113079.

30. Statista (2024). Total number of battery electric cars registered in Germany as of January 1st, between 2008 and 2024.
31. Sun, P., Bisschop, R., Niu, H., & Huang, X. (2020). A Review of Battery Fires in Electric Vehicles. *Fire Technology,* 56(4), 1361–1410. doi:10.1007/s10694-019-00944-3.
32. Sun, Z., Wang, Z., Liu, P., Qin, Z., Chen, Y., Han, Y., et al. (2022). An Online Data-Driven Fault Diagnosis and Thermal Runaway Early Warning for Electric Vehicle Batteries. *IEEE Transactions on Power Electronics,* 37(10), 12636–12646. doi:10.1109/TPEL.2022.3173038.
33. Tekin, N., Acar, A., Aris, A., Uluagac, A. S., & Gungor, V. C. (2023). Energy consumption of on-device machine learning models for IoT intrusion detection. *Internet of Things,* 21, 100670. doi:10.1016/j.iot.2022.100670.
34. van Lamsweerde, A. (2000). Requirements engineering in the year 00. In C. Ghezzi, M. Jazayeri, & A. L. Wolf (Eds.), *the 22nd international conference, Limerick, Ireland, 04.06.2000 - 11.06.2000* (pp. 5–19). New York, New York, USA: ACM Press. doi:10.1145/337180.337184.
35. Wang, J., Zhang, S., & Hu, X. (2021). A Fault Diagnosis Method for Lithium-Ion Battery Packs Using Improved RBF Neural Network. *Frontiers in Energy Research,* 9. doi:10.3389/fenrg.2021.702139.
36. World Maritime News (2020). Misdeclared Lithium Battery Cargo Caused Cosco Pacific's Fire.
37. Yao, L., Fang, Z., Xiao, Y., Hou, J., & Fu, Z. (2021). An Intelligent Fault Diagnosis Method for Lithium Battery Systems Based on Grid Search Support Vector Machine. *Energy,* 214, 118866. doi:10.1016/j.energy.2020.118866.
38. Zhang, M., Ouyang, M., Lu, L., He, X., Feng, X., Liu, L., et al. (2017). Battery Internal Short Circuit Detection. *ECS Transactions,* 77(11), 217–223. doi:10.1149/07711.0217ecst.
39. Zhang, W., Lyu, N., & Jin, Y. (2023). Internal short circuit warning method of parallel lithium-ion module based on loop current detection. *Journal of Energy Storage,* 72, 108796. doi:10.1016/j.est.2023.108796.