Data-driven anomaly detection in large battery packs

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Abstract—Early detection and tracing of anomalous operation in battery packs are critical to improving performance and ensuring safety. This paper presents a data-driven approach for online anomaly detection in battery packs that uses real-time voltage and temperature data from multiple Li-ion battery cells. Mean-based residuals are generated for cell groups and evaluated using Principal Component Analysis (PCA). The evaluated residuals are then thresholded using a cumulative sum control chart to detect anomalies. A statistical testing of the proposed approach is performed on experimental data from a battery electric locomotive injected with model-based anomalies. The proposed anomaly detection approach has low false positive rate and accurately detects and traces the synthetic anomalies. The performance of the proposed approach, compared with direct thresholding of mean-based residuals, shows 56% faster detection time, 12% less false negatives, and 60% fewer missed anomalies, while maintaining a comparable false positive rate. The mild external short circuits associated with cell balancing are detected in the voltage signals and necessitate voltage retraining after balancing. Temperature residuals prove to be critical, enabling anomaly detection of module balancing events within 14 minutes that are unobservable from voltage residuals.

Index Terms—Anomaly detection, data-driven fault diagnosis, lithium ion battery pack, Principal Component Analysis, battery safety

I. INTRODUCTION

Large battery systems are being widely used in energy storage applications such as the power grid, electric vehicles, and electric locomotives. Li-ion batteries (LiBs) have high energy density, power density, long cycle life, and extended calendar life, making them well-suited for many of these applications. Feng et al. [1], however, list several recent accidents due to failure of LiBs, often due to thermal runaway. Thermal runaway may be triggered by thermal, mechanical, and electrical abuse that leads to an internal short circuit (ISC), accelerated temperature rise, and irreversible exothermic electrochemical side reactions [2]. Overcharge and overdischarge can also lead to thermal runaway [3]. Balancing circuit failure and external short circuit (ESC) can induce anomalous operation of the battery cells. Sensor anomalies, related to voltage, temperature and current measurements, might mislead the battery management system (BMS) to take erroneous control actions resulting in undesirable events. Thus, it becomes critical to have an early and quick detection followed by appropriate actions to avoid fault propagation, ensuring safe and reliable operation of LiB packs.

The time series data outputs of a battery system are non-stationary due to the time-varying current and environmental conditions. Thus, direct thresholding of voltage and temperature may not be sufficient to detect anomalies, especially at anomaly initiation when the voltage and temperature deviations are small. To make the data stationary, voltage and temperature residuals, the difference between the measurements and the expected responses are often used. Previous research focuses on cell-level anomaly detection using model-based residual estimation and thresholding [4]–[10]. State observers such as Extended Kalman Filters (EKF) [11]–[12], Adaptive EKF [10], Unscented Kalman filters (UKF) [13]–[14] and non-linear observers [4] have been used along with parameter estimation techniques such as recursive least squares [8]–[12] [13]–[15] and particle swarm optimization [9] [15] to generate residuals. Voltage, temperature, and state of charge (SoC) residuals are compared against predetermined thresholds for anomaly detection [10] [14] [16] [17]. Generating model-based residuals is computationally expensive for battery packs as it involves estimators for many cells. Computational complexity can be reduced through bar-delta filtering, cell mean models, and cell difference models to estimate the SoC of each cell [12] [15] [18]. Several works are reported in literature that detect different types of battery-related [5]–[9] and sensor-related [10] [11] [19] [20] anomalies. However, most of the aforementioned approaches are applicable to only one type of fault [8]–[11]. Some techniques work only if no two faults occurs at the same time [17] [20] [21]. Some of the aforementioned approaches require parameter estimation by performing specific characteristic tests [7] [10] [19].

Apart from model-based approaches, data-driven models, utilizing the cell-to-cell redundant voltage information in battery packs, are used for anomaly detection. Correlation-based methods detect and trace voltage anomalies using correlation-coefficient between cell voltages [21]–[23]. However, these methods can be sensitive to measurement noise [24]. Entropy-based anomaly detection methods detect voltage anomalies by monitoring the entropy measure such as Shannon Entropy [25]–[27]. Sun et al. [28] detect and locate short circuit anomalies in battery packs by thresholding...
the modified z-score of the relative entropy of individual cells with the pack median. Shannon Entropy was also used for thermal runaway prognosis by detecting thermal faults [29]. These methods have high computational cost, and their performance is dependent on the choice of entropy measure and computation window especially in case of noisy data [24]. Machine learning (ML) based anomaly detection approaches that have been applied to other domains and LiBs [30] include classification, clustering, nearest neighbor, statistical, information theoretic and spectral based techniques [31]. ML techniques such as neural networks [32], k-means clustering algorithm [33], support vector machines [34] and random forest classifiers [2, 35] have also been applied to anomaly detection in battery systems. However, most of these techniques require large amounts of labeled battery fault data for training.

Among other data driven approaches, Principal Component Analysis (PCA) is a promising unsupervised anomaly detection algorithm that has been extensively used in anomaly detection for multivariate systems [36-39]. Wang et al. [38], for example, proposed sensor fault detection for a chiller system using PCA on the process variables. Schmid et al. [39] proposed a PCA-based approach that detects voltage anomalies in group of cells by applying PCA on voltage data processed using outlier robust sample studentization. In [40], these authors extend their method to include kernel PCA-based method to detect internal short circuit (ISC) faults using voltage signals.

This paper presents an anomaly detection scheme that combines PCA and cumulative sum (CUSUM) control chart to detect and locate voltage and, for the first time, temperature anomalies in groups of Li-ion cells in real-time. The voltage and temperature residuals are the difference between the measured cell signals and the mean signals of the cell group. Unlike model-based approaches, median-based and mean-based residuals (MBR) reduce the effect of aging as all the cells in the cell group experience similar loading and environmental conditions during their life. In the proposed approach, the MBRs are processed using PCA to capture cell-to-cell information including the inconsistencies, and thresholded using CUSUM control chart to detect anomalies. Experimental validation of the proposed approach is performed on external short circuit data from a battery electric locomotive. We compare the proposed approach using PCA processed MBRs (PCA Method) with the direct thresholding of voltage and temperature MBRs (Direct Method). [41]. Statistical testing with model-based synthetic anomalies injected to nominal experimental data demonstrates detection of electrical and thermal faults. The detection time, recovery time, false negative rate, missed anomaly rate, and false positive rate statistics are compared for the two methods.

II. ANOMALY DETECTION ALGORITHMS

Mean-based residual generation is proposed for both voltage and temperature. We assume that the cells within a group behave similarly under nominal conditions. These cell groups could be battery strings consisting of series/parallel connected cells that are spatially, thermally, chemically, and electrically similar. The MBRs of voltage and temperature, in a cell group with n cells, are calculated from

\[ x_i(t) = X_i(t) - \mu_X(t) \]

where \( X_i \) is the voltage/temperature of the \( i^{th} \) cell and the mean \( \mu_X(t) \) is the average over all the cells

\[ \mu_X(t) = \frac{1}{n} \sum_{i=1}^{n} X_i(t). \]

The first and simplest anomaly detection scheme (Direct Method) directly compares each residual signal with a predetermined threshold [41]. For earlier anomaly detection, PCA Method captures cell-to-cell heterogeneity using PCA. Figure 1 shows the block diagram for anomaly detection using PCA Method. Both methods rely on parameters derived from k samples of the residuals of nominal anomaly-free data. This training data provides the mean of the voltage/temperature residuals of each cell \( \mu_X, \sigma_X \) and standard deviation of voltage/temperature residuals for all the cells \( \sigma_{V,T} \) which are used to calculate the z-score. Application of PCA directly on residuals would point the first principal component towards the mean of the data, instead of the direction of highest variance of the residuals.

The training data is placed in the matrix, \( X \in \mathbb{R}^{n \times k} \) and decomposed via singular value decomposition to \( X=U \Sigma V^T \), where, \( U \in \mathbb{R}^{n \times n} \) is the left singular matrix, \( S \in \mathbb{R}^{n \times n} \) is the singular value matrix and \( V \in \mathbb{R}^{k \times n} \) is the right singular matrix. The number of principal components, \( p \), is selected to provide a cumulative percent variance of 90% [57]. The truncated left singular matrix \( U_r \) is the first \( p \) columns of \( U \).

In real-time, \( x(t) \) is measured, mean shifted and normalized by the training data \( \mu_X, \sigma_X \) and \( \sigma_X \) to estimate the z-score as

\[ \tilde{x}(t) = \frac{x_i(t) - \mu_{X,r,i}}{\sigma_{X,r}} \]

The reconstructed normalized residuals are

\[ \hat{x}(t) = U_r \hat{x}(t) \]

Statistical process control (SPC) charts have been widely used in residual-based anomaly detection for stationary processes. Shewhart, CUSUM and exponentially weighted moving average (EWMA) control charts are commonly used in univariate SPC [36, 42]. Among these, the CUSUM control chart is one of the most effective in detecting small deviations in monitored signals [36, 42]. CUSUM control charts have been used in model-based anomaly detection for battery systems [10, 11, 41].

PCA Method reduces the normalized residual vector to a scalar using RMSE and uses CUSUM statistics [42] to threshold the filtered RMSE. A simple first order low pass filter, with a cut-off frequency of 4.9 mHz, is used to filter the RMSE for robust detection. However, Direct Method directly thresholds
the absolute values of filtered voltage and temperature residuals using CUSUM statistics where the filter has a cut-off frequency of 8.4 mHz. The positive deviation CUSUM, $C^+[t] = \max(0, C^+[t-1] + (y[t] - \mu_c) - K)$ and negative deviation CUSUM, $C^- [t] = \max(0, C^- [t-1] - (y[t] - \mu_c) - K)$, with $C^+[0] = C^- [0] = 0$, and $K$ is chosen to be $4\sigma_c$ for lower false positives, where, $\mu_c$ and $\sigma_c$ are mean and standard deviation of the thresholding variable, $y[t]$, for the anomaly-free training data. Both $C^+$ and $C^-$ are compared against $5\sigma_c$ control limits for Direct Method [42]. In PCA Method, it is sufficient to compare $C^+$ against $5\sigma_c$ control limit because PCA always produces positive deviation in RMSE. Voltage and temperature anomalies are detected independently from $C^+\_V$ and $C^+\_T$, respectively.

If an anomaly is detected, then the anomalous cell has the maximum absolute error in reconstructed residuals. The first and first two principal components are used to reconstruct the voltage and temperature residuals, respectively, for good tracing performance [43].

### III. Synthetic Anomalous Data

LiBs have been commonly modeled using electrochemical and equivalent circuit models (ECM). The former are more accurate and explain the electrochemical processes that occurs inside a battery but computationally expensive [44]. The latter are computationally efficient and can provide sufficient accuracy to be widely used in real-time applications [45]. Thevenin’s equivalent circuit models have been widely used to model LiB [4, 13, 14], sometimes includes a short circuit resistance to model LiB cells under internal short circuit [3, 46, 47]. Higher order dynamic thermal models are available in literature [6, 7], but often a lumped thermal model is sufficiently accurate [4].

One of the main challenges in testing anomaly detection algorithms is lack of experimental anomalous data. We adopt a hybrid experimental-model approach rather than relying exclusively on model-based data. Anomalies are injected into voltage and/or temperature of the anomalous cell. Two sensor anomalies, Loose voltage and temperature sense leads, are injected by adding bias terms with noise into the experimental data. Figure 2 shows the schematics of the anomaly injection approach to create synthetic anomalous data for internal short circuit, air flow anomalies and voltage dropouts. Thevenin’s equivalent circuit model with short circuit resistance and a first order lumped thermal model are used to generate anomalous voltage and temperature data, respectively [41]. In the electrical model, the state propagation for SoC ($\dot{\theta}$) and diffusion voltage ($V_c$), and the output equations are:

$$ I_b(t) = I_{sc}(t) + I(t), $$
$$ \dot{\theta}(t) = -\frac{I_b(t)}{36Q}, $$
$$ \dot{V}_c(t) = -\frac{1}{R_1C_1}V_c(t) + \frac{I_b(t)}{C_1}, $$

$$ V(t) = \frac{OCV(\theta(t)) - V_c(t) - I(t)R_0}{R_0 + R_{sc}}R_{sc}, $$

where $R_0$ is the Ohmic resistance, $R_1$ is the polarization resistance, $C_1$ is the polarization capacitance, $Q$ is the capacity, $R_{sc}$ is the short circuit resistance, and $OCV$ is open circuit voltage as a linear function of $\theta$. The thermal behavior can be modeled using the dynamic model,

$$ T(t) = a \left( I(t)^2R_0 + I_{sc}(t)^2R_{sc} + \frac{V_c(t)^2}{R_1} \right) + b(T(t) - T_{amb}(t))F(t), $$

where $a$ is the thermal dissipation coefficient and $b$ is the thermal inertia coefficient. $T_{amb}$ is the ambient temperature and $F$ is the fan status (0 for off and 1 for on). This thermal model incorporates the heat generation due to ISC modeled as Joule’s heating [48].

Six performance indices are used to evaluate anomaly detection performance: detection time ($DT$), recovery time ($RT$), false negative rate ($FNR$), false positive rate ($FPR$), missed anomaly rate ($MAR$), and true tracing rate ($TTR$). $DT$ is the time between the anomaly start and detection. $RT$ is the elapsed time between anomaly end and flag reset. FNR is the percentage of false negatives between first detection and the end of the anomaly. $FPR$ is the percentage of the time that anomalies are flagged in the nominal data. $MAR$ is the
ratio of missed detections to total anomalies. The true tracing rate (TTR) is the percentage of time the anomalous cell is located accurately when an anomaly is detected. Thus, an ideal approach will have low DT, low RT, low FPR, low FNR, low MAR and high TTR.

IV. RESULTS AND DISCUSSION

A. Battery system and data

This study uses experimental current, voltage, temperature and fan status data from a Wabtec FLXDrive battery electric locomotive battery pack consisting of 825 cells in a 275S-3P arrangement. The 3P cells are considered as a single equivalent cell with same voltage, three times the capacity, and each cell receiving 1/3 the current. Twenty five cell groups are formed with 11 similar cells each. The voltage (V) and surface temperature (T) are measured for each cell and current (I) is measured for the entire battery pack (VTI data) during nominal locomotive operations. The current is positive during discharging and negative during charging. The battery pack is air cooled and a fan blows air into the pack to enhance the convective heat transfer. The ambient temperature (T_{amb}) and fan status (F) are also measured for each sub-group. All the measurements are sampled at 1 Hz. During cell balancing, a passive circuit discharges the cells to the lowest SoC within the series string through a shunt resistance of 100Ω.

B. Statistical testing using synthetic anomalous data

The model parameters are batch least square estimates, R_0, R_1, C_1, Q, a and b. The anomaly model parameters are anomaly type, anomaly magnitude (\( \vartheta \)), start time (\( t_a \)) and anomaly duration (\( \Delta t_a \)). The anomaly magnitude ranges from 0 to 1, for no anomaly to

Fig. 3. Examples of nominal (solid) and synthetic anomalous (dashed) voltage and temperature data associated with a (a) loose voltage sense lead (b) ISC (c) loose temperature sense lead (d) voltage drop-out (e) air flow anomaly.
most severe anomaly considered, respectively. ISC is modeled with \( R_{sc} = \exp \big( 9(1 - 0.6\vartheta)^2 \big) - 1 \) (See Fig. 3(b)). The voltage drop-out anomaly is modeled with \( R_{sc} = \exp \big( 9(1 - 0.6\vartheta)^2 \big) - 1 \) (See Fig. 3(d)). The air flow anomaly is modeled with \( b = (1 - \vartheta)\hat{b} \), where \( \hat{b} \) is the nominal value of thermal inertia coefficient (See Fig. 3(e)). Figure 3(a) and (c) correspond to loose voltage and temperature sense leads, respectively. Figure 4 shows that the maximum voltage and temperature deviations as functions of the anomaly magnitude for all five anomalies are similar.

Both anomaly detection algorithms are trained with 24 hours of data and tested on a different 24 hours of data. Figure 5 shows an example of anomaly detection on a cell group with a mild \( (\vartheta = 0.2) \) air flow anomaly injected into cell 3 at \( t_a = 12.78 \) hours with a deviation \( \Delta t_a = 7.2 \) hours. The parameters obtained from the training process in PCA Method are reported in Table II. The nominal current is shown in Fig. 5(a). The voltage and temperature of the cells are tightly clustered, as shown in Fig. 5(b) and (c), respectively, before the anomaly is injected. The anomalous MBR of cell 3 temperature is smaller than its nominal MBR, as shown in Fig. 5(d). Figure 5(e) shows that \( C_{+T}^{+} \) and \( C_{-T}^{-} \) do not cross their thresholds. Thus, Direct Method fails to detect this mild anomaly. Fig. 5(f) shows the anomaly being detected using PCA Method as the temperature anomaly score, \( C_{+T}^{+} \) crosses the threshold around 38.67 minutes after anomaly injection. \( C_{+T}^{+} \) increases gradually, indicating a persistent anomaly. Figure 5(g) shows the corresponding anomalous cell being located with 76% accuracy. Figure 6 shows the anomaly score increasing non-linearly with anomaly magnitude. Thus, larger anomalies are substantially easier to detect.

To evaluate the FPR, 24 hours of nominal experimental data from twenty five cell groups of 11 cells each is processed using both methods. Direct Method and PCA Method show
Fig. 7. Variation of performance indices of Direct Method (□) and PCA Method (♦) with anomaly magnitude for ISC.

### TABLE I

**OUTPUTS FROM TRAINING PROCESS IN PCA METHOD**

| Voltage PCA | Temperature PCA |
|-------------|-----------------|
| $p_v$       | $p_f$           |
| $\sigma_{v_f} [V]$ | $\sigma_{T_f} [^\circ C]$ |
| $\mu_{c,v}$ | $\mu_{c,T}$     |
| $\sigma_{c,v}$ | $\sigma_{c,T}$ |
| $\nu_{threshold}$ | $T_{threshold}$ |
| 0.0018 | 0.3205 |
| 0.0042 | 0.0355 |
| 0.0366 | 0.0082 |
| 0.1830 | 0.0410 |

Both methods show similar detection rate for $\Delta V \geq 26 mV$ and $\Delta T \geq 2.4^\circ C$, respectively. Figure 8(b) shows the TTR versus $\vartheta$ for PCA Method. Tracing accuracy increases with increasing anomaly magnitude. Anomalous cells are correctly traced with more than 95% accuracy for voltage and temperature deviations greater than 7$mV$ and 0.3$^\circ C$, respectively.

### C. Experimental ESC testing

Cell balancing in the battery electric locomotive involves connecting a 100$\Omega$ shunt resistor across the cell’s terminals. This is a mild ($\vartheta = 0.47$) ESC or micro short circuit [15]. One single cell balancing event and 13 module balancing events are used to evaluate the PCA Method for ESC detection. Figure 9 shows the single cell ESC fault initiated at 50 minutes, causing cell 10 voltage (dashed line) to drop while current is zero. PCA Method on the voltage data detects ESC within 255 minutes. The algorithm did not detect anomaly from the temperature data. The anomalous cell 10 is accurately traced 70% of the time. Even though the example in Fig. 9 shows the application of PCA Method to a zero current operation, this method can detect ESC even if the current is non-zero because the residual of the shorted cell voltage would behave differently compared to the nominal cell-to-cell relationship.

During module balancing, all 11 cells experience ESC. The pack current, cell voltages, and cell temperatures are shown in Fig 10(a), (b) and (c), respectively. Figure 10(d) shows that temperature PCA detects the anomaly within 16.3 minutes. Voltage PCA, however, does not detect the anomaly because all the cells are balancing. Statistical testing on 13 different module balancing events showed that temperature PCA detected the fault within 13.5 min, on average, with a $FNR$ of 2.3%. Voltage PCA, however, was ineffective with 99% $FNR$. 

low average FPR of 1.9% and 2.9%, respectively. To explore the overall performance of proposed anomaly detection algorithms, we test performance on families of synthetic anomalous data. Each anomaly is tested on all 25 cell groups with magnitude varying from 0.1 to 1 in steps of 0.1. Figure 7 shows the DT, RT, FNR, and MAR results for ISC. PCA Method detects ISC anomalies quicker (lower DT) and more accurately (lower FNR) than Direct Method. PCA Method misses fewer anomalies overall than Direct Method and detects all anomalies with $\vartheta \geq 0.4$. As anomaly spans until the end, there is no RT in this example. Generally speaking, RT of PCA Method is longer than Direct Method.
TABLE II
AVERAGE PERFORMANCE INDICES FROM STATISTICAL TESTING

| Anomaly type          | ISC Method | Air Flow Method | Loose Temperature Sense Lead Method | Loose Voltage Sense Lead Method | Voltage dropout Method |
|-----------------------|------------|-----------------|-------------------------------------|---------------------------------|------------------------|
|                       | Direct     | PCA             | Direct                              | PCA                             | Direct                 | PCA                    |
| DT [min]              | 280        | 102             | 312                                 | 46                              | 0.75                   | 0.72                   | 16                     | 6                   | 320                   | 252                   |
| FNR [%]               | 47         | 28              | 26                                  | 2                               | 46                     | 16                     | 36                     | 28                  | 49                    | 42                    |
| MAR [%]               | 33         | 8               | 19                                  | 0                               | 46                     | 14                     | 46                     | 32                  | 26                    | 49                    |
| RT [min]              | 0          | 0               | 0                                   | 0                               | 47                     | 257                    | 424                    | 552                 | 0                     | 0                     |

Fig. 8. PCA Method (a) missed anomaly rate versus anomaly magnitude; (b) true tracing rate versus anomaly magnitude: □ ISC, ◄ airflow, □ loose temperature sense lead, ◻ loose voltage sense lead and △ voltage drop-out.

Fig. 9. Detection using PCA Method on experimental data with ESC in cell #10, initiated at 50 min (vertical dotted): (a) Pack current (b) Voltage of 11 cells (cell#10 dashed) (c) Temperature of 11 cells (cell#10 dashed) (d) $C_V^+$ with its threshold (dashed)

Fig. 10. Detection using PCA Method on experimental data with ESC in all cells, initiated at 50 min (vertical dotted): (a) Pack current (b) Voltage of 11 cells (c) Temperature of 11 cells (d) $C_T^+$ with its threshold (dashed)
D. Retraining after balancing events

Balancing events occur periodically to equalize the SoC of cells in the string. Balancing is an ESC event that changes the cell-to-cell voltage relationship. The first two principal components (PCs) of voltage and temperature, before, during, and after balancing events, are compared in Fig. 11 and Fig. 12 respectively. Both voltage and temperature PCs before and during the balancing do not match. Figure 11 also shows that the cell-to-cell voltage relationship before and after balancing are different. Thus, voltage PCA needs to be retrained after balancing to adapt to the new nominal characteristics and avoid false positives. However, Fig. 12 shows that temperature PCs are similar before and after balancing. This is as expected because balancing only changes the relative SoC of the cells, not the electro-thermal cell characteristics. Thus, the temperature PCA does not need retraining after balancing events.

![Fig. 11. First two voltage principal components before balancing (solid), during balancing (dotted) and after balancing (dashed)](image1)

![Fig. 12. First two temperature principal components before balancing (solid), during balancing (dotted) and after balancing (dashed)](image2)

V. Conclusion

This paper shows that mean-based voltage and temperature residuals for a group of similar cells effectively detects electrical and thermal anomalies in battery systems. Mean-based residuals convert real-time voltage and temperature measurements to stationary data. These residuals are filtered, and CUMSUM thresholded to detect anomalies in the Direct Method. Thus, the Direct Method detects anomalies wherein the temperature and/or voltage data deviates significantly from the mean. In the PCA Method, PCA is used to reconstruct the normalized residuals which are then scalarized using RMSE as additional steps, giving the added ability to detect anomalies wherein the temperature and/or voltage data deviates from cell-to-cell. Both methods require nominal training data to establish normalization constants, thresholds, and the left singular matrix (for PCA Method). Both methods detect and trace synthetic internal short circuits, airflow constrictions, and loose and broken sensor connections. False positive rates are low (<3%) and can be reduced via increased thresholds but with an increase in missed detections. Overall, PCA Method outperformed Direct Method by 40–60% and is able to detect all anomalies with voltage and temperature deviations greater than $4mV$ and $0.15^\circ C$, respectively. Experimental ESC anomalies associated with balancing are detected within 14 minutes, relying on temperature residuals for module-level events. Voltage PCA retraining is required after cell balancing events.

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