ISSN: 2754-4915

Journal of Material Sciences & Manufacturing Research

Research Article

Open Access

A Basic Study on the Diagnosis Method of Internal Short Circuit based on Feature Extraction and Separation Technique

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ABSTRACT

Lithium-ion batteries are widely used in energy storage systems (ESS) and electric vehicles due to superior performance. However, most safety problems in the use process of the lithium-ion battery are attributed to internal short circuits, there are a lot of factors leading to the internal short circuit. Short circuit in the lithium-ion battery affects the electrochemical reaction and then generating a larger short circuit current. Besides, the thermal runaway is the result of a failure of the separator inside Li-ion batteries, small discharge pulses of a few mV were detected at the time of separator damages. Therefore, the fault diagnosis by internal short circuit of lithium batteries has attracted more attention to prevent the fire accidents. This paper aimed to suggest a diagnostic model for separator of LFP (Lithium iron phosphate) pouch cell as a basic research work using continuous pulse analysis method such as feature extraction and separation technique of pulse source for timely diagnose the short circuit fault. In other words, this paper provided a method that can identify the separator failure before thermal runaway in the aspect of a potential explosion and fire prevention. The internal short circuit signal for diagnosis of LFP pouch cell was investigated by forming artificial defects at the separator part compared with normal battery. To investigate the short circuit signal, artificial defect specimens are prepared as a pouch type, pulse signal was analyzed in terms of pulse waveshape (Skewness) and frequency (Fast Fourier Transform, FFT) compared with normal battery and artificial defect pouch cell. To calculate the continuous acquisition pulse signal, python code was developed. As a result, it is found that the pulse signal of artificial defect specimen shown high frequency and low skewness characteristics. Whereas, in the case of a normal battery, it showed characteristics of relatively low frequency and high or middle skewness. From our research work, the results revealed that the pulse shape and feature contain useful information which can help to understand degradation behavior of the LFP pouch cells. This result is expected to be applicable various batteries with presence a defect at the separator of battery.

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Received: July 21, 2023; **Accepted:** July 24, 2023; **Published:** July 31, 2023

Keywords: Fault Diagnosis, Pulse Signal, Li-Ion Battery, LFP Battery, Separator Defects, Battery, Short Circuit Signal, Artificial Defects, Diagnosis Model, Pulse Features

Introduction

Lithium-ion (Li-ion) batteries had continuously improved their performances in the last decade [1]. Lithium-ion batteries are widely used in various applications such as energy storage systems and electric vehicles etc. due to their superior performance and effectiveness. Besides, lithium-ion battery has become the important energy storage solution owing to high power density, energy density, high charge-discharge cycle lifetime and long lifespan [2-5]. Thus, the technology of Li-ion battery is considered a suitable alternative than that of other energy storage systems [1]. However, there are some safety problems such as BMS (Battery management system) fault, battery fault, sensor fault and thermal runway etc. despite the superior benefits of Li-ion batteries in various applications.

In general, a lithium-ion battery is composed of four elements: an cathode, an anode, an electrolyte and a separator. A cathode is manufactured by coating a mixture using an active material of lithium oxide on a aluminum thin film, and an anode by coating a mixture of an active material made of graphite on a copper thin film. The separator is a synthetic resin such as polyethylene (PE) or polypropylene (PP), and serves as a medium for moving lithium ions during charging and discharging.

The diagnosis technology for Li-ion battery and LFP battery is essential for ensuring the reliability and safety. However, the technology for battery fault diagnosis is very difficult to detect faults at an early stage in terms of reliability.

Recently, diagnosis technology for safety of Li-ion battery has been developed and improved, some technology can detect and evaluate progressive faults and predict under sudden faults during the operation of Li-ion batteries to reduce the risks of batteries [6-10]. Recently, a lot of work has been devoted to improving diagnosis technology to effective and accurate identification of failures for the Li-ion batteries. Jia Wang suggested a fault diagnosis method for the electric vehicle power battery using the improved radial basis function (RBF) neural network [9]. The diagnosis concept was collected fault information of Li-ion battery using battery test equipment and the fault levels were then determined. Yulong Zhang investigated fault diagnosis technology at a macro level based on statistical analysis, models, signal processing, knowledge and data-driven etc [10]. Nicolae Tudoroiu developed the intelligent least short time memory (LSTM) deep learning classification technique to detect possible anomalies in measurements dataset within a particular Li-ion battery type [11]. For the state of charge (SOC) and battery faults estimation, a Joint State and Parameter Extended Kalman Filter (JEKF) estimator is developed. Shuowei Li suggested a fault diagnosis method based on signal decomposition and two-dimensional feature clustering, symplectic geometry mode decomposition (SGMD) was introduced to obtain the components characterizing battery states and distance-based similarity measures with the normalized extended average voltage and dynamic time warping distances to evaluate the state of batteries [12]. Rui Cao proposed an internal short circuit diagnosis algorithm for battery packs with high accuracy and high robustness via voltage anomaly detection, this technology adopt the mean-difference model (MDM) to characterize large battery packs [13]. Ruilong Xu suggested a data-driven battery aging mechanism analysis and degradation pathway prediction approach, a non-destructive aging mechanism analysis method based on the open-circuit voltage model is proposed [14]. In addition to the above research work, many technologies have been developed and suggested for predict battery faults and life based on machine learning as well as signal analysis method [8,15-17].

From the above view point, the internal short circuit of Li-ion batteries is considered as one of the main reasons for the battery faults such as thermal runaway and explosion. In this paper, diagnostic model and technology were proposed to detect separator damage as an electrical pulse analysis method to prevent fire or explosion by detecting an electrical signal in the early stages of separator damage of the LFP pulse cell. To detect the electrical fault signal of a few mV from separator damage, two kinds of specimens were prepared. One is normal battery and another one is artificial defect battery at the separator part. To identify the electrical signal according to separator failure, fault pulse signal was analyzed in terms of pulse shape, frequency component and amplitude of pulses in real-time from continuous acquisition pulse waveform.

The target of application of this diagnosis technique is included in mobility for the purpose of logistics activities such as electric vehicles and trailer etc.

In this paper, Section 1 describes the introduction of the research work, Section 2 presents a test configuration and specimens used in this research work. Section 3 describes the results and discussion, and Section 4 presents the final conclusions and future directions of the research in this field.

Experimental Configuration

Figure 1 and 2 shows experimental configuration and specimens for pulse detection of LFP pouch cell. Two kinds of specimens are used in this paper. All specimens are LFP (Li-FePO4) batteries and battery capacitor is 36.34mAh. Each specimen was connected with battery cycler system, the pulse waveform of internal short circuit was detected with HFCT sensors in real-time, pulse measurement condition was -1.0 A discharge. HFCT sensor is placed in the negative side cable. All pulses including internal short circuit signal and noise signal coming from HFCT sensors to signal detector, two kinds of features of each pulse are calculated, and then short circuit was determined by characterized clusters of pulses on the skewness-frequency classification (*S-F*) map. All electrical pulses were detected as a nano-second unit.

The detected internal short circuit pulses by HFCT sensors are strongly influenced by the short circuit amplitude of LFP pouch cells. The diagnostic technology in this paper based on electrical pulse analysis method as a feature extraction and separation technique have been developed to classify the noise signal and internal short circuit signal. Each waveform pulse is composed of two quantities. One is the pulse waveshape (skewness) and another one is the equivalent frequency (TauF). The definition of these parameters is as follows:

$$f = fftfreq(len, 1e8) \tag{1}$$

$$x = |fft(s\_norm)/len| \tag{2}$$

$$TauF = \sqrt{\sum(f^2 * x^2)} \tag{3}$$

where, fftfreq(N, time) is sampling frequency when window length N and sampling length time are used, fft(x) is Fourier transform of the pulse data x.

$$d' = |h(d)| : envelope \tag{4}$$

$$feature\ skewness = skewnes(d') \tag{5}$$

where, $skewness(x) = m_3/m_2^{3/2}$ is Pearson's asymmetry coefficient

function, $m_i = 1/n\ \Sigma(x_n - x) N_n = 1$, x is mean of x, $hb(x)$ is

Hilbert transform function.

The detail source code about skewness and equivalent frequency is shown in Figure 3(a) and (b), respectively. The example of envelope by Hilbert transform is shown in Figure 3 (c).

The feature extraction and separation of internal short circuit pulses is based on a clustering technique that relies on a skewness and frequency classification (*S-F*) map. In the case of first feature (skewness), it presents the degree of asymmetry of the pulse. After changing the pulse waveform into an envelope (smooth connecting the peaks of the waveform) through the Hilbert transform, the skewness of the envelope is obtained using the Pearson asymmetric coefficient equation. In second feature (frequency, TauF), it is the standard deviation of the pulse converted to the frequency domain using the Fourier transform. The pulse waveform period (frequency, TauF) and s_norm are discrete Fourier transforms to calculate the feature Tau. In other words, classification (*S-F*) map can offer various information to help distinguish and understand various detected pulses.

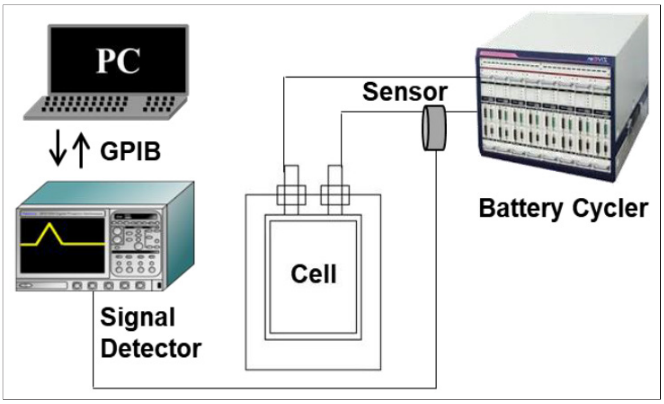


Figure 1: Test Configuration for Diagnosis of LFP Pouch Cell

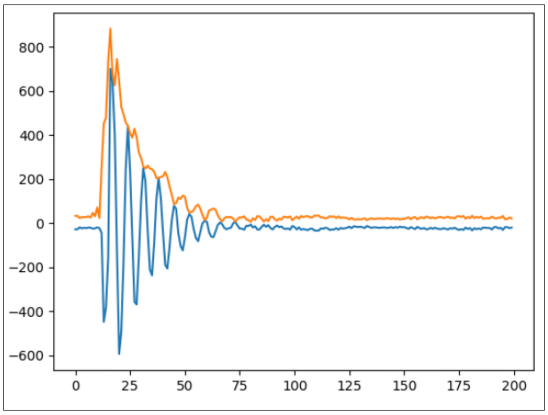
Figure 2: Normal Specimen (Left), Artificial Defect Specimen (Right)

```python
def compute_skewness(data, h_envelope=True, idx=0):
    if h_envelope:
        analytic = hilbert(data)
        envelope = np.abs(analytic)
        feat = scipy.stats.skew(envelope, axis=-1)
        # plt.plot(data[idx, :])
        # plt.plot(envelope[idx, :])
        # plt.show()
```

(a) First Feature Point for Skewness

```python
def compute_TF(d: np.array, Fs=1e8): # 10 ns
    """
    Input :
        d : 2-d np.array of shape (num_batch, sample length=200)
    Output :
        Tau_f : 1-d array of shape (num_batch, sample length=200)
        Tau_t : 1-d array of shape (num_batch, sample length=200)
    """
    # d = np.genfromtxt('./LS-partial-discharge/abcd1.csv', delimiter=',').T[0, np.newaxis]
    # Fs=1e8
    sample_len = d.shape[-1]
    num_sample = d.shape[0]
    Ns = 200
    t = np.linspace(0, 0.000002, Ns)
    s_norm = d / np.sqrt(np.sum(d**2, axis=-1, keepdims=True)/sample_len)
    Ts =t[1]-t[0]
    #Tau_F
    f = np.fft.rfftfreq(sample_len, Ts)
    f = np.tile(f, (num_sample,1))
    X = np.fft.rfft(s_norm)
    X[:, 1:] = X[:, 1:] * 2
    X = X / sample_len
    X_abs = np.abs(X)
    Tau_f = np.sqrt(np.sum(f**2 * X_abs**2, axis=-1)); Tau_f
    return Tau_f, Tau_t
```

(b) Fourier Transforms for Feature TauF



(c) Example of Envelope by Hilbert Transform

Figure 3: The source code for separation and feature extraction of pulse waveform

Experiment Results and Discussion

From Figure 4(a)-(c), it can be seen that pulse extraction and separation results by classification (S-F) map with -1.0A discharging condition. It can be seen in Figure 4, where three types of pulses (detected in ambient noise pulse and LFP normal/abnormal batteries) can be observed: (a) most pulses with low value of equivalent frequency (< 45 MHz) and high skewness (> 3.5), (b) most pulses with low value of equivalent frequency (<40 MHz) and low skewness (>3.5) and (c) pulses with high equivalent frequency (>50 Mhz) and low skewness (>3.0). In general, the pulse feature of the internal short circuit has high equivalent frequency and low skewness characteristics.

Figure 5(a)-(c) show pulse count with -1.0A discharging condition. The results found that the peak value of pulse count was 10^2 at 41 MHz for ambient noise pulse. In the case of normal sample, the peak value of pulse count was 10^2 at 25 MHz. In other words, equivalent frequency of normal battery sample was lower than that of ambient noise pulse. Whereas, in pulse count of artificial defect sample, peak value is formed at 53 MHz, meaning that detected pulse coming from defect sample can be predicted as high equivalent frequency.

Figure 6(a)-(d) show the results of various pulse waveform in two types of batteries such as normal battery and artificial defect battery with -1.0A discharging condition. In the figure 6, y-axis and x-axis are pulse amplitude and time domain, respectively. In the case of ambient noise pulse and pulse of normal battery, the amplitude of pulse was relatively lower than that of artificial defect signal. In other words, amplitude of noise and the normal battery signal are less than 100. Whereas, artificial defect signal has some features such as narrow pulse width, high frequency component and high amplitude (greater than 150) compared with ambient noise and normal battery signal. From above results, the amplitude of pulse might be influenced by separator condition. In other words, discharge pulses having high amplitude and high frequency characteristics occurs at the time of separator damages, S-F map parameters and amplitude of pulses can identify the separator failure before thermal runaway.

Suggested feature extraction and separation technique are generally used in power facility such as power cable, GIS (Gas Insulated Switchgear), Oil filled transformer as well as various field for diagnosis and prevention in the early stage of the insulation breakdown of power equipment. Fault signal occurrence is highly correlated to weakened insulation strength. It is because the insulation damage changes insulation properties such as dielectric constant and resistance, and then more free electrons are emitted due to local electric field concentration in the damaged insulation part resulting in an increase in leakage current. In other words, partial discharge signal having high frequency and high amplitude could be detected at the damaged insulation part. In this paper, by implementing feature extraction and separation technique, we have focused on diagnosis and prevention possibility of internal short circuit for LFP pouch cell, fault signal generated by an internal short circuit could be detected in the early stage of separator damage before thermal runaway.

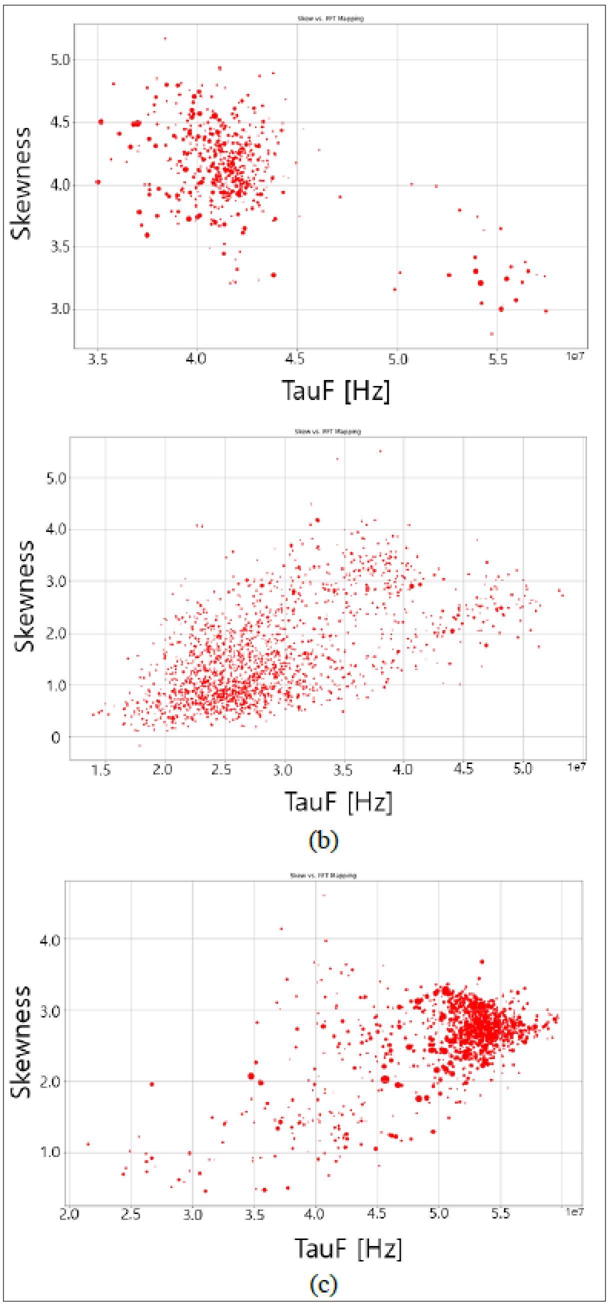


Figure 4: The feature extraction and separation results with -1.0A discharging condition (a) Ambient Noise Pulse, (b) Pulse Waveform of Normal Sample, (c) Pulse Waveform of Artificial Defect Sample

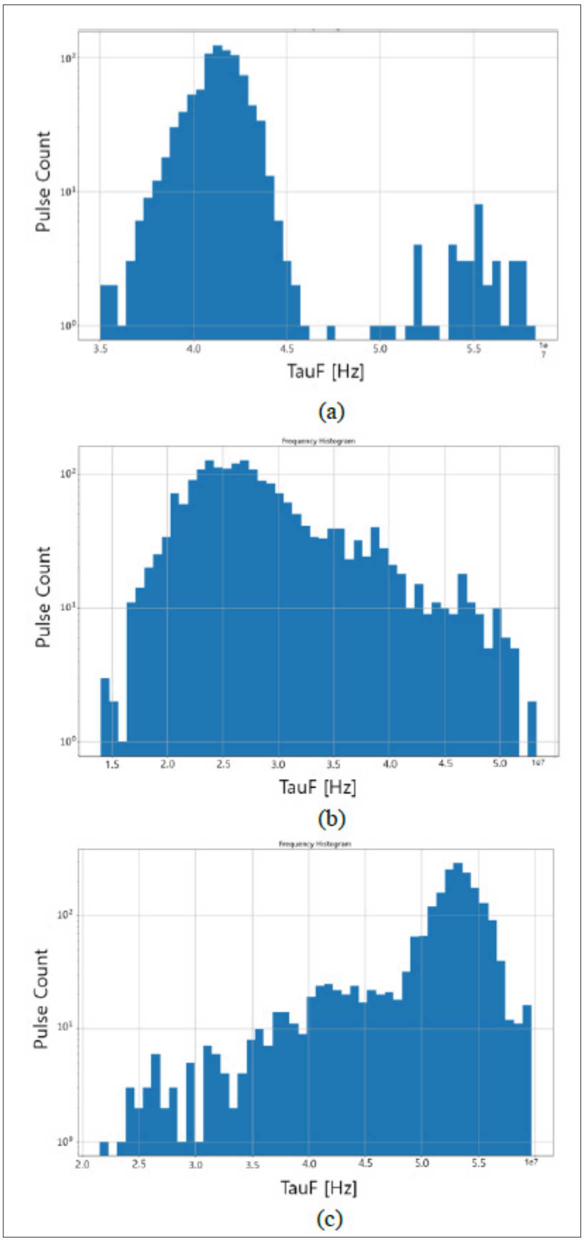


Figure 5: The pulse count results with -1.0A discharging condition (a) Ambient Noise Pulse, (b) Pulse Waveform of Normal Sample, (c) Pulse Waveform of Artificial Defect Sample

Conclusion

Recently, many researchers have focused more on the diagnosis technique of Li-ion batteries to prevent the fire accidents. Besides diagnosis technique has become of huge interest to accurately diagnose their state-of-health (SOH). At present, Li-ion batteries are diagnosed by impedance, capacity measurements as well as statistical analysis. At the current technical level, above diagnosis techniques are efficient measurement methods for diagnosing SOH of Li-ion batteries. In this paper, we have focused on feature extraction and separation technique by detecting continuous pulse waveform of LFP pouch type battery cell with discharging condition. In addition, pulse waveform of ambient noise signal and normal battery signal was compared with artificial defect signal to investigate the possibility.

The experimental results are summarized as follows:

- In the case of ambient noise signal and normal battery signal, most pulses with low value of equivalent frequency and high or middle skewness, most pulse counts are formed at 41 MHz (ambient noise signal) and 25 MHz (normal battery signal), respectively. Besides, the amplitude of pulse was relatively low than that of artificial defect signal.
- Artificial defect signal has some features such as narrow pulse width, high frequency component (53 MHz) and high amplitude differs from ambient noise and normal battery signal.
- Explosion or fire caused by the LFP pouch cell can be prevented by electrically detecting the fault signal in the early stage of separator damage before thermal runaway. In this paper, the electrical pulse signal from the separator damage could be detected. Further work is needed on additional validation step.

For Further research work is necessary to present accurate reference values for clear distinction between internal short circuit signal and normal signal. Besides, for additional validation of diagnostic technique, further work is needed on long-term aging test of separator of LFP pouch cell.

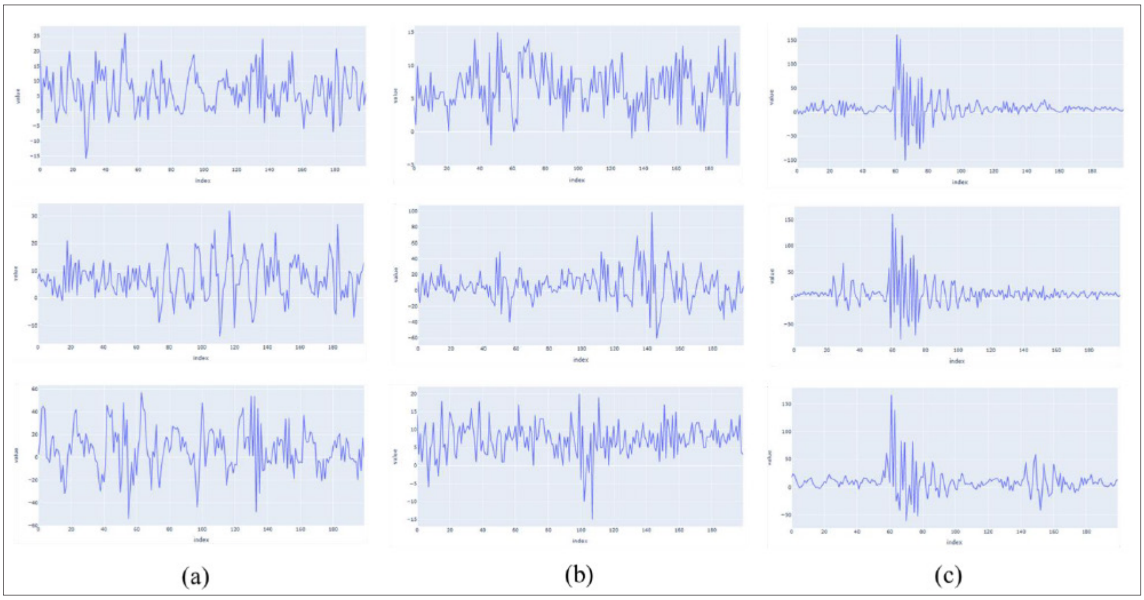


Figure 6: Various pulse waveform in two types of batteries such as normal battery and artificial defect battery with -1.0A discharging condition (a) Ambient Noise Signal, (b) Normal Battery Signal, (c) Artificial Defect Signal.

Acknowledgement

This work is supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (RS-2021-KA162618)

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