A deformation-based approach to the SoH estimation of collided lithium-ion batteries

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Abstract: Extensive research work has been carried out mainly focusing on the assessment and prediction of battery cell State of Health (SoH) under operating conditions, however limited contributions focus on SoH following collision impacts. This paper proposes a method for estimating the battery cell SoH from collision deformation features. Experimental tests of collision impact were designed and realized on brand new battery cells to investigate deformation features. Deformed battery cells were subject to a 3D scanning procedure to retrieve the contour data, subsequently a number of geometrical features were extracted from the 3D image instances. The battery cells damage characterization was carried out by characterizing both physical and electrical performances following the collision impact tests. An intelligent assessment was carried out by adopting a neural network-based supervised machine learning paradigm for classification of deformed battery cells into safe, latent danger and unsafe cells respectively. Training and testing results show a clear pattern between geometrical deformation features and battery cells SoH, with classification accuracy up to 96.7% demonstrating the suitability of the proposed method for an effective assessment. Within electric vehicles applications, such method can provide a basis for safety design enhancement of lithium-ion battery system via finite element simulation of collisions impacts.

Key words: Lithium-ion battery; Collision; SoH; Battery Deformation

1. Introduction
The electric vehicle industry and market have rapidly developed in the recent years. The lithium-ion (Li-ion) batteries are largely used as a storage system technology for electric vehicles as they are characterized by high energy density, light weight, fast charge, and relatively low cost [1].

The battery is applied to the electric vehicle in the form of battery pack, and the single battery would affect the life of the whole battery pack due to its health status, including capacity reduction, low voltage or high internal resistance [2]. So the state of health (SoH) of Li-ion battery is crucial aspect in battery management system (BMS) [3]. Extensive research work is available on SoH prediction methods for Li-ion batteries under normal operating conditions, such methods are mainly divided into four categories: direct measurement [4], closed-loop estimation of parameter identification based on battery model [5], open-loop estimation based on durability model [6] and data driven methods [7]. In recent years, the collision-related safety accidents of electric vehicles have increased, rising a research interest in collision...
safety issues of Li-ion batteries [8]. Depending on the collision impact significance and severity, three scenarios can be identified for the Li-ion battery cells performance. The best-case scenario implies that battery cells are not affected by the impact and can keep work normally. The worst case scenario depicts the occurrence of combustion and explosion due to thermal runway determining the battery cell catastrophic failure [9]. A third scenario is identified, in which the Li-ion battery cells do not show any sign of failure in the short time, but potential safety risks may be revealed in a later stage during usage, such scenario is known as latent danger [10]. In this context, it is particularly important to accurately estimate the battery cell SoH after the collision so that unsafe and potentially dangerous batteries could be replaced in time to avoid catastrophic failures and to ensure the safety of the whole battery pack. It also provides a decision-making support on the use of safe batteries. Currently, available BMSs can achieve an accurate estimation of battery SoH under normal working conditions, however such estimation does not take into account collision events resulting in a limitation of its application scope. Literature survey and industry best practices review highlighted a limited effort in Li-ion cells SoH assessment following collisions. Simeone et al. [11] proposed a method for evaluating latent danger safety issues in Li-ion batteries after collision impacts through sensing force signals and performing a pattern recognition via ensemble learning paradigm. The disadvantage is represented by the need of installing force sensors for each battery module in the battery pack to acquire real-time force signals which does not help the improvement of battery system from a design perspective. The mechanical response of Li-ion batteries after collision is extremely complex because of physical and chemical changes involved. Physical changes are related to the battery shell and internal coating materials, as well as to electrolyte film (SEI) formed inside the battery [12]. Chemical changes include reactions from the contact between positive and negative electrodes due to the piercing of the diaphragm and electrolyte oxidation reactions occurring when the safety valve drops. Xia et al. [13] found out that when the depth of deformation in the axial direction of the battery reaches 2.5 mm, this determines a short circuit inside the battery cell. This shows that cells deformations are related to the SoH, however, it has not been investigated which specific deformation features are more relevant to the SoH assessment. In this respect, this paper proposes an experimental approach to the SoH classification in Li-ion batteries after collision impacts based on geometrical deformation features and machine learning pattern recognition.

The remainder of this paper illustrates the realization of a collision impact test experimental campaign to obtain quantitative deformation data on battery cells, subsequently the SoH is evaluated in terms of physical and electric safety performance. Using 3D scanning technology, contour images of damaged battery cells specimens are retrieved, allowing for computation of deformation features, which were then inputted in a pattern recognition neural network, with the aim of classifying the SoH in three safety classes. Results and applications are eventually discussed with reference to an integrated BMS.

2. Experiments and methods

In this paper, the behavior of Li-ion battery cells after collision impact is studied under discharge conditions. Li\textsubscript{x}C\textsubscript{6}/LiCoO\textsubscript{2} battery cells were chosen as experimental specimens in this study, the main cell properties are shown in Table 1. Since the State of Charge (SoC) can affect the mechanical properties [14], the experimental tests were carried out on fully charged battery cells (SoC =100%).

| Parameter                  | Value          | Parameter                               | Value |
|----------------------------|----------------|-----------------------------------------|-------|
| Nominal capacity           | 2250mAh        | Continuous maximum charge current       | 2.15A |
| Rated capacity             | 2150mAh        | Continuous maximum discharge current    | 10A   |
| Nominal voltage            | 3.7V           | Cut off voltage                         | 2.75V |
| Charge voltage             | 4.2±0.05V      | Size                                    | 18mm  |

Collision experimental tests are carried out by dropping down a stainless-steel cylinder onto the battery cell specimen from a height of 1 m [15]. The collision test rig is shown in Figure 1(a). The mass (kg) blocks used in the tests are respectively: 2, 2.35, 2.5, 3, 4, 6 and 10. To simulate operating conditions,
three types of collision interfaces were designed as shown in Figure 1(b). By combining the experimental parameters, a total number of 61 experimental tests were carried out as reported in Table 2. The experimental tests were repeated at least three times in order to improve the experiment reliability.

Table 2. Experimental programme

| Interface type | I   | II  | III |
|----------------|-----|-----|-----|
| Mass (kg)      | 4   | 6.34| 10  |
|                | 2   | 2.35| 2.5 |
|                | 2   | 5   | 4   |
|                | 6.34| 3   | 4   |
|                | 2.5 | 4   | 3.5 |
| Repetitions    | 6   | 7   | 3   |
|                | 10  | 4   | 4   |
|                | 4   | 3   | 3.5 |
|                | 3   | 4   | 4   |

Figure 1. 3D Model of battery collision test device(a); Interface types(b)[11]

2.1. SoH characterization
In this paper, the battery cells SoH is characterized in terms of physical damages and functional performance, i.e. internal resistance and capacity. A visual inspection along with a number of charge and discharge tests and internal resistance tests were performed on collided battery cells specimens. According to the safety classification standard reported in [11], the collided battery cell specimens are classified by using a set of parameters, including electrolyte leakage, breakage, deformation, discharge continuity, internal resistance, 3C-rated discharge capacity. Batteries are divided into three categories. The assessment led to the definition of three SoH classes:

- **Class 1 - Safe cell**: the battery cell can display enough maximum power and discharge effectively to ensure the normal operation of the equipment.
- **Class 2 - Latent danger cell**: these cells are characterized by a performance degradation in capacity, power and service life, leading to a more likely malfunction compared to normal batteries with potential safety issues.
- **Class 3 - Unsafe cell**: the damage extension doesn’t allow for charging and discharging, this class includes cells showing electrolyte leakage, burn or explosion during the experiment.

2.2. Geometrical features computation
Following the collision tests the battery cell specimens were subject to a three-dimensional contour scanning to obtain information on deformation characteristics. The side and top views of the obtained
3-D model are reported in Fig. 2.

Figure 2. 3-D model of deformed battery cell specimen. (a) maximum deformation, (b) left and right expansion.

The deformation characteristics were computed as five geometrical features described below with reference to Fig. 2
- Maximum deformation ($D_{max}$) [16] corresponding to the maximum displacement after the collision test
- The volume change ($\Delta V$) [17], i.e. the difference between the battery cell specimen volume after and before the collision. This was computed directly by the 3-D data acquisition software.
- The maximum expansion on left and right side ($\varepsilon_L$ and $\varepsilon_R$) [18] after the collision test compared to a fresh battery as shown in Fig. 2(b).
- The curvature of maximum deformation point ($\kappa_{D_{max}}$) [19], i.e. the degree of curvature in correspondence of $D_{max}$. This was achieved firstly by fitting the contour data points using an 8° degree Fourier function as shown in Fig. 3b, then by applying the formula shown below:

$$
\kappa_{D_{max}} = \frac{|f''(x_{D_{max}})|}{\left[1 + f'(x_{D_{max}})^2\right]^{3/2}}
$$

Figure 3. Contour data points scatter (a); Fourier curve fitting (b)

2.3. Machine learning-based decision-making

Deformation features extracted from battery contour data were used to train an Artificial Neural Network
pattern classifier for SoH classification purposes

A 3-Layer feed-forward back-propagation NN was built with the following architecture:

- Input layer with 5 nodes corresponding to the deformation-related geometrical features in the input feature vector, i.e. $[D_{\text{max}} \Delta V \varepsilon_L \varepsilon_R K_{D_{\text{max}}}]$.
- Hidden layer with 50 nodes
- Output layer with 3 nodes corresponding to the SoH classes defined in the previous section.

3. Results and discussions

The ANN performance, in terms of success rate, is reported in Figure 4 in a form of confusion matrix. Results show an accuracy of 96.7%, showing a clear pattern between deformation features and classify the SoH classes. In particular, concerning the Class 1 (safe cells) and Class 3 (unsafe cells) the ANN can classify all the specimen instances, while 2 misclassifications occur for Class 2 (latent danger cells) suggesting the need to refine the class definition criteria and the use of additional deformation features.

![Confusion Matrix](image)

The encouraging results obtained have the potential to enable a SoH estimation system which can be coupled with a finite element simulation for diverse operation conditions.

Due to the very nature of collision phenomena, the SoH assessment in battery cells after collision results extremely difficult from a computational point of view. To tackle this issue, the deformation features can be easily computed from the Finite Element Simulation, and they can be used to feed the trained pattern recognition model to estimate the battery SoH. Specifically, the battery module and pack design phase can be assisted by the use of the pattern recognition model developed in this paper, can allow for a more reliable estimation of battery module and pack SoH to guarantee an optimal design from a safety perspective.

4. Conclusions

In this research, a method has been proposed for battery cell SoH estimation based on collision deformation features. Experimental collision tests on battery cells were carried out and a number of geometrical deformation features were computed from collided cell specimens, namely maximum deformation, curvature in correspondence of maximum deformation point, maximum expansions on the left and right sides and volume change. Geometrical features were then used as input for a pattern recognition for SoH classification purposes achieving a very high accuracy. Following an electric vehicle crash, the battery SoH can be accurately estimated to avoid dangerous safety hazards, with a great potential in crash safety tests. From a finite element analysis perspective, the deformation characteristics can be extracted from simulation runs, and the SoH of battery can be predicted offline by
using this method to optimize safety performances in battery pack design phase.

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