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A non-invasive method for state-of-charge estimation of Li-ion batteries using Fibre Bragg Grating-based sensors

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Abstract: Fibre Bragg Gratings are employed as input of a state-of-charge prediction algorithm for Lithium-ion batteries. Data gathered allowed the development of a dynamic time-warping algorithm for prediction of the state of charge of battery.

1. Introduction

Lithium-Ion batteries are well known as a key technology for modern energy storage systems, with major applications both in electric vehicles and the wide range of portable devices used on a day-to-day basis. This type of battery has been shown to be the most effective to meet the energy requirements of these devices, allowing as they do both high peak power and high capacity [1].

Despite all the advantages seen in using Lithium-ion batteries over other energy storage technologies, there are still clear limitations in their use, which mainly are related to the safety and the optimization of the battery lifespan and its capacity. For this reason, a number of studies involving better modelling of key Lithium-ion battery parameters to allow a better understanding of the dynamics of their chemistry and thus to maximize their performance, while not compromising the safety of their operation, have been carried out.

The methods usually used to measure the battery state-of-charge (SOC) are based on voltage and current measurements, using such data to create models that simulate as closely as possible the actual electrochemical state of the batteries [1]. However, these methods have limitations and must be used together to enhance the reliability of the measurement and thus improve the real-life operation of the Lithium-ion battery systems needed for many operational uses. Fibre optic sensors have proven very valuable for obtaining data on a wide range of physical and chemical systems and thus potentially can be used here to allow better battery characterization. Fibre Bragg Gratings (FBG) used as the basis of a sensor system take full advantage of their immunity to electromagnetic interference and their being good insulators, with the additional advantage of being easily multiplexed as compared to their electrical counterparts such as thermocouples or strain gauges. For these reasons, FBG-based technology has previously been widely applied to the measurement of key parameters such as temperature [2] and strain [3] in Lithium-ion batteries, as a knowledge of these parameters is essential for the better understanding of the lithiathion/delithiation processes and their influence on the battery SOC.

Although the integration of FBGs *inside* the battery cell has proven feasible, the thrust of this work has been to measure the strain and temperature *outside* the battery package where the data are easier to obtain. Such an approach can be equally effective for the applicability of this kind of measurement in industry. It is well known that battery performance can be affected by the integration of fibres *inside* the battery cell [4]. A similar approach has already been proven useful to enhance the performance over that available from conventional sensors for thermal characterization [5]. Building on the above, the focus of this work has been to extend this approach to multi-parameter measurement, recognizing that a knowledge of strain measured plays a key role in understanding the dynamic of the process [3] and thus can help enhance battery performance and safety.

The search for a reliable model has been the key to both the good performance and the safety of Li-ion batteries. A good state estimator can make a key difference to enhance energy storage and meet sector requirements and recently a major effort has been made on the data processing side to allow all the data from sensors to be read to give the key performance parameters for the batteries. Thus this work has aimed to apply the advantages of FBG-based sensor technology to measure simultaneously the strain and temperature conditions in Lithium-ion batteries, along with creating an algorithm based on dynamic time warping. The aim has been a proof-of-concept of a non-invasive optical fibre-based sensor method to create a self-sensing ‘smart-battery’ capable of optimized operation and thus to meet better the high performance required in measurement and demanded by the next generation of systems where Lithium-ion based power is vitally important.

2. Experimental Methods

The FBGs used in this work were manufactured using the phase mask method and inscribed in photosensitive fibres supplied by Fibercore (PS1250/1500), using ultraviolet light from a high power KrF excimer laser. The batteries were each instrumented with 3 FBG-based sensors, set at an angle of 45 degrees to each other and the known relationship between the signals from the sensors are used to compensate the temperature effects on each of the FBG-based strain measurement devices. All FBG-based measurements were performed using a Micron-Optics SM-130 interrogator, operating at 1 kHz.

Further, in order to create an effective comparison of the performance of the system developed with well-established methods, a constant-current/constant-voltage (CC-CV) procedure was adopted for the battery charging following a CC discharge, which included a Coulomb-counting set-up used in parallel with the fibre sensors, to allow a measurement of the current and the voltage of the cell. Fig. 1 shows a photograph of the set-up used, showing the FBG-based strain sensors.

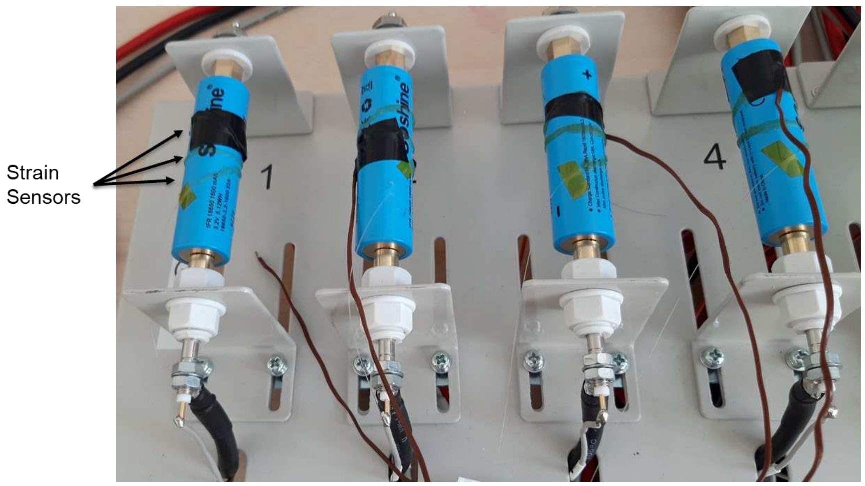

Fig. 1. Battery cycling setup, with embedded FBG-based strain sensors.

The batteries examined in this work were 3.2 V, 1.6 Ah, cylindrical $LiFePO_4$ cells and as can be seen from Fig. 1, four such cells were used. All charge/discharge cycles were performed at 1C, as shown in Fig. 2. where the blue plot shows the FBG-based sensor signal, after temperature compensation has been applied.

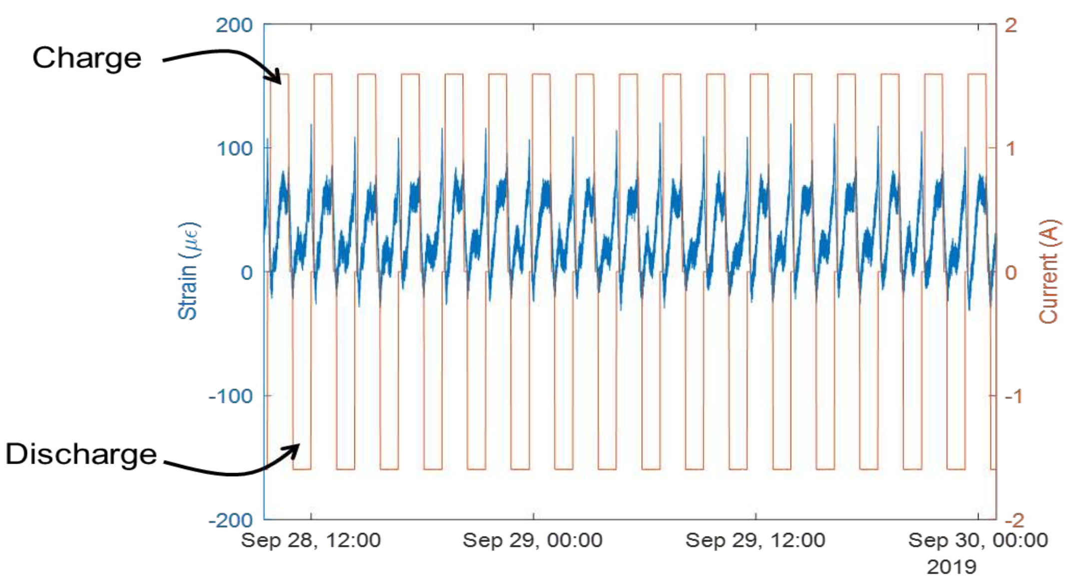

Fig. 2. CC-CV charges and CC discharges (orange) along with the FBG strain response (blue).

Subsequently to the acquisition of all the cycling data, the dynamic time warping (DTW) method was used to evaluate the SOC of the cells. The rationale is that the Euclidean distance between the signals will be the least as it approaches the test data – for instance, if the cell is at 50% SOC, the Euclidean distance will be at a minimum when a comparison is made with half of the charging plot and higher to other values.

3. Results of the investigation

The tests carried out showed that level of repeatability of the FBG-based sensor data is high enough to enable it to be used as the input to the DTW algorithm developed. As can be seen from Fig. 2, all the charges/discharge cycles have a similar span and shape, with a maximum strain of 100 με monitored. After applying the DTW approach to the charging and discharging data, a performance graph can then be drawn, this then showing how reliable are the predictions using (only) the optical data. The graph is created by comparing the known SOC to the data when the minimum Euclidean distance is achieved, i.e. if the actual SOC is X%, the Euclidean distance should be minimum when testing a portion of X% of the whole charging activity. Fig. 3 shows the performance graph for the system under investigation (with a resolution of 1%).

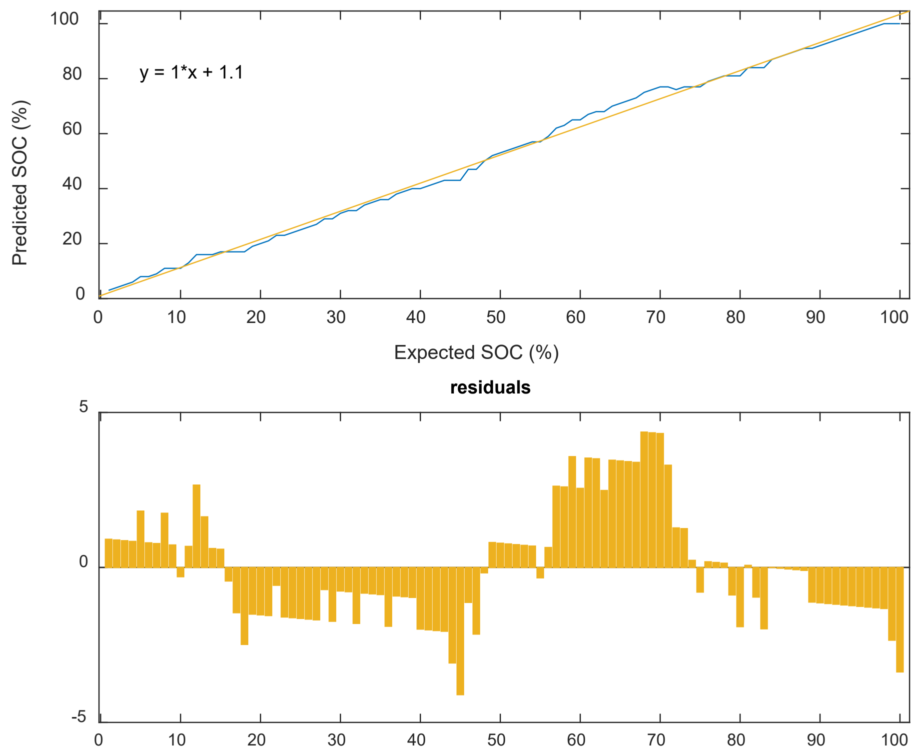

Fig. 3. Performance test for the prediction of SOC using DTW algorithm on FBG data.

The graph illustrating the performance test shows that the fitting is very close to the actual value, which means the predictions method applied is good. The residuals show the maximum error that the system generates, in this case this being less than 5%. It also shows that the higher errors are prone to occur in the regions of the strain curve (Fig. 2) where the slope is not varying much, a well-known limitation of the DTW algorithm [6]. This behaviour is present for both the charging and discharging cases.

The resolution is probably the most sensitive parameter of the system. As the resolution becomes smaller, the comparative data will also become smaller and the difference more difficult to resolve – for instance, it is clearly harder to identify the difference between measurements of 10% and 11% than between measurements of 10% and 20%. It means that to achieve the desired 1% resolution, the system must be even more reliable so the DTW can identify even small differences from the graphs. Using finer resolution also increases the computational costs as the original data must be compared to a higher number of portions of the training data. Fig. 4a shows how sensitive the response can be to different values of resolution from 1% to 10%. The other highly important parameter to be tailored in this application is the training data size, i.e. the number of cycles needed as comparison to achieve a good performance. This number cannot be set to be as high as desirable as that would cause the computational cost to be impractical. This can be seen from the following choice of parameters, which represents a poor choice: if there are 100 cycles used as the training data and a resolution of 1%, the number of DTW iterations needed to draw the performance graph would be 10000, which typically would require a few hours to compute all the values. Fig. 4b shows the behaviour of the performance as the training data size increases from 10 cycles to 50 cycles. It can be noted that both 40 and 50 cycles have roughly the same response, which means that increasing the training data will not increase the system accuracy in the same ratio as the computational cost will increase.

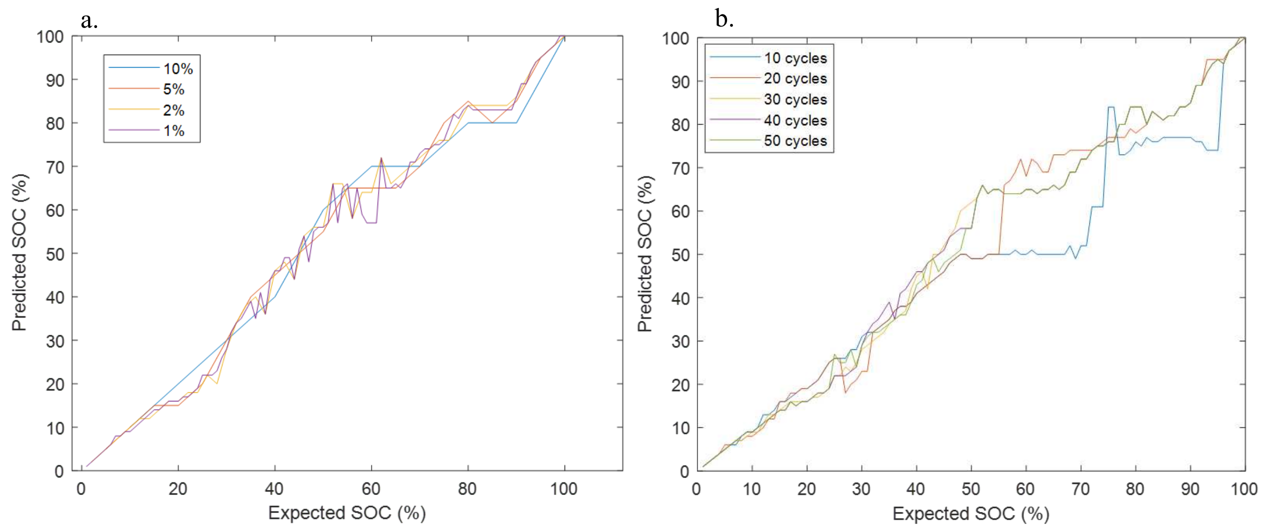

Fig. 4. Comparison of performance using (a) different resolution and (b) training data sizes.

4. Summary

The data obtained from the cycling tests carried out with the batteries have shown a very characteristic dynamic, that can be related directly to the capacity using machine learning algorithms, such as the dynamic time warping. As a result, predictions on the state of charge of $LiFePO_4$ batteries were successfully accessed using the DTW, with the use only of the optical signals from the FBG-based sensors. The signals required for the predictions were gathered from those FBG-based sensors which were externally placed in the bodies of the cylindrical shaped batteries, in this way not influencing the normal operation of the batteries but allowing the measurements to be taken.

The algorithmic parameters studied such as resolution, training data size (number of cycles) and data smoothing must be well tailored for the method to have the higher accuracy of the prediction and the best performance needed, regardless of the input data.

Future work will continue the development of the monitoring system, aiming to measure the state of health of the batteries using the same approach combining this with using the data from multiple sensors simultaneously to achieve higher accuracy in the results obtained.

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