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Electric vehicles performance estimation through a patterns extraction and classification methodology

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HIGHLIGHTS

- A battery signal pattern extraction approach is provided.
- We illustrate that extracted patterns illustrate the battery performance level.
- Clustering algorithms are used to demonstrate visual interpretations of patterns behaviors.
- We obtain accurate shape classification performance.
- Battery performances are estimated through simple measurements.

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ABSTRACT

Direct estimation of battery performance is a major challenge as ageing process is a complex phenomenon not directly measurable. In this work a new methodology is provided to estimate global battery performances under real-life electric vehicle use. Such performances are estimated through battery signals patterns extraction. These signals patterns are used to identify physical degradation behavior of batteries.

The analysis framework is composed of patterns extraction, clustering algorithms, summarizing data representation in the feature space of cluster distances and classification algorithms. This methodology is then applied on datasets, acquired from batteries used on electric vehicles, without controlled environmental conditions.

The classification algorithm accuracy is studied on the obtained real data. The results suggest that battery signals patterns analysis provides an innovative technique for online estimation of the battery performance level. A detection of dysfunctions caused by ageing is also made, only based on battery signals pattern extracted during real vehicle accelerations.

1. Introduction

Lithium-ion (Li-ion) batteries are becoming the battery of choice in Electric Vehicles (EV) utilization. However, battery health and lifetime remain a major drawback to the use of Li-ion batteries in stringent life requirements. In EV context, accurate battery health assessment is primordial to improve the users confidence in the battery range. Indeed, it is one of the biggest obstacles to widespread acceptance of EVs. Market experts evaluated the effects of low range resources of EVs, as a significant feature for users' purchase intentions [1].

The overall performance of batteries is not constant along the vehicle life. Reduction of battery performances is caused by various internal and external mechanisms and is characterized by the capacity fade as well as an impedance augmentation [2]. For an electric vehicle (EV) utilization, the degradation of battery performances can be characterized by a diminution of the global vehicle autonomy available with a full charge [3].

Significant efforts have been achieved in order to understand the complex battery ageing process [4]. The aim for EV applications is to estimate the performance level of the battery with few measurements, in order to obtain online estimations of the battery performance level. Furthermore, ageing is a complex phenomenon,

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difficult to estimate with only few experiments and with online constraints. All these constraints create an intricate compromise between the model accuracy and its complexity [3].

Different methods are used to estimate the notion of battery performance level. These studies and methodologies come from many various fields such as electrochemical modeling [5,6] or performance modeling [7]. The diversity and multitude of existing studies dealing with battery ageing provide a large amount of information. However, most battery ageing studies are based on direct factors dependency and have limited prediction ability. These investigations mainly rely on simulated data, under controlled conditions, which is not totally representative of a real EV use [3].

Moreover, many data-driven methodologies are focused on the battery capacity estimation [8–10]. However, most of these data-driven approaches perform well on their training data only, under specific operational experiments, inducing robustness and generalization mistakes. In real life, external conditions cannot be controlled and these learned models are subject to misestimations. Thus, an accurate way of estimating battery capacity in real-time based on real EV using data-driven algorithm still requires investigations [3].

Battery performance changes can induce modifications of its electrochemical reactions in specific conditions [11], as highlighted by incremental capacity analysis and differential voltage analysis [12–14]. Thus, the battery degradations over time lead to a modification of its behavior through the utilizations [15,16]. These modifications can be detected with the different battery measures coming from real EV use. They can provide indications about the battery performance level. This behavior alteration is the focus of this study and will be used to estimate the battery performance level.

To explore battery performance evolution using only real-life vehicle test data is difficult and challenging. The opportunity considered here is to analyze the battery signals behavior, from data collected from real-life EV operations. In our view, revisiting battery signals behaviors using pattern extraction, analysis and classification tools may provide new insights about the relationship between these signals and the global battery performance level, being able to improve battery diagnosis and prognostics.

In this work, we propose an alternative approach by only using a data-driven methodology developed from a set of real EV uses. Such a methodology requires a large amount of training data in the development phase. In the EV context this training data requirement is very restrictive and costly. To face this problem, we investigate whether it is possible to extract relevant features from current and voltage signals collected during real EV uses, under uncontrolled conditions. A key issue explored by this paper is how battery capacity can be estimated during real EV uses, without specific requirements, based only on real use data and extracted features.

Section 2 presents the global theoretical framework and details the methods used for the extraction and classification of specific signals patterns. This will lead to an estimation of the battery capacity level, during its real uses. We study the most appropriate extracted patterns for performance classification, we also address the choice of distance metrics used for comparing battery features. In Section 3, accuracy of the methodology is evaluated for several types of classifiers, using real data. We show that an accurate analysis of the patterns morphological variation, can reveal meaningful changes in the underlying battery performances. Finally, Section 4 presents a large discussion of the proposed framework and its applications. Conclusion is given in Section 5.

2. Proposed method

The signals analysis framework is used in diverse application fields, showing for example its ability in classification tasks [17,18]. The main applications of signal processing and machine learning techniques are the clustering and classification methods, which aim to separate observations into groups in the unlabeled cases [19]. Such algorithms produce a major step in data analysis and exploration. Cluster analysis is a common unsupervised learning technique for partitioning a dataset into subsets of data elements that are similar according to some distance metric [20]. Furthermore, based on clustering, groups analysis results led to producing interesting interpretations.

The pattern analysis framework used in this study is illustrated in Fig. 1. The first step consists in a signal pattern extraction from real measured battery data, to observe the battery behavior modifications. Then, different classification methods are used to test whether the different signal morphologies represent different battery performance levels.

2.1. Datasets

Three EV instrumented $LiFeO_4$ (LFP) batteries datasets are used in this study. In each dataset, the battery signals are acquired at 10 Hz frequency, during non-controlled real EV uses, thereby data representative of a large variety of conditions an EV battery can be processed. Moreover, using real data ensures compatibility of developed methodologies for embedded uses. These batteries are used on three different EV, following a vehicle sharing concept, as several drivers alternatively take these EV for their personal travels. Thus, these experimentations are representative of the different ways an EV can be used.

Table 1 holds the main details of the battery design and their characteristics. Battery 1 and Battery 3 have a final capacity lower than Battery 2, inducing a higher degradation level and thus a more important modification of their behavior. Note that the end of life (EOL) criteria of the battery is usually defined with a capacity level equal to 80%.

2.2. Pattern extraction

The methodology proposed in this work is based on the assumption of the battery behavior modification over time. The aim is to explore the battery response depending on its performance levels. For a similar battery request, it is possible to detect battery ageing effects based on signals shape such as current and voltage [12,21]. Thus, both current and voltage profiles present significant behavior modifications, throughout battery life requiring investigation, characterizing their performance levels.

However, these signal modifications are low and complex to identify. To observe a battery behavior alteration, it is necessary to compare battery signals under comparable uses. For example, during an identical speed profile criterion, the battery voltage does not react the same way depending on its ageing level.

To observe and compare those signals modifications, we have to consider only a short length signal, with a unique and common dynamic that could be used as a common reference. Hence, the signal investigation requires the definition of criteria permitting the extraction of battery patterns. Thus, duration and speed acceleration criteria define pattern extraction conditions. These extraction criteria depend on vehicle and battery characteristics and have to be consequently adapted. The impact of these duration criteria is discussed further in the following sections. Based on these criteria, the obtained patterns can allow the identification of different behaviors according to their corresponding battery performance levels.