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Temperature dependent power capability estimation of lithium-ion batteries for hybrid electric vehicles

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ABSTRACT

The power capability of lithium-ion batteries affects the safety and reliability of hybrid electric vehicles and the estimate of power by battery management systems provides operating information for drivers. In this paper, lithium ion manganese oxide batteries are studied to illustrate the temperature dependency of power capability and an operating map of power capability is presented. Both parametric and non-parametric models are established in conditions of temperature, state of charge, and cell resistance to estimate the power capability. Six cells were tested and used for model development, training, and validation. Three samples underwent hybrid pulse power characterization tests at varied temperatures and were used for model parameter identification and model training. The other three were used for model validation. By comparison, the mean absolute error of the parametric model is about 29 W, and that of the non-parametric model is around 20 W. The mean relative errors of two models are 0.076 and 0.397, respectively. The parametric model has a higher accuracy in low temperature and state of charge conditions, while the non-parametric model has better estimation result in high temperature and state of charge conditions. Thus, two models can be utilized together to achieve a higher accuracy of power capability estimation.

1. Introduction

Due to the shortage of oil energy and the raising of public environmental awareness [1], electric vehicles (EVs) are becoming more and more popular [2]. Hybrid electric vehicles (HEVs) are claimed to be the most energy efficient and to produce the lowest amount of greenhouse gas emissions compared to electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) [3]. The hybrid architecture is exploited to achieve better fuel economy and lower exhaust emissions [4]. HEVs improve on the traditional internal combustion engine (ICE) vehicle due to its ability to reduce the emissions of greenhouse gases [5]. With lithium-ion batteries in the vehicle's power system, an HEV combines an ICE and an electric motor. To ensure that the HEV operates at the maximum efficiency, the ICE provides average power at constant speed area, while the electric motor which is usually powered by batteries satisfies the high power demand by delivering short, high power discharges and charge current pulses during a vehicle's acceleration, gradient climbing and regenerative braking [6]. As one of the critical components, battery performance determines the safety, reliability and efficiency of the vehicle system [7]. Battery's power capability affects the vehicle's acceleration and maximum speed performance [8] as well as braking performance [9]. Power capability is the ability of a battery to accept or deliver power at a given time [10]. If the battery cannot deliver enough discharging power, the vehicle may fail to restart or inhibit acceleration. If the charging power during a vehicle's regenerative braking operation is beyond the acceptable range for the batteries, the converted energy from the vehicle's kinetic energy would be wasted. Moreover, things may get worse that the charging current may exceed the battery's design limit and result in high current if battery management systems (BMS) did not set a proper current limit. This may cause thermal issues due to rapid heat generation and temperature rise. It may reduce the battery's lifespan by damaging the internal chemical

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materials further. Since batteries' power capability directly affects the safety and reliability of HEV operation, an overview of usable power will be significantly helpful. A power performance map which presents batteries' usable power in terms of the operation conditions (i.e. temperature, voltage, available capacity) will provide a guide to fully utilize the batteries to the extremes while maintaining safety. Moreover, accurate estimate of battery power capability provides a basis for the strategy of vehicle power management [11]. Optimal power and energy management [12] for HEV and PHEV is able to utilize two sources, ICE and batteries, efficiently and thus achieve the best fuel economy [13]. Therefore, estimating power capability accurately and generating a power performance map are crucial functions of the BMS.

Guidelines for batteries used as an auxiliary propulsion source in HEVs have been established by the US Department of Energy (DOE) for use in the Partnership for a New Generation of Vehicle (PNGV) program [14]. HEV duty cycle and battery requirements are described by Nelson [15]. The power requirements for batteries in HEVs are specified in terms of a characteristic time instead of a maximum C-rate [16]. To note, a C-rate is a measure of current at which a battery is discharged relative to its maximum capacity. Idaho National Engineering & Environmental Laboratory (INEEL) proposed an evaluation method for determining a battery's power capability called the hybrid pulse power characterization (HPPC) test [17]. Using this method, it is easy to determine a battery's power capability, which is represented by 10-s pulse discharge or charge peak power regarding different factors such as ambient temperature or state of charge (SOC) of the battery. SOC is a measure of the amount of charge stored in a battery at the present moment. In addition, the real driving conditions of HEVs can be simulated through changing the test control conditions based on conducting the HPPC test in laboratory environments. Subsequently, detailed information of a battery's power capability can be imported into a BMS to provide an optimal operation guideline for HEVs.

Real-time power demands usually vary with the instantaneous working condition of the HEV. History of power consumption, speed changes and road information can be used to estimate the real-time state of power capability (SOP) of the HEV [18]. To note, SOP is used to measure that the ICE and battery can meet the real-time power demand or not. A variety of studies have been conducted on the online prediction of SOP [19], which is commonly indicated by peak power [20]. The definition of peak power as the maximum discharge or charge power that can be maintained constant for10 s within the operational design limits is proposed by Plett [10]. Additionally, he presented a dynamic cell model for available power prediction of battery packs taking account current limit, voltage limit, and SOC limit. The difficulty is that this dynamic cell model is hard to simulate for on-board applications due to the low efficiency and high cost of complicated computation. To date, there are several approaches for online peak power prediction. Xiong et al. [9] proposed a dynamic electrochemical-polarization (EP) model based on multiple parameters. A data-driven adaptive SOC and SOP joint estimator was established to which the adaptive extended Kalman filter (AEKF) was subsequently applied for more convergent results [21]. Efforts to improve the model, such as higher estimation accuracy as well as parameter updates requiring less computation, were made by the authors [22]. Pei et al. [23] presented a training-free parameter and state estimator for online peak power estimation. An equivalent circuit model was used and a dual extended Kalman filter (DEKF) was applied for online parameter identification. Jiang et al. [24] presented the testing methods for battery peak power with comparative analysis. In addition, experiments were designed to verify the accuracy of the peak power estimation results in this work. These studies focused on real-time instantaneous power state prediction of batteries. However, the battery power supply can drop to zero almost instantly once its peak power exceeds the constraint boundary, such as current or voltage limitation, in accordance with the BMS control strategy. The ICE cannot take over providing power immediately since it takes time for the engine to respond. Thus the vehicle would stop moving, which is known as the “car frustration phenomenon” due to the instant disappearance of momentum. This phenomenon would degrade the user experience of driving and could also affect the braking performance of the vehicle, thus leading to traffic accidents. Therefore, estimating exact power capability of an HEV battery and implement a power performance map into BMS in advance can present a view of real-time usable power while driving to guide optimal operation as well as to guarantee the safety and reliability of HEVs.

The investigation of power capability was specified for lithium-ion manganese oxide batteries ($LiMn_2O_4$), which are widely used in HEVS. As a bulk phase, $LiMn_2O_4$ possesses excellent rate capability [25]. Moreover, it is highly favored as a positive electrode due to its merits such as lower cost, lower toxicity, and superior safety than V-, Co-, or Ni-based electrodes [26]. In this study, a 10-s pulse discharge peak power was used to represent the power discharge capability of batteries. Similarly, corresponding application can be adopted for the charging case. Temperature dependency of power capability was investigated based on the experimental results of HPPC test. Both a parametric model and non-parametric model using data-driven approach were built to accurately estimate the power capability of $LiMn_2O_4$ batteries. A key advantage is that our models are only based on the data from several parameters whose real-time states are easily obtained while comparing with other model-based peak power estimators, which have more difficulty obtaining real-time model parameters accurately, such as the equivalent circuit model-based estimator or the electrochemistry model-based estimator. The performance of two proposed models were compared and evaluated via a list of statistical metrics under different temperatures and different SOCs.

The reminder of the paper is arranged as follows. Section 2 demonstrates an experimental platform and tests under varied ambient temperatures for power capability determination. Section 3 analyzes the variation of test samples and illustrates the temperature dependency of power capability. An operating map of power in terms of temperature and SOC are presented as well. In section 4, both the parametric model and non-parametric model using data-driven approach are used for power estimation. The test data of three battery cells are used for model parameter identification or model training. In section 5, the model validation results of two models are compared using statistical measures. Detailed discussion is presented including the applicability of two models. Finally, conclusions and suggestions for future work are given in section 6.

2. Experiments

The experimental platform is shown in Fig. 1. It consisted of 5 parts: (1) six lithium-ion $LiMn_2O_4$ battery cells; (2) a temperature controlled chamber; (3) Digatron battery test system; (4) a data logger to record the battery data; and (5) a PC to give the orders and monitor data information. The test samples were composed of a graphite negative electrode and a lithium manganese oxide (LMO) positive electrode. Their basic specifications are given in Table 1. The open circuit voltage–SOC test and HPPC test at various ambient temperatures were conducted for the test samples. During the tests, data (current, voltage, and temperature of each cell) was measured and logged in1 second intervals.