Control Engineering Practice 56 (2016) 37–48

Contents lists available at ScienceDirect

Control Engineering Practice

journal homepage: www.elsevier.com/locate/conengprac

Model-based real-time thermal fault diagnosis of Lithium-ion batteries

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ARTICLE INFO

Article history:
Received 9 February 2016
Received in revised form
2 July 2016
Accepted 2 August 2016

Keywords:
Lithium-ion batteries
Fault diagnosis
Thermal faults
Observer
Adaptive threshold

ABSTRACT

Ensuring safety and reliability is a critical objective of advanced Battery Management Systems (BMSs) for Li-ion batteries. In order to achieve this objective, advanced BMS must implement diagnostic algorithms that are capable of diagnosing several battery faults. One set of such critical faults in Li-ion batteries are thermal faults which can be potentially catastrophic. In this paper, a diagnostic algorithm is presented that diagnoses thermal faults in Lithium-ion batteries. The algorithm is based on a two-state thermal model describing the dynamics of the surface and the core temperature of a battery cell. The residual signals for fault detection are generated by nonlinear observers with measured surface temperature and a reconstructed core temperature feedback. Furthermore, an adaptive threshold generator is designed to suppress the effect of modelling uncertainties. The residuals are then compared with these adaptive thresholds to evaluate the occurrence of faults. Simulation and experimental studies are presented to illustrate the effectiveness of the proposed scheme.

1. Introduction

Li-ion batteries are becoming the dominant energy storage solutions in electric and hybrid electric vehicle applications due to their high specific power and energy as well as relatively longer life. For such demanding applications, these batteries must perform reliably and pose no safety threats. One such issue that greatly impacts the safety, stability, performance and life of a Li-ion battery is thermal behaviour. There are many reported instances of thermal runaway in Li-ion batteries leading to fires, for example, in Wang et al. (2012). Temperature imbalances among multiple cells in a battery pack could also greatly influence the aging behaviour of the battery, as reported in Bandhauer, Garimella, and Fuller (2011). Therefore, thermal management strategies are essential to mitigate these effects and avoid catastrophic failures of the battery. In line with these needs, in this paper, a model-based real time diagnostics scheme is proposed for the detection and isolation of a set of faults that affect surface and core temperature dynamics of the battery.

Numerous thermal modelling studies have been conducted on rechargeable Li-ion batteries. The objectives of the proposed thermal models fall under two categories: 1) to ensure proper thermal management system design under normal (faultless) operating conditions, and 2) to provide predictive capability for thermal abuse responses (see Doughty, Butler, Jungst, & Roth, 2002). Comprehensive thermal models developed in Kim, Pesaran, and Spotnitz (2007); Guo et al. (2010); Maleki and Shamsuri (2003); Hallaj, Maleki, Hong, and Selman (1999) provide a more accurate understanding of the cell behaviour under abuse conditions like overheating and external short circuits. Since these 3D models require high computational capabilities, currently their use in battery management systems (BMS) may only be viable for industrial/stationary storage applications (see Chen, Wan, & Wang, 2005). In vehicle applications, simple one-dimensional thermal models that compute the average lumped temperature of the cell are viable for real-time BMS implementations. For example, one such model is presented in Smith and Wang (2006). As a trade-off between the comprehensive and simplified modelling approaches, a two-state thermal model that predicts the surface and core temperature of a battery cell has also been proposed in Doughty et al. (2002) and Park and Jaura (2003). These two-state models provide more information than the lumped model while retaining computational simplicity. In this paper the two-state thermal model is adopted to design and analyze our proposed thermal fault diagnosis scheme.

In the literature, several estimation techniques are proposed for Li-ion batteries. Two main categories of such estimation schemes

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http://dx.doi.org/10.1016/j.conengprac.2016.08.002
0967-0661/

are: 1) electrochemical model-based approaches: Dey, Ayalew, and Pisu (2015a); Dey, Ayalew, and Pisu (2015b); Klein et al. (2013); Moura, Chaturvedi, and Krstic (2012) and, 2) equivalent circuit model-based approaches: He, Xiong, Zhang, Sun, and Fan (2011), Charkhgard and Farrokhi (2010), Hu and Yurkovich (2012), Kim (2006), Plett (2004), and Gould, Bingham, Stone, and Bentley (2008). However, fewer works address the temperature estimation problem of Li-ion batteries. An adaptive observer for core temperature estimation was presented in Lin et al. (2013). A battery cell temperature estimation algorithm was presented in Debert, Colin, Bloch, and Chamaillard (2013) based on Linear Parameter Varying (LPV) thermal model and a polytopic observer. Richardson, Ireland, and Howey (2014) presented a method for battery internal temperature estimation by combining impedance and surface temperature measurements. A Kalman filter-based approach is presented in Kim, Mohan, Siegel, Stefanopoulou, and Ding (2014) to estimate the radial temperature distribution of a cylindrical battery cell under unknown cooling conditions. Papazoglou, Longo, Auger, and Assadian (2014) and Feig, Billitteri, Longo, and Auger (2014) have also explored Kalman filtering techniques for battery temperature estimation. The correlation between thermal imbalance and cell degradation has been studied in Merla et al. (2016).

Compared to the estimation problems, battery real-time diagnostics problems are even less explored or reported in the literature. The reported works are mainly concerned with sensor and/or actuator fault detection (see Marcicki, Onori, & Rizzoni, 2010; Liu, Ahmed, Rizzoni, & He, 2014; Lombardi, Zarudniev, Lesecq, & Bacquet, 2014; Dey, Mohon, Pisu, & Ayalew, 2015c); Singh, Izadian, and Anwar (2013) presented an algorithm for detecting overcharge and over-discharge faults. An electrochemical fault diagnostics scheme has been recently presented in Dey and Ayalew (2015); Marcicki et al. (2010); Liu et al. (2014) and Biron, Pisu and Ayalew (2015) used a one-state lumped thermal model for fault detection. However, none of these approaches exploit the two-state thermal model which can potentially capture more information on thermal dynamics including the core temperature. Therefore, these existing approaches may not be able to detect and isolate internal thermal faults. The main contribution of the present paper is that it proposes a two-state thermal model-based diagnostic scheme that takes the core temperature dynamics into account. The novelty of the proposed diagnostic scheme with respect to the existing thermal diagnostic schemes (Marcicki et al., 2010 & Liu et al., 2014), lies in its capability of detecting and isolating two sets of faults: faults that affect the core temperature dynamics (e.g. thermal runaway fault) and faults that affect the surface temperature dynamics (e.g. convection fault). Note that, this work explores the problem of thermal fault diagnosis which is different from the previous works of present authors that explores electrochemical state estimation (Dey, Ayalew, & Pisu, 2015), combined state and parameter estimation (Dey, Ayalew, & Pisu, 2015), sensor fault diagnosis (Dey, Mohon, Pisu, & Ayalew, 2015) and, electrochemical fault diagnosis (Dey & Ayalew, 2015) problems.

Model-based fault diagnosis of dynamic systems has been an active research area for several decades and explored for various applications. For some recent results in this area, please refer to Gao, Ding, and Cecati (2015). There are some existing estimation-based approaches for fault diagnosis, e.g. sliding mode observer (Edwards, Spurgeon, & Patton, 2000), Kalman filter (Alessandri, Caccia, & Veruggio, 1999), H_∞ filter (Zhong, Ding, Lam, & Wang, 2003). Essentially, these approaches utilise output estimation errors as residual signals, which are used for fault diagnosis. Typically, a fault is diagnosed if the residual is non-zero. However, the sliding mode observers may be ineffective in diagnosing incipient faults due to chattering problems. The H_∞ filter also suffers from similar problem as it might mask the incipient faults. The Kalman filter based approaches generally assume a Gaussian probability distribution of the uncertainties which might not be true in practical applications. Therefore, a Lyapunov-based nonlinear observer approach is adopted in this work which does not suffer from the aforementioned issues.

One of the main challenges in model-based diagnostics arises from the uncertainties. Due to modelling, parametric and measurement uncertainties, the residuals will be nonzero even in no fault conditions. Several methods have been proposed to deal with fault diagnosis problem in presence of modelling uncertainties, e.g. sliding mode observers (Yan & Edwards, 2007), adaptive estimators (Patton & Klinkhieo, 2009; Patton, Putra, & Klinkhieo, 2010). However, most of these approaches require assumptions on the structures of distribution matrices of the faults and uncertainties which may not always be met in practice. On the other hand, some diagnostic approaches have also been proposed to deal with modelling uncertainties without any assumptions on the distribution matrices. One of such approaches is the use of non-zero thresholds (Emami-Naeini, Akhter, & Rock, 1988). Essentially, the residuals are compared against some non-zero thresholds to conclude the occurrence of the faults. There are two types of thresholds that are used in literature, fixed thresholds (e.g. Emami-Naeini et al., 1988) and adaptive thresholds (e.g. Zhang, Polycarpou, & Parisini, 2002 in time domain, Ding & Frank, 1991 in frequency domain). In case of dynamic uncertainties, fixed thresholds may need to be set at much higher levels therefore potentially leading to higher miss detection rates whereas lowering fixed thresholds might increase the false alarm rate. Further, fixed thresholds might not be effective for some systems where the operating conditions, control signals and uncertainties have significant variations. In such cases, adaptive thresholds might be effective in improving the robustness of the diagnostic scheme. Essentially, the adaptive threshold generator generates a dynamic threshold based on the nominal system dynamics and known bounds of the uncertainties. For implementation purpose, these approaches utilise filters that provide a dynamic threshold with which the observer output error (residual signal) is compared to diagnose the faults. In this paper, we adopt the adaptive threshold approach in conjunction with the observers to design the diagnostic scheme.

In this paper, the preliminary work on model-based thermal fault diagnosis that is presented in the brief conference paper (Dey et al., 2015) is extended by: 1) considering a more comprehensive battery cell model including essential nonlinearities and incorporating a nonlinear observer design approach to deal with the nonlinearities, 2) considering temperature dependency of the internal resistance of the battery cell, 3) considering the effect of modelling uncertainties and designing an adaptive threshold generator to suppress their effects in the diagnostic scheme, 4) including some experimental results. An observer-based approach for model-based diagnosis is adopted here (Gertler, 1998). A nonlinear observer is designed using a two-state thermal model and voltage and temperature measurements. The output errors of the observer are used as the primary residuals, which have the idealised property of being zero in a non-faulty condition and non-zero otherwise. However, due to the presence of modelling uncertainties, the residuals are generally non-zero even in the absence of the faults. To deal with this issue, an adaptive threshold generator is used. The adaptive threshold generator is essentially a filter that is designed based on the nominal error dynamics of the observer and known uncertainty bounds (Zhang et al., 2002). The adaptive threshold generator provides dynamic thresholds to which the residuals are compared. If the residual crosses the threshold a fault is declared. Simulation and experimental studies are provided to validate the proposed algorithm.