Abstract

Lithium-ion batteries are gaining popularity in the scientific community. Compared to lead acid, nickel metal hydride (NiMH), and nickel-cadmium (NiCd) batteries, they are more energy efficient and have a higher power density. Furthermore, their long life cycle, small size, lightweight, wide temperature operation range, rapid charge capability, low self-discharge rate, no memory effects, etc., make them suitable for a wide range of applications, including laptops, mobile phones, and electric vehicles. However, without adequate monitoring and control of the batteries through a battery management system (BMS), issues like safety, reliability, durability, and cost would arise. Precise estimations of the state of charge (SoC) and the state of health (SoH)is the most crucial task of the BMS. It provides vital information about the battery's charge level and aging level, which may be utilized to perform maintenance or modify operational methods to extend its service life. SoC is the available capacity (in Ah) as a percentage of the battery's rated capacity that can be used to calculate the potential energy of a battery. Battery SoH measures its ability to store and distribute electrical energy relative to a new battery. This thesis presents a joint estimator of online parameter identification and an improved adaptive extended Kalman filter (AEKF) for SoC estimation of Li-ion batteries. The estimation process is based on a second-order equivalent circuit model (ECM), addressing the problem of ill-conditioning while estimating the SoC in real-time. The optimal parameters are computed using a three-state decoupled parameter estimation approach: i) ohmic resistance estimator using recursive least square (RLS) method, (ii) Tikhonov regularisation with Kalman filter (KF) for the fast time constant estimate, which improves system conditioning, and (iii) slow time constant measurement utilizing lookup table-based method. Finally, SoC estimation is achieved using a modified AEKF with fading weight factor mechanism. The estimated SoC is used in a closed-loop feedback with parameter estimation, verifying the algorithm's correctness and speed of convergence. The Chi-square test improves the AEKF's adaptive measurement covariance introduction time. The technique was validated under various operating circumstances using experimentally generated trending current patterns. In addition, this proposed model-based diagnostic procedures have been integrated into a cloud-based system, ensuring continuous and accurate battery state monitoring. All battery-related data is measured and sent to the cloud via the Internet of Things (IoT), where the proposed diagnostic algorithms analyze the information and estimate the SoC. The suggested estimating method has a low computing cost, making it suitable for real-time industrial applications. The following work in the thesis presents the estimation process of SoH. Data-driven approaches are promising for SoH estimation since they can perform well without human intervention and have excellent nonlinear prediction abilities. Majority of studies assume that the training data is sufficient. But in the real world, collecting data is often time-consuming and expensive. This thesis suggests transfer learning to make the model less dependent on data for monitoring battery health. Many techniques presume that the distributions of training and testing data are same. A model that works for one data set might not work for another due to distribution mismatch. In this thesis, we suggest using a Gaussian process regression-based adaptive transfer learning method (AT-GPR) where learning systems can be constructed by automatically assessing source-to-target task similarity. A semi-parametric Bayesian transfer kernel is proposed to train the target task model. The proposed method is validated using data from two publicly available data sets on cyclic battery aging in various operating situations. Experiments demonstrate that AT-GPR produces accurate prediction results; nevertheless, only 20% of the target data set is used for training.

Keywords: Lithium-ion Battery, equivalent circuit model, ill-conditioning, Tikhonov regularized Kalman filter, state-of-charge estimation, adaptive extended Kalman filter, real-time implementation, state-of-health estimation, adaptive transfer learning, Gaussian process regression.