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Critical review of on-board capacity estimation techniques for lithium-ion batteries in electric and hybrid electric vehicles

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HIGHLIGHTS

- Discussion of challenges and issues for on-board capacity estimation.
- Review of model-based, electrochemical model-based and data driven-based approaches.
- Review of ICA/DVA and aging prediction-based models.

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ABSTRACT

This work provides an overview of available methods and algorithms for on-board capacity estimation of lithium-ion batteries. An accurate state estimation for battery management systems in electric vehicles and hybrid electric vehicles is becoming more essential due to the increasing attention paid to safety and lifetime issues. Different approaches for the estimation of State-of-Charge, State-of-Health and State-of-Function are discussed and analyzed by many authors and researchers in the past. On-board estimation of capacity in large lithium-ion battery packs is definitely one of the most crucial challenges of battery monitoring in the aforementioned vehicles. This is mostly due to high dynamic operation and conditions far from those used in laboratory environments as well as the large variation in aging behavior of each cell in the battery pack. Accurate capacity estimation allows an accurate driving range prediction and accurate calculation of a battery's maximum energy storage capability in a vehicle. At the same time it acts as an indicator for battery State-of-Health and Remaining Useful Lifetime estimation.

1. Introduction

Lithium-ion batteries (LIBs), as an alternative energy storage technology to lead-acid or nickel-metal hydride batteries, are becoming more popular for various applications, such as electric and hybrid electric vehicles. Their higher specific or volumetric power and energy density, high cycle lifetime and decreasing costs have made them more attractive for the aforementioned applications. Their operation strategy needs to be optimized in order to extend their lifetime (durability) and prevent critical operating conditions (e.g., overcharging, charging at low temperatures or high currents rates), which yield accelerated aging. In Ref. [1], the authors provide a wide overview regarding challenges and issues for health prognostic of LIBs. Furthermore, Bárre et al. [2] discusses various aging mechanisms of LIBs in EVs. Techniques based on electro-chemical models, equivalent-circuit models, statistical models, etc. for impedance rising and capacity fading during a battery's lifetime in order to estimate State-of-Health (SoH) and Remaining Useful Lifetime (RUL) are addressed and compared. Indeed, the topic of on-board capacity estimation has not been sufficiently discussed in the past. The main scope of this study is to give an overview over available techniques for on-board capacity estimation, while the strengths and weaknesses of each methodology are discussed.

Battery capacity with ampere hours or ampere seconds as a unit corresponds to the amount of charge extractable from the battery

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Nomenclatures

AEKF	Adaptive extended Kalman filter
BMS	Battery management system
CC–CV	Constant current–constant voltage
CDKF	Central difference Kalman filter
DEKF	Dual extended Kalman filter
DVA	Differential voltage analysis
EoL	End of life
EKF	Extended Kalman filter
EMF	Electro motive force
EV	Electric vehicle
ECM	Equivalent circuit model
HEV	Hybrid electric vehicle
ICA	Incremental capacity analysis
KF	Kalman filter
LIB	Lithium-ion battery
LFP	Positive electrode active materials with a common formula $LiFePO_4$
LS	Least square
LTO	Negative electrode active materials with a common formula $Li_4Ti_5O_{12}$
NEDC	New European Driving Cycle
NMC	Positive electrode active materials with a common formula of $Li_x(Ni_xMn_yCo_z)O_2$
OCV	Open circuit voltage
PDE	Partial differential equation
PDF	Probability density function
PHEV	Plug-in hybrid electric vehicle
RLS	Recursive least square
SampEn	Sample entropy
SEI	Solid electrolyte interface
SPM	Single particle model
SoH	State-of-Health
SoC	State-of-Charge
SoF	State-of-Function
SPKF	Sigma point Kalman filter
UDDS	Urban dynamometer driving schedule
UKF	Unscented Kalman filter
V2G	Vehicle-to-grid
WLS	Weighted least squares
WRLS	Weighted recursive least squares

until cut-off discharge voltage limit is reached when starting from a fully charged state. One important issue is that the capacity is not a constant parameter, and it decays over the battery's lifetime due to internal aging processes when the battery is cycled or even if it is not being used due to calendar aging [3,4]. In automotive applications, battery temperature, discharging and charging current rates, the Depth-of-Discharge (DoD) during battery operation and the State-of-Charge (SoC) during rest periods are the major degradation factors [1]. From an electro-chemical point of view, the capacity loss of LIBs generally occurs because of the loss of cyclable lithium due to SEI formation, and the impedance increase is mainly due to side reactions occurring in the anode. Furthermore, aging processes due to, e.g., defoliation of active mass, increase of internal resistance or contact loss can lead to capacity loss [1,2,5–8]. However, SEI formation does not occur for LIBs with $Li_4Ti_5O_{12}$ (LTO) anode materials, and their capacity loss happens mainly due to capacity loss in the cathode [9,10].

Due to the decrease of battery performance over the battery lifetime, an accurate prediction of SoH and State of Energy (SoE) is essential. SoH and SoE are time dependent variables, which are often consulted to track the characteristic changes of the LIBs while the battery is aging. Insufficient estimation accuracy may yield serious or even catastrophic issues. (e.g., Prediction of Battery packs fail or inaccurate estimation of driving range).

Actual battery capacity and actual battery impedance are important indicators for SoH estimation. The SoH is usually defined either.

- as a ratio between the actual battery capacity at nominal conditions (nominal temperature and nominal discharge current) and the battery's nominal capacity, i.e., $SoH_c = C_{actual}/C_{nominal}$, or
- as a ratio between the actual battery impedance value at nominal conditions and its nominal impedance, i.e., $SoH_r = R_{actual}/R_{nominal}$.

Generally, for applications where the available energy in the battery plays the most important role, such as electric vehicles (EVs) or plug-in hybrid EVs, the end of life (EoL) criteria of a battery is often defined as the decrease of its capacity to 70% or 80% of its initial value [11–13]. In applications where the available power is more important, such as in pure hybrid electric vehicles (HEVs), the EoL is often defined as being reached when the battery impedance is doubled [11]. At the same time, for SoE, the EoL criteria is defined as being reached when its value is limited to 20% of the energy loss in comparison to its nominal value [14].

In Fig. 1, a possible integration of capacity estimation algorithm in the battery management systems (BMS) is illustrated.

Generally, methods for on-board capacity can be divided into the following four categories Fig. 2:

1. Voltage-based estimation methods using open circuit voltage or, strictly speaking, the electro motive force (EMF) and SoC correlation during an idle or operation time,

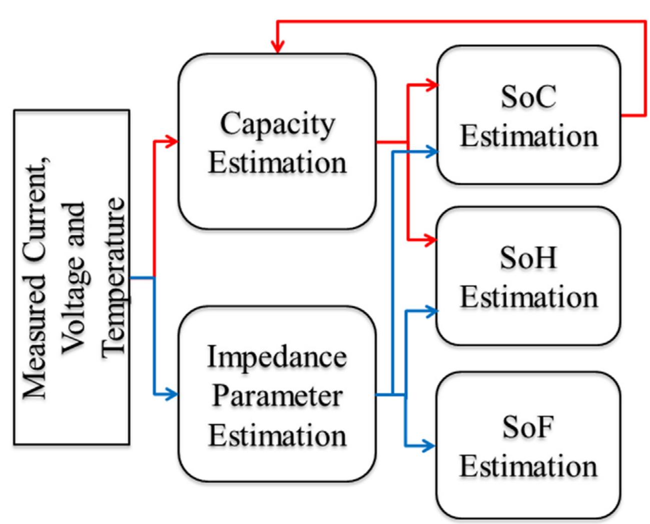

Fig. 1. Integration framework of capacity estimation in the context of a simplified battery management system.