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Development of Lithium-Ion Battery State Estimation Techniques for Battery Management Systems

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as part of the collaborative doctoral degree and/or fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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LIST OF SYMBOLS

c_e	Lithium-ion concentration in electrolyte
c_s	Lithium-ion concentration in solid electrode
c_{sd}	Discretised lithium-ion concentration in solid electrode
c_{suf}	Surface lithium-ion concentration
$c_{s,max}$	Maximum possible solid-phase lithium-ion concentration
c_{s_mean}	Mean lithium-ion concentration in solid electrode
c_{s_total}	Total number of lithium-ions in solid electrode
DCR	Battery direct current resistance
D_e	Lithium-ion diffusion coefficient in electrolyte
D_s	Lithium-ion diffusion coefficient in solid electrode
E_a	Maximum available energy
F	Faraday's constant
I	Battery loading current
$I_{D,max}$	Maximum discharge current
$I_{C,min}$	Minimum charge current
i_e	Local current in the electrolyte
i_0	Exchange current density
j_n	Molar flux
n_p	The number of cells connected in parallel
n_s	The number of cells connected in series
P_{chg}	Charge power capability
$P_{C,min}$	Minimum charge power
P_{dis}	Discharge power capability
$P_{D,max}$	Maximum discharge power
P_{Gibbs}	Battery Gibbs power
P_{inst}	Battery instantaneous available power
P_{res}	Power dissipation in battery internal resistance
Q_0	Battery initial capacity

Q_a	Battery actual capacity
Q_N	Battery nominal capacity
R^2	Coefficients of determination
R_c	Empirical contract resistance
R_p	Radius of spherical solid particles
r_{eff}	Kinetic rate constant
SOC	Battery state of charge value
SOE	Battery state of energy value
T	Absolute temperature
T_{bas}	Based temperature
U	Cell terminal voltage
V_{max}	Permitted maximum cell terminal voltage
V_{min}	Permitted minimum cell terminal voltage
V_{OCV}	Open circuit voltage
η_s	Over potential
Φ_s	Electric potential in solid electrode
Φ_e	Electric potential in the electrolyte
ΔQ	Cumulative capacity

LIST OF ABBREVIATIONS

ADB	Active discharge balance
AEKF	Adaptive extended Kalman filter
BMS	Battery management system
CB	Charge balance
CC	Constant current
CDB	Charge-discharge balance
CV	Constant voltage
DCR	Direct current resistance
DEKF	Dual extended Kalman filter
DST	Dynamic stress test
DV	Differential voltage
DVA	Differential voltage analysis
ECM	Electrical circuit model
EKF	Extended Kalman filter
EM	Electrochemical model
EOC	End of charge
EOD	End of discharge
EV	Electric vehicle
FL	Fuzzy logic
FP	Feature point
GHG	Greenhouse gas
HPPC	Hybrid pulse power characterization
IC	Incremental capacity
ICA	Incremental capacity analysis
KF	Kalman filter
LS	Least-square
MAE	Maximum absolute error
MAPE	Mean absolute percentage error

MPC	Model predictive control
NN	Neural network
NPF	Nonlinear predictive filter
OCV	Open circuit voltage
PDB	Passive discharge balance
PDE	Partial differential equation
PF	Particle filter
PI	Proportional-integral
RE	Relative error
RMSE	Root mean square error
SEI	Solid-electrolyte interphase
SMO	Sliding-mode observer
SOC	State of charge
SOE	State of energy
SOH	State of health
SOP	State of power
SPM	Single particle model
SVM	Support vector machine
SVR	Support vector regression
UDDS	Urban dynamometer driving schedule

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ABSTRACT

Lithium-ion batteries are being widely used as an enabling energy storage for electric vehicles, renewable energy storage systems, and power grids, etc., as they always exhibit high energy density and long life cycle along with environmental friendliness. However, overly pessimistic or optimistic estimates of lithium-ion battery states would result in waste or abuse of battery available capabilities and may even lead to fire and explosion risks. The safety and reliability of battery utilization necessitate the accurate and reliable state estimation techniques in battery management systems (BMSs). This thesis focuses on the development of the estimation methods of lithium-ion battery states of interest, which are capable of determining internal battery status accurately.

The first phase of this thesis centers on battery electrochemical model simplification and discretization for incorporating the co-estimation algorithm of battery state of charge (SOC), capacity, and resistance based on the proportional-integral (PI) observers. A physics-based battery model that has the capability to describe the electrochemical reaction process inside the battery is first developed. Trinal PI observers are then employed to implement the co-estimation task. It takes the influence of battery aging on SOC estimation by furnishing the state equations with up-to-date capacity and resistance estimates into account, thereby improving the SOC estimation accuracy.

To achieve high estimation accuracy with low computation costs, SOC and capacity estimation approaches based on the incremental capacity analysis and differential voltage analysis are subsequently investigated. Feature points extracted from the SOC based incremental capacity/differential voltage (DV) curves are applied for developing the estimation algorithm of battery SOC and capacity. Besides, an extended Kalman filter and a particle filter are served as the state observers in an SOC estimator based on the DV model for further improving the performance of estimation.

With the credible SOC estimates, a state of energy (SOE) estimator based on a quantitative relationship between SOC and SOE is proposed in the next step, and a moving-window energy-integral technique is then incorporated to estimate the battery maximum available energy. Through the analysis of ambient temperature, battery discharge/charge current rate, and cell aging level dependencies of SOE, the relationship between SOC and SOE can be quantified as a quadratic function for SOE estimation. The simplicity of the proposed SOE estimation method can avoid the heavy computation cost required by the conventional model-based SOE estimation methods.

Finally, two state of power capability predictors are designed for a battery to sufficiently absorb or deliver a certain amount of power within its safe operating region. A battery direct current resistance model for quantitatively describing its temperature dependence is proposed and implemented on the battery capability prediction in the first method, which is beneficial to reduce the memory-consumption and dimension of the power characteristic map embedded in BMSs for applications. Different from the conventional methods using the limits of macroscopically observed variables for power prediction, the second method investigates a physical mechanism-based power prediction method and quantifies the relationship between battery power capability and surface lithium concentration for instantaneous peak power prediction. The proposed methods are experimentally verified with various cell aging levels and ambient temperatures.

The proposed approaches for accurately modelling and estimating lithium-ion battery states in this thesis can contribute to safe, reliable and sufficient utilization of the battery. The developed methods are pretty general, and therefore are promising to provide valuable insight to the investigations of other types of batteries with various chemistries.