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

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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.