

UNIVERSITY OF TECHNOLOGY SYDNEY  
Faculty of Engineering and Information Technology

**Measurement, Modelling and State Estimation  
Techniques for Lithium-ion batteries**

by

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A THESIS SUBMITTED  
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## Certificate of Authorship/Originality

I, Qi Yao, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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# Dedication

My Uncle, Chengjin Yao

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# List of Publications

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- J-1. **Q. Yao**, D. D. -C. Lu and G. Lei, "Rapid Open-Circuit Voltage Measurement Method for Lithium-ion Batteries Using One-cycle Bipolar-current Pulse," in IEEE Journal of Emerging and Selected Topics in Industrial Electronics, doi: 10.1109/JESTIE.2020.3041711.
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- C-2. **Q. Yao**, D. D. Lu and G. Lei, "A Simple Internal Resistance Estimation Method Based on Open Circuit Voltage Test Under Different Temperature Conditions," 2018 IEEE International Power Electronics and Application Conference and Exposition (PEAC), Shenzhen, 2018, pp. 1-4.

## Under Process Journal Papers

- J-3. **Q. Yao**, D. D. -C. Lu and G. Lei, "A Sensorless Temperature Estimation Method For Lithium-ion Battery Using Recurrent Neural Network With Gated Recurrent Unit"
- J-4. **Q. Yao**, D. D. -C. Lu and G. Lei, " An Empirical Comparison of Different Recurrent Neural Networks for Battery State of Charge Estimation

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# Abbreviation

BMS - Battery Storage System

EV - Electric Vehicle

BMS - Battery Management System

SOC - State of Charge

SOH - State of Health

LMO -  $\text{LiMn}_2\text{O}_4$

NCM -  $\text{LiCo}_x\text{Ni}_y\text{Mn}_z\text{O}_2$

NCA -  $\text{LiNi}_{0.8}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$

LFP -  $\text{LiFePO}_4$

ECM - Electric Circuit Model

RC - Resistor Capacitor

OCV - Open Circuit Voltage

RNN - Recurrent Neural Network

AI - Artificial Intelligence

EIS - Electrochemical Impedance Spectroscopy

RMSE - Root Means Square Error

MAE - Mean Absolute Error

PDE - Partial Differential Equations

P2D - Pseudo-Two-Dimensional

SPM - Single Particle Model

OCBCP - One Cycle Biopolar Current Pulse

SRC - Switched Resistor Circuit

ESR - Equivalent Series Resistance



DC - Direct Current

AC - Alternating Current

DAQ - Data Acquisition

DTF - Discrete-time Fourier transform

PWM -Pulse Width Modulation

CCM -Continuous Conduction Mode

FNN - Feedforward Neural Network

AHC - Ampere Hour Counting

DD - Data Driven

MB - Model-Based

LSTM - Long Short-Term Memory

GRU - Gated Recurrent Unit

BiRNN - Bidirectional Recurrent Neural Network

LSTM-RNN - Long Short-Term Memory Recurrent Neural Network

GRU-RNN - Gated Recurrent Unit Recurrent Neural Network

BiLSTM-RNN - Bidirectional Long Short-Term Memory Recurrent Neural Network

# ABSTRACT

## **Measurement, Modelling and State Estimation Techniques for Lithium-ion batteries**

by

Qi Yao

Lithium-ion batteries have been widely adopted in energy storage systems for electric vehicles (EVs), electric portable devices, smart grid, and renewable energy systems because of their high energy density, long lifetime, and low self-release rate. When lithium-ion batteries are used in real applications such as EVs, they normally work with power converters, which can deliver power from the batteries to the load and regulate the system output voltage. However, Lithium-ions batteries also have a critical safety concern. As chemical products, the battery states such as state of charge (SOC) cannot be directly measured by sensors; the only directly measurable signals of lithium-ion batteries during battery operation are terminal voltage, operational current and temperature. Some models have been established to calculate information of the battery states using measured signals. However, the inherent chemical characteristics of lithium-ion batteries mean that it is difficult to achieve a highly accurate online battery state monitoring or estimation. When the battery state is estimated inaccurately, it will waste the available capacities, reduce battery lifetime, and could even lead to fire or explosion. To avoid these issues, lithium-ion batteries should be well-monitored and managed by a battery management system (BMS).

This thesis focuses on improving the efficiency, reliability and estimation accuracy for the BMS of lithium-ion batteries from signals measurement, battery modelling and state estimation perspectives. First, this thesis develops an improved battery modelling techniques by proposing a rapid and accurate open circuit volt-

age (OCV) measurement method. Second, this thesis develops practical battery impedance measurement techniques, which can be used for offline battery modelling and online states monitoring. Third, a sensorless battery surface temperature estimation has been proposed to improve the reliability and reduce the cost of the BMS. Fourth, as artificial intelligence (AI) technology has developed, more recurrent neural network (RNN) based battery SOC estimation methods have been proposed. This thesis comprehensively evaluates previous methods from theoretical and experimental perspectives and proposes a RNN model with suitable hyper-parameter setting for online SOC estimation with high accuracy and low computational burden.