A WHITE-BOX APPROACH FOR HEALTH PROGNOSIS OF LITHIUM-ION BATTERIES UNDER DYNAMIC OPERATING CONDITIONS

NITIKA GHOSH

CENTRE FOR AUTOMOTIVE RESEARCH AND TRIBOLOGY
INDIAN INSTITUTE OF TECHNOLOGY DELHI
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A White-Box Approach for Health Prognosis of Lithium-Ion Batteries under Dynamic Operating Conditions

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Nitika Ghosh

Centre for Automotive Research and Tribology

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CERTIFICATE

This is to certify that the thesis entitled "A White-Box Approach for Health Prognosis of Lithium-Ion Batteries under Dynamic Operating Conditions", submitted by Nitika Ghosh to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** in Centre for Automotive Research and Tribology, is a record of the original, bona fide research work carried out by her under our supervision and guidance. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in parts or in full to any other University or Institute for the award of any degree or diploma to the best of our knowledge.

Dr. Deepak Kumar
Centre for Automotive Research and Tribology, Indian Institute of Technology Delhi, New Delhi

Dr. Akhil Garg
School of Mechanical Engineering, Huazhong University of Science and Technology, Wuhan, China

Dr. Alexander Warnecke
Hella GmbH & Co. KGaA, Lippstadt, Germany

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ABSTRACT

In this thesis, health prognosis of commercial 18650 lithium-ion batteries (LiBs) which includes estimation of state of health (SoH) and prediction of remaining useful life (RUL) in mobility applications is investigated through lifetime testing and modelling. The lifetime tests investigate the impact of temperature, C-Rate, depth of discharge (DoD) state of charge (SoC) and dynamic loading profiles.

Results from the lifetime test and other battery datasets are used in the health indicator (HI) extraction that are more practical as compared to already existing HIs such as battery capacity or internal resistance in dynamic operating conditions. The results showed that the HIs resonates with the ageing process and can be easily measured using battery external variables without additional testing.

The extracted HIs after the data pre-processing are used for the development of the white-box ageing model. The HI based neural network (NN) combines system *a priori* knowledge with the non-linear approximation capability suitable for dynamic on-board driving conditions. In white-box model architecture, each circuit element of the electrical equivalent circuit model (ECM) is replaced with a dedicated NN that provides computational intelligence for flexible system identification.

The white-box model results are used as guidance for the RUL prediction using radial basis function finite Gaussian sum particle filter (RBF-FGSPF). The model virtually predicts the end of discharge voltage to extract an HI 'Discharge pulse power (DPP)' and is correlated to battery RUL. Finally, RUL is estimated as a function of DPP and cycle number.

The model is implemented with an Industrial Internet of Things (IIoT) based digital twin (DT) via Microsoft Azure Services, encompassing data collecting, time synchronisation, data processing, and model updating features. The DT approach utilises an enhanced domain adaption technique of transfer learning to mitigate the distribution discrepancies between the training and testing datasets. Three application programming interfaces (APIs), specifically Google Directions, Google Elevation, and OpenWeatherMap, are utilised for online implementation to gather data for modelling historical driving patterns of the reference electric vehicle (EV) model that accurately reflects real-time driving scenarios. The proposed model demonstrates commendable accuracy across various validation scenarios involving different temperatures and driving profiles for three distinct realistic routes, thereby providing significant insights into its relevance for battery health monitoring in industrial applications.

सारांश

इस शोध प्रबंध में वाणिज्यिक 18650 लिथियम-आयन बैटरियों का स्वास्थ्य प्रक्षेपण, जिसमें स्वास्थ्य की स्थिति का अनुमान और गतिशीलता अनुप्रयोगों में शेष उपयोगी जीवन का पूर्वानुमान शामिल है, जीवनकाल परीक्षण और मॉडलिंग के माध्यम से जांचा गया है। जीवनकाल परीक्षणों में तापमान, C-Rate, डिस्चार्ज की गहराई, चार्ज की स्थिति और गतिशील लोड प्रोफाइल का प्रभाव जांचा गया है। जीवनकाल परीक्षणों और अन्य बैटरी डेटा सेट्स के परिणामों का उपयोग स्वास्थ्य संकेतकों (HI) के निष्कर्षण में किया गया है, जो पहले से मौजूद HIs जैसे बैटरी क्षमता या आंतरिक प्रतिरोध की तुलना में अधिक व्यावहारिक हैं, विशेषकर गतिशील ऑपरेटिंग परिस्थितियों में। परिणामों ने यह दिखाया कि HI उम्र बढ़ने की प्रक्रिया के साथ मेल खाते हैं और अतिरिक्त परीक्षणों के बिना बैटरी के बाहरी चर का उपयोग करके आसानी से मापे जा सकते हैं। डेटा प्री-प्रोसेसिंग के बाद निकाले गए HIs का उपयोग श्वेत-बॉक्स उम्र बढ़ने मॉडल के विकास में किया गया है। HI आधारित न्यूरल नेटवर्क सिस्टम के पूर्व ज्ञान को गैर-रेखीय अनुमानण क्षमता के साथ जोड़ता है, जो गतिशील ऑन-बोर्ड ड्राइविंग परिस्थितियों के लिए उपयुक्त है। श्वेत-बॉक्स मॉडल आर्किटेक्चर में, प्रत्येक सर्किट तत्व को एक समर्पित NN से बदला जाता है, जो लचीले सिस्टम पहचान के लिए गणनात्मक बुद्धिमत्ता प्रदान करता है। श्वेत-बॉक्स मॉडल के परिणामों का उपयोग रैडियल बासिस फंक्शन फिनाइट गॉसियन सम पार्टिकल फिल्टर का उपयोग करके RUL (Remaining Useful Life) पूर्वानुमान के लिए मार्गदर्शन के रूप में किया जाता है। यह मॉडल डिस्चार्ज वोल्टेज के अंत की आभासी भविष्यवाणी करता है ताकि एक HI 'Discharge pulse power' निकाला जा सके, जो बैटरी के RUL से संबंधित होता है। अंत में, RUL को DPP और साइकिल संख्या के एक फलन के रूप में अनुमानित किया जाता है। यह मॉडल Microsoft Azure सेवाओं के माध्यम से एक औद्योगिक इंटरनेट ऑफ थिंग्स (IIoT) आधारित डिजिटल ट्विन के साथ कार्यान्वित किया जाता है, जिसमें डेटा संग्रहण, समय समन्वयन, डेटा प्रसंस्करण और मॉडल अद्यतन जैसी सुविधाएं शामिल हैं। DT दृष्टिकोण प्रशिक्षण और परीक्षण डेटा सेटों के बीच वितरण असंगतियों को कम करने के लिए ट्रांसफर लर्निंग की एक उन्नत डोमेन अनुकूलन तकनीक का उपयोग करता है। तीन

एप्लीकेशन प्रोग्रामिंग इंटरफेस (APIs), विशेष रूप से Google Directions, Google Elevation, और OpenWeatherMap का उपयोग ऑनलाइन कार्यान्वयन के लिए किया जाता है ताकि संदर्भ इलेक्ट्रिक वाहन मॉडल के ऐतिहासिक ड्राइविंग पैटर्न के लिए डेटा एकत्र किया जा सके, जो वास्तविक समय ड्राइविंग परिदृश्यों को सही ढंग से दर्शाता है। प्रस्तावित मॉडल विभिन्न तापमानों और ड्राइविंग प्रोफाइलों के लिए तीन विशिष्ट वास्तविक मार्गों में विभिन्न सत्यापन परिदृश्यों में प्रशंसनीय सटीकता प्रदर्शित करता है, इस प्रकार यह बैटरी स्वास्थ्य निगरानी के लिए औद्योगिक अनुप्रयोगों में इसके महत्व पर महत्वपूर्ण अंतर्दृष्टि प्रदान करता है।

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EV	Electric vehicle
ICE	Internal combustion engine
HEV	Hybrid electric vehicle
ISG	Integrated starter generator
PHEV	Plug-in hybrid electric vehicle
BEV	Battery electric vehicle
EVSE	Electric Vehicle Supply Equipment
CMS	Central management system
SoH	State-of-Health
SoC	State-of-Charge
LiB	Lithium-ion batteries
Ni-MH	Nickel Metal Hydride
LMO	Lithium Manganese Oxide
LFP	Lithium Iron Phosphate
NMC	Lithium Nickel Manganese Cobalt Oxide
LTO	Lithium Titanate Oxide
LiS	Lithium Sulphur
ESS	Energy storage system
LLI	Loss of lithium inventory
LAM	Loss of active material
CL	Conductivity loss
SEI	Solid-Electrolyte Interphase
IR	Internal resistance
RUL	Remaining Useful Life
EoL	End-of-Life
GHPF	Gauss Hermite Particle Filter
SVR	Support Vector Regression
ANN	Artificial Neural Network
ECM	Electrical equivalent circuit model
EchM	Electrochemical model
RC	Resistor-capacitor
EKF	Extended Kalman Filter
DEKF	Dual extended Kalman Filter
UKF	Unscented Kalman Filter
PF	Particle Filter

HPPC	Hybrid Pulse Power Characterization
DC	Direct current
AC	Alternating current
LS	Least square
RLS	Recursive Least Square
SPM	Single Particle Model
EIS	Electrochemical Impedance Spectroscopy
PDF	Probability Distribution Function
BMS	Battery Management System
SVM	Support Vector Machine
RVM	Relevance Vector Machine
CC	Constant current
CC-CV	Constant current-constant voltage
AdNN	Adaptive Neural Network
HMM	Hidden Markov Model
DEDVD	Duration of equal discharging voltage difference
DECVD	Duration of equal charging voltage difference
LGPFR	Linear Gaussian Process Function Regression
QGPFR	Quadratic Gaussian Process Function Regression
ARMA	Auto-regressive moving average model
ARIMA	Auto-regressive integrated moving average model
RNN	Recurrent Neural Network
LSTM	Long-Short Term Memory
PSO	Particle Swarm Optimization
EMD	Empirical mode decomposition
HI	Health indicator
GBDT	Gradient Boosting Decision Tree
RF	Random Forest
EML	Explainable Machine Learning
IML	Interpretable Machine Learning
SHAP	Shapley values
MLP	Multi-layer perceptron
CNN	Convolutional Neural Network
GRU	Gated Recurrent Unit
QFR	Quantile Forest Regression
OCV	Open-circuit voltage
TL	Transfer Learning
DL	Deep Learning

MMD	Maximum Mean Discrepancy
MK-MMD	Multi-kernal Maximum Mean Discrepancy
CORAL	Correlation Alignment
TATN	Temperature Adaptive Transfer Network
IIoT	Industrial Internet of Things
PI	Proportional Integral
NEDC	New European Drive Cycle
WEqNN	White-box equivalent Neural Network
Ethp	Energy-throughput
FLNN	Functional Link Neural Network
ELM	Extreme Learning Machine
MSE	Mean squared error
GDBP	Gradient descent back-propogation
ReLu	Rectified Linear Unit
CB	Cross-battery
CP	Cross-profile
CT	Cross-temperature
CU	Check-ups
CEI	Cathode-Electrolyte Interphase
DVRT	Deviational Voltage over Relaxation Time
BCT	Box-Cox Transformation
BTL	Battery testing lab
SR-UKF	Square-root Unscented Kalman Filter
PHM	Prognostics and Health Management
RBFN	Radial Basis Function Neural Network
FGSPF	Finite Gaussian Sum Particle Filter
DPP	Discharge Pulse Power
RSD	Remaining SoC to be discharged
FPGA	Field Programmable Gate Array
TADT	Transfer adaptive digital twin
API	Application Programming Interface
GPS	Global Positioning System
RoE	Region of extraction
RKHS	Reproducing Kernal Hilbert Space
FC layer	fully-connected layer
MCU	Micro-controller Unit
BP	Battery pack
MAPE	Maximum Available Percentage Error