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This thesis is dedicated to my late father, Narendran Nair.N.P.

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Contents

Abstract

Energy storage systems (ESSs) have emerged as a core component of the smart grid. This is driven by sustainable energy ecosystems and electrification initiatives. Accurate health prognostics and predictive maintenance are essential for the safe and reliable operation of these ESS. Modern energy storage devices (ESDs), such as lithium-ion batteries (LIBs) and supercapacitors (SCs), exhibit complex degradation patterns and operational characteristics. These factors require sophisticated health monitoring systems. Monitoring is essential to guarantee optimal performance, avoid catastrophic failures, and maximize operational longevity across a wide range of environments and usage conditions.

These ESS face significant challenges in health monitoring because of their nonlinear degradation trends, changing electrochemical dynamics, and a wide range of operating conditions at different temporal scales. The existing techniques for life estimation in ESS fail to capture the multifaceted characteristics, especially when handling short-term fluctuations and long-term degradation trends in fluctuating driving cycles. These conventional techniques for health prognostics lack the interpretability and transparency for critical decisions in ESS. This is essential for understandable decisions and predictions made by the hybrid deep learning models.

This thesis introduces an extensive framework for life estimation in ESDs by developing novel hybrid deep learning architectures that address fundamental challenges in predicting state of charge (SOC), state of health (SOH), and remaining useful life (RUL). The novel hybrid architectures integrate advanced temporal pattern recognition with sequential modeling, thereby effectively capturing multiscale dependencies in these ESS. Another contribution of the research is the integration of explainable artificial intelligence (XAI) techniques into the prognostic framework. This integration increases the clarity of the predictions made by the black-box models with a transparent representation of the decision-making process, and ranks the significant features. These research methods are validated experimentally across varying temperatures, driving cycles, and operating conditions in both synthetic datasets and real-time experimental data obtained using a specific testbed with hall sensors.

The first part of this research concentrates on SOC estimation in LIBs, which is a critical parameter for maximizing performance and prolonging battery life. Incorrect estimation of SOC could lead to limited driving range of EVs, inappropriate charging methods, and abnormal stopping. This is addressed via a hybrid model that combines a gated recurrent unit (GRU) and a multi-head dilated temporal convolutional network (MHDTCN). A unique property of MHDTCN is that it can learn patterns on a wide range of temporal scales through varying dilation rates and thus be able to capture long-term dependencies and change gracefully to highly dynamic operating patterns. This is supplemented by the GRU component that puts emphasis on short-term dependencies and sequential relations so that the temporal modeling is balanced. Crucially, the framework incorporates SHapley Additive exPlanations (SHAP) for interpretability, opening up the possibility to quantify and visualise feature contributions. This means predictions of SOC are not only accurate but also interpretable, which engenders users' trust and informs vital operational decisions.

The second part of the research focuses on SOH estimation for LIBs, which is the long-term capacity and safety of the battery. In contrast to SOC, which changes quickly over time, SOH degrades slowly, and its accurate estimation is essential to schedule maintenance, anticipate breakdown, and extend the life expectancy. To address this issue, a multi-faceted temporal convolutional network with dynamic weight adaptation (MFDWA) in combination with a GRU is proposed. The proposed MFDWA model incorporates multiple temporal convolutional branches with different dilation factors, which allows it to learn degradation patterns at multiple temporal scales. Attention is injected in the architecture through attention blocks that detect and select important input features, and a dynamic weight adaptation mechanism that changes branch importance according to the metadata evolving in the battery. These mechanisms work in conjunction, making the model more versatile under various operation conditions and battery combinations. The GRU achieves sequential consistency by retaining relevant previous states. In the same manner as the SOC model, the SOH model adapts SHAP for interpretability, which enables practitioners to see essential features contributing to the degradation. The combined features of flexibility and transparency make it an effective strategy for long-term health diagnosis in LIBs.

The research further broadens its focus to RUL prediction in SCs that are becoming more and more popular for their high power density and extended working life. Although the cycle life of SCs is longer than that of LIBs, their capacity also diminishes under continuous and intensive process. The accurate prediction of RUL is the key to their reliable operation, which is particularly important in applications with frequent charge–discharge cycles. A novel hybrid model, which consists of a custom dilated temporal convolutional network (CDTCN) and a GRU, is proposed to solve this problem. The CDTCN uses customized dilation rates in its different branches, which allows the model to learn short-term, mid-term, and long-term dependencies in SC degradation patterns. The GRU layer captures temporal dependencies; thus, the framework has the potential to learn consistent evolution paths. To ensure the validity of the model, a testbed is specifically built in, which comprises of hall sensors that monitor the current charging and discharging at a real time cycle with variation in current rates. This direct acquisition of real-time data ensures that the model is trained and validated based on realistic operating conditions. Moreover, XAI methods are incorporated to emphasize features most influential to predict RUL, and hence, predictions are not only accurate but also interpretable to the ESS deployment practitioners.

Building upon these insights, the final part of the research introduces the Temporal Convolutional Transformer (TCT) for RUL estimation in SCs. The TCT model leverages both TCNs and Transformer-based self-attention mechanisms, and forms an effective tool to learn local and long-range dependencies in nonlinear ageing problems. On the one hand side, TCNs with dilated convolutions are successful in learning local degradation profiles, yet on the other hand, self-attention mechanisms are very well suited to capture global temporal relationships. Their incorporation in the TCT provides strong purposes to handle complex degradation patterns that cannot be accommodated well by each architecture alone. The TCT approach is validated through real time experimental data acquired on a test-bed that includes of hall sensors, low-pass filters, and microcontrollers. The hybrid structure illustrated in the experiment samples has revealed the innovation of combining convolutional efficiency and attention-based flexibility toward the next-generation SC RUL approach.

The unifying contribution of this thesis is a comprehensive framework that provides the solution for all three dimensions of ESS health monitoring, that is, SOC, SOH and RUL estimation, by combining different hybrid deep learning architectures designed in combination with explainability mechanisms. The balance between accuracy and computational efficiency is a particular characteristic of the models, which can be used even when resources are limited, preserving the transferability to different datasets and working conditions. The fact that XAI is integrated means that these models are not black box ones, but transparent and can be trusted and understood in their decision-making. In addition, the experiment designs for data generation represent a strong resource to evaluate model performance in realistic and challenging conditions.

Overall, this research contributes to the development of ESS prognostics by proposing hybrid architectures that integrate temporal convolution, recurrent modeling and attention mechanisms with interactive tools to create reliable, accurate and transparent health monitoring solutions. In focusing on both LIBs and SCs, the thesis underscores the synergistic nature of these two technologies and proposes predictive models that facilitate their incorporation into sustainable energy systems. The interpretable, experimentally validated models developed here can be used to improve predictive maintenance programs and are consistent with the more general aim to construct safe, reliable and sustainable energy systems for the future.

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List of Abbreviations

Abbreviation	Description
ABC	Artificial bee colony
AI	Artificial intelligence
ANN	Artificial neural network
ASTLSTM	Active state tracking long short-term memory
BiLSTM	Bidirectional long short-term memory
BMS	Battery management system
BWGRU	Bidirectional weighted gated recurrent unit
C	Capacity
CDTCN	Custom dilated temporal convolutional network
CNN	Convolutional neural network
DAE	Denoising autoencoder
DBLSTM	Deep bidirectional long short-term memory
DBN	Deep belief network
DNN	Deep neural network
ECM	Equivalent circuit model
EKF	Extended Kalman filter
EOL	End-of-life
ESD	Energy storage device
ESR	Equivalent series resistance

Abbreviation	**Description**
ESS	Energy storage system
EV	Electric vehicle
FAFF	Fuzzy adaptive federated learning
FNN	Feedforward neural network
KF	Kalman filter
LSI	Life span indication
LSSVVM	Least square support vector machine
GNN	Graph neural network
GPR	Gaussian process regression
GRU	Gated recurrent unit
HNEI	Hawaii National Energy Institute
HWFET	Highway fuel economy test
Huber-loss(t)	Huber loss function at time step t
I	Current
iBiGRU	Improved bidirectional gated recurrent unit
LA92	LA92 dynamometer driving schedule
LIB	Lithium-ion battery
LIME	Local Interpretable Model-agnostic Explanations
LR	Linear regression
LSTM	Long short-term memory
MAE	Mean absolute error
MFDWA	Multifaceted TCN with dynamic weight adaptation
MHDTCN	Multi-head dilated temporal convolutional network
MMHA	Mask multi-head attention
NARx	Nonlinear autoregressive exogenous model
OCV	Open circuit voltage

Abbreviation	**Description**
PSO	Particle swarm optimization
ReLU	Rectified linear unit
RFE	Recursive feature elimination
RF-RS	Random forest-random space
RMSE	Root mean squared error
RNN	Recurrent neural network
RUL	Remaining useful life
SBLSTM	Stacked bidirectional long short-term memory
SHAP	SHapley Additive exPlanations
SC	Supercapacitor
SOC	State of charge
SOH	State of health
T	Temperature
TCN	Temporal convolutional network
TCT	Temporal convolutional transformer
UDDS	Urban dynamometer driving schedule
UKF	Unscented Kalman filtering
US06	US06 supplemental FTP driving schedule
V	Voltage
VMD	Variable mode decomposition
XAI	Explainable artificial intelligence

List of Symbols

Symbol	Description
$A_{b,t}$	Attention weight in branch b at time t
A_j	Self-attention output at time j
B	Number of branches
Bi_b	Bias term in branch-wise attention
$b_{b,m}, b_{h,n}, b_m$	Bias parameters of convolutional filters
$D_{b,m}$	Dilation rate of the m-th layer in branch b
$D_{b,n}$	Dilation rate of the n-th layer in branch b
$D_{h,n}$	Dilation rate of the n-th layer in head h
$D_{\text{long},m}$	Dilation rate of the m-th long-term branch
$D_{\text{med},m}$	Dilation rate of the m-th medium-term branch
$D_{\text{short},m}$	Dilation rate of the m-th short-term branch
D_j	Dense layer projection output at time j
d_k	Dimension of key vector in attention mechanism
$F_{b,t}$	Output of branch b at time t
F_j	Fused global feature representation at time j
F_t	Fused global feature representation at time t
F_{out}	Final output feature dimension size
H	Number of attention heads
i, p	Sample index

Symbol	**Description**
j, t	Time step index
K, Q	Kernel size of convolution filter
k, q	Feature dimension index
K_b, Q_b	Query and Key matrices for attention mechanism
λ	Weight adaptation factor (branch fusion)
M_b, N_b, N_h	Number of dilated convolutional layers in head/branch
$O_j^{(b)}$	Output of branch b at time j
$W_{h,n,i}, W_{b,m,u}, W_{m,u}$	Weight parameters of convolutional filters
X	Sequential input data
$X_{b,t}$	Attended input in branch b at time t
$Y_{b,n,t}, Y_{h,n,t}$	Output of n-th layer in head/branch
$Z_{h,t}$	Output of head h at time t
Z_t	Fused output of all heads at time t