Teaching of Machine Learning-based Control of Storage Devices

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Győr, September 9, 2025

Contents

I. INTRODUCTION

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Subject name:
Controlled storage Devices AJNM_BMTA026

Credits: 5 credits

Contact hours: 28 hours

Number of Students: 5-20

Main Subject	Degree	Study Level	Study Mode
Engineering - General	MSc	Masters	On Campus

Specific course information	
Description of course	The goal of the course is to provide a comprehensive overview on the latest energy storage technologies with system approach. State-Of-The-Art applications of modelling and control of the storage units are presented for pertaining to solve problems in battery management and control. Relationships and mathematical models are also described so that the students are able to solve numerical problems. A particular attention is paid to up-to-date controlled storage problems of Electric Vehicles. A further relevant goal is to look into the future, so promising development trends are also presented.
Prerequisites	No prerequisite.
Type of course	Elective from a basket of required courses.

Specific goals for the course	
Specific outcomes of instruction	After passing the course, the students should be able to account for different technologies for energy storage that can be used in electrical systems and for batteries' life cycle in electrical system applications. The students should be able to derive, develop and use models for batteries in the context of electrical systems and analyze battery storage systems for different applications. The students should be able to understand and analyze how battery storage in electrical systems influence the electricity market and the cooperation between energy and transport systems. In addition the students should be able to build and **apply State-Of-The-Art methods** of modelling and control of the storage units for pertaining to solve problems in battery management and control, with special regard to Electric Vehicle applications.

List of topics

- Driving forces of distributed energy generation and energy storage. Centralized and distributed energy generation.
- Needs and requirements with respect to energy storage. Principles and devices of electrical energy storage.
- Parameters and characteristics of electrical energy storage devices and systems. Energy storage state-of-the-art.
- Large scale energy storage. Role of hydrogen energy storage.
- Properties and characteristics of flywheel systems.
- Properties and characteristics of electrochemical energy storage systems.
- Fundamentals of lithium batteries.
- Battery modelling.
- SoH and Lifetime of batteries.
- Challenges and requirements of Electrical Vehicles regarding electrical energy storage. Aspects of device/system selection and design.
- Fundamentals of design of storage device systems, control of storage systems with AI
- Prospects and future trends of electrical energy and storage systems.

Evaluation

Midterm evaluation

Test

Assignment

The project work covers laboratory measurements on lithium-ion batteries, modeling in Matlab/Simulink and reporting the result of investigations in written and oral form

Exam: written/oral

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II. EV AS THE DRIVER OF BATTERY INNOVATION

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- EVs reduce GHG emissions & fossil fuel dependence
- EV adoption drives battery innovation (safety, lifetime, cost)
- **Li-ion dominates**: high energy density, efficiency, recyclability
- Challenge: **battery aging & degradation** → SOC/SOH estimation essential

Battery Management Systems (BMS)

-State of the Art and Challenges

The key areas of developing sophisticated algorithms and techniques to enhance the accuracy and efficiency of BMS:

SoC Estimation:	**Cell Balancing**	**Thermal Management**	**Fault Detection and Diagnosis, SoH**
✓ Accurate estimation of the battery's State of Charge is crucial for optimizing the performance and range of electric vehicles.	✓ Essential to ensure uniform charging and discharging of individual battery cells within a pack	✓ Efficient thermal management is crucial for maintaining the temperature of the battery within safe operating limits.	✓ BMS designs include fault detection and diagnosis capabilities to identify and mitigate potential issues in the battery system.

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Challenges that faced the development of BMS design for electric vehicles:

- ✓ Accuracy and Reliability
- ✓ Scalability and Adaptability
- ✓ Computational Efficiency
- ✓ Cost and Integration

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Battery models for real-time operation:

- ✓ Equivalent Circuit Models (ECMs)
- ✓ Grey-Box Models
- ✓ Hybrid Models
- ✓ Electrochemical Models
- ✓ Data-Driven Models

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State of Charge (SOC) Estimation Methods

Coulomb Counting	Voltage-Based Methods	Current Integration and Recursive Estimation	Model-Based Approaches	Machine Learning and Data-Driven Methods	Hybrid Approaches
-one of the simplest and widely usedclassic methods for SoC estimation	-estimate SoC by analyzing the battery's terminal voltage	-These methods combine voltage and current measurements with recursive algorithms to continuously update the SoC estimate	-leverage battery models, such as equivalent circuit models or electrochemical models, to estimate SoC	-Machine learning techniques, including neural networks and support vector machines, have gained popularity for SoC estimation	-Machine learning techniques, including neural networks and support vector machines, have gained popularity for SoC estimation

BMS architectures, and the challenges posed by embedded systems constraints:

- Centralized BMS Architecture
- Hybrid BMS Architectures
- Distributed BMS Architecture
- Real-Time Processing
- Communication Protocols
- Energy Efficiency

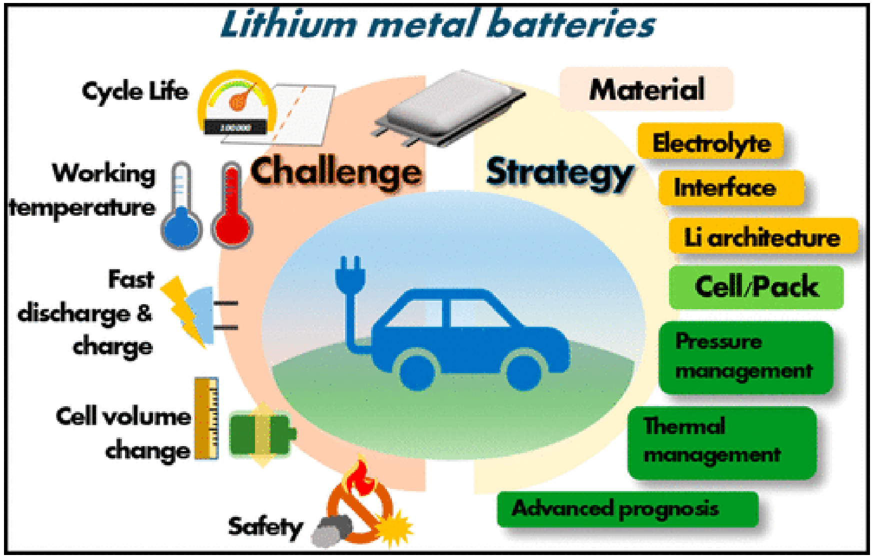
Gaps in existing solutions / need for development

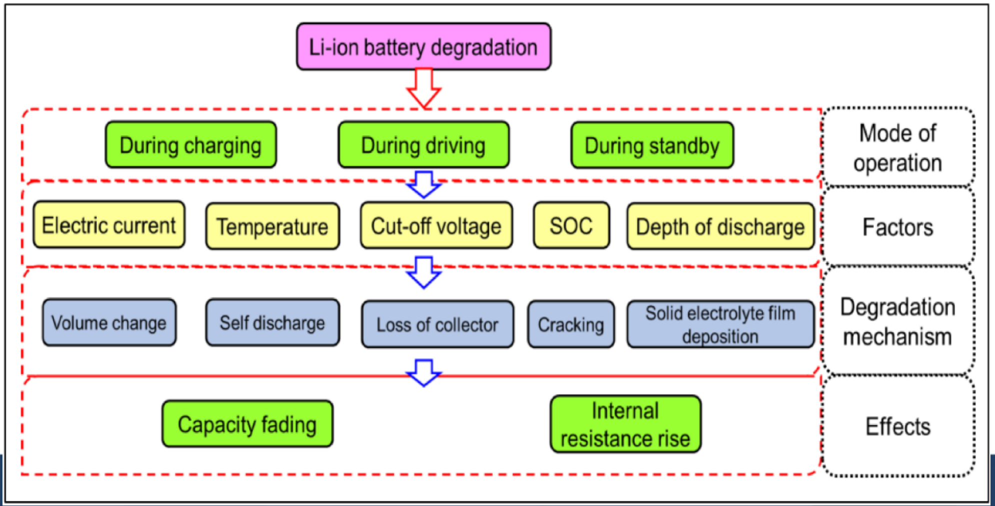
- Integration of SoC Estimation Methods with BMS Architectures
- Real-time SoC Estimation under Dynamic Conditions
- Scalability of BMS Architectures
- Resource-efficient Embedded BMS Designs
- Cross-Compatibility and Standardization
- Cybersecurity and Data Integrity
- Environmental Impact
- Real-world Validation and Testing

BMS SOH

-Lithium-Ion Battery Aging Mechanisms

Lithium-ion battery aging is a multifaced process influenced by various electrochemical, thermal, and mechanical factors. Aging mechanisms is pivotal for developing accurate predictive models and effective mitigation strategies.

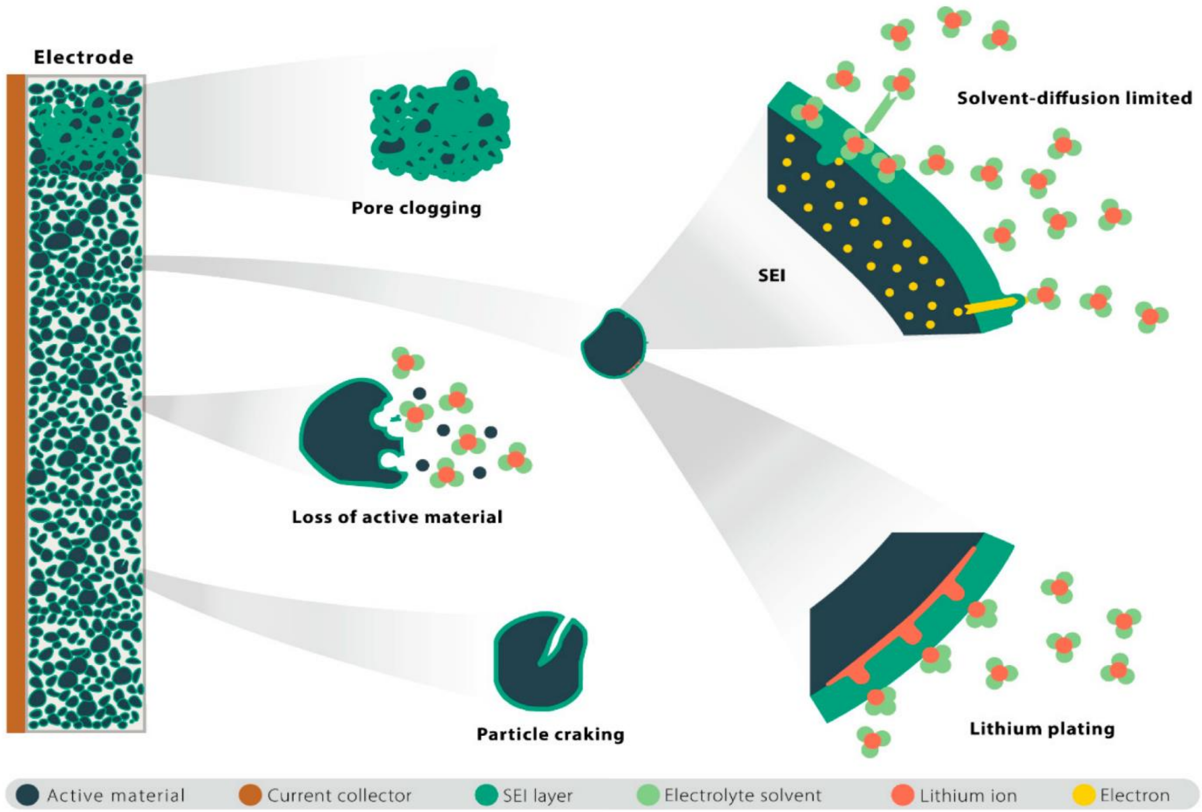




Electrochemical Aging

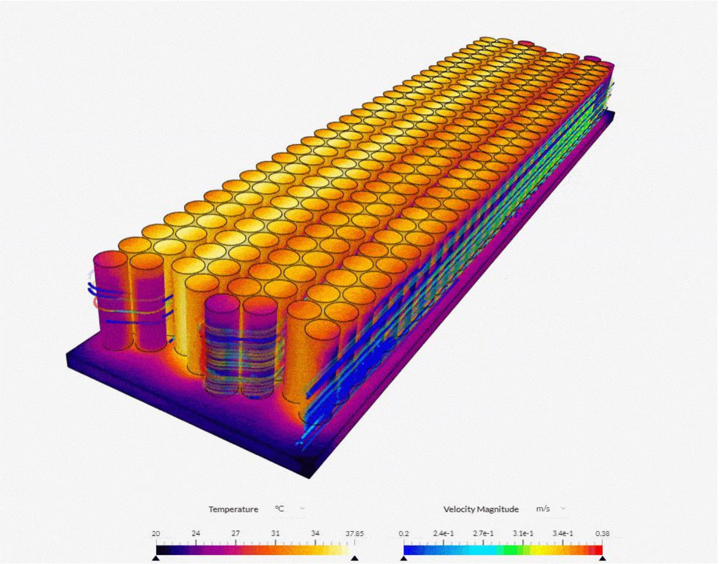
Occurs primarily due to chemical reactions at the electrode-electrolyte interface during charge and discharge cycles.

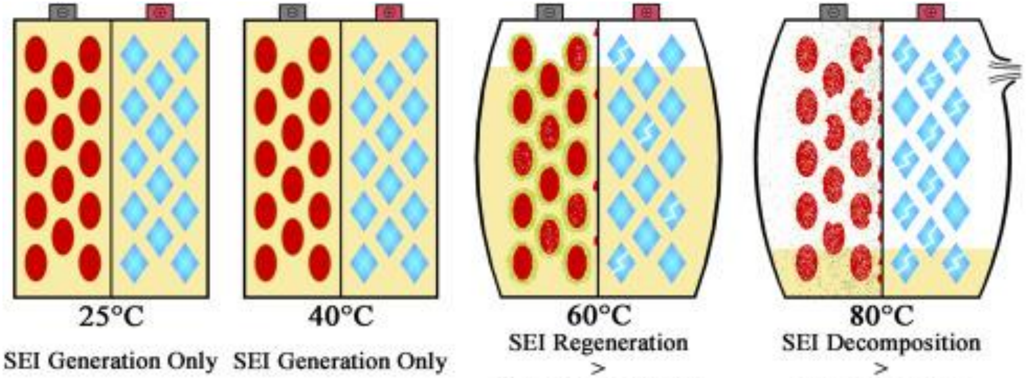
This process involves mechanisms such as solid-electrolyte interphase (SEI) formation, lithium plating, and electrode material degradation.



Thermal Aging

Temperature fluctuations influencing the rate of aging processes. Elevated temperatures accelerate chemical reactions, promoting faster degradation and reducing the overall lifespan of lithium-ion batteries.

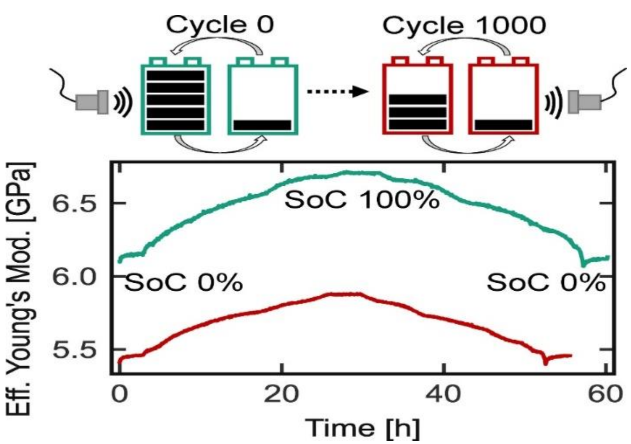


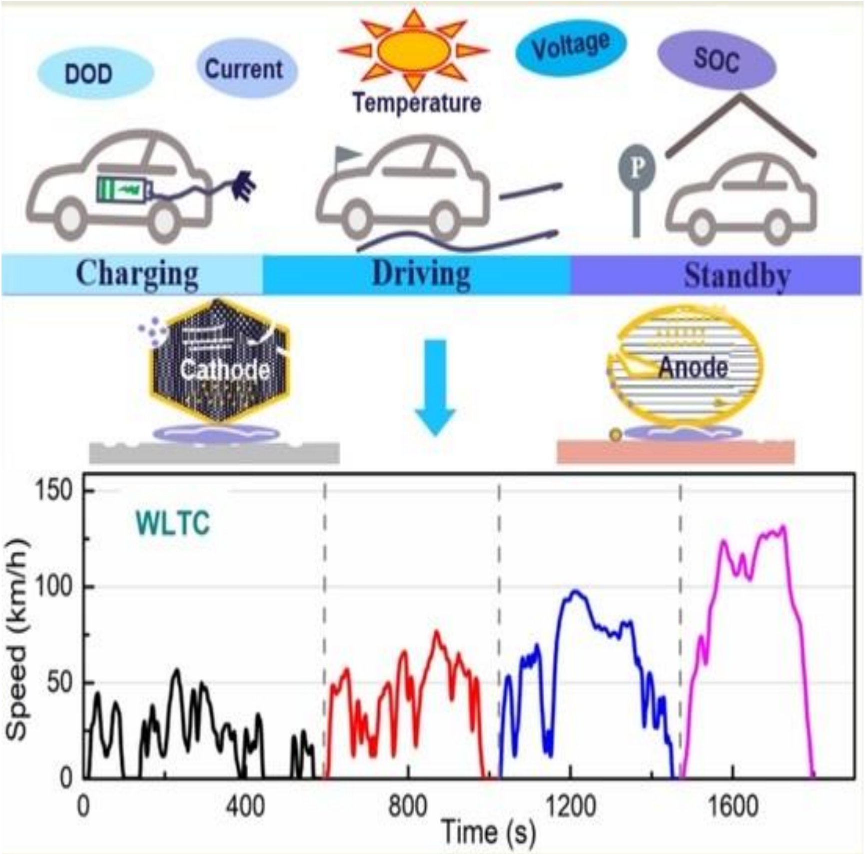


Solid-Electrolyte Interphase (SEI) Formation

Mechanical Aging

Physical stresses and strains within the battery components, often induced by the repeated charge and discharge cycles. This can result in structural changes and mechanical degradation, impacting the overall integrity and performance of the battery.





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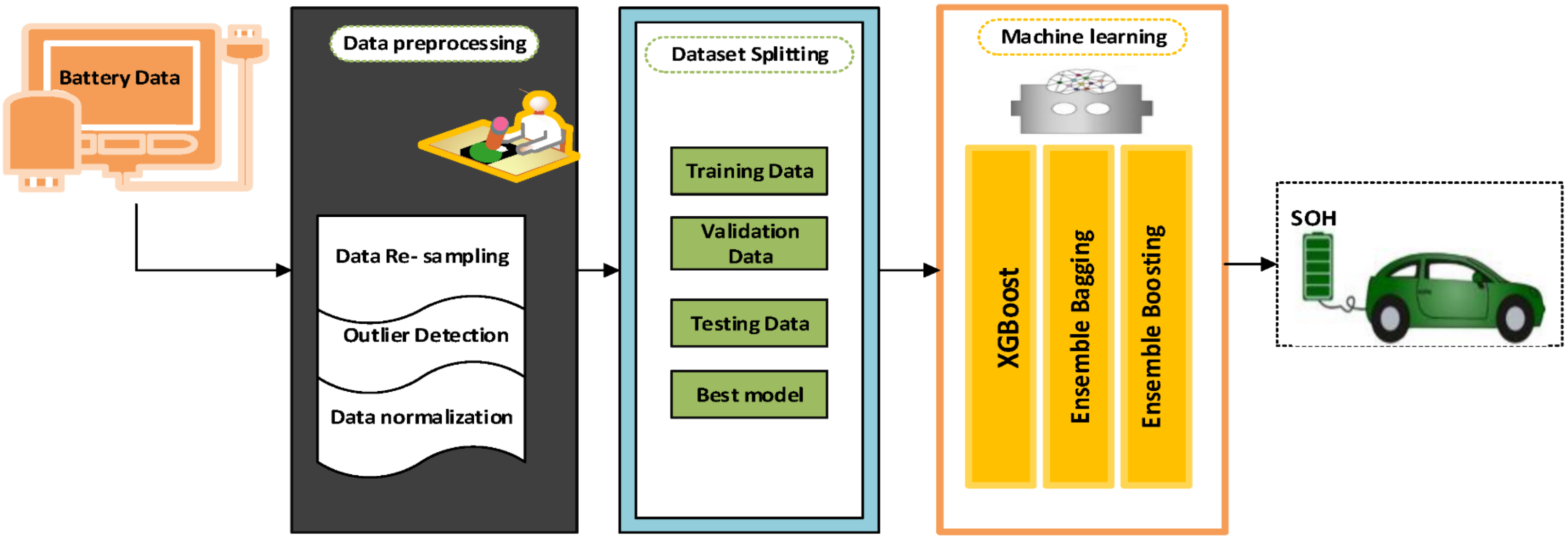
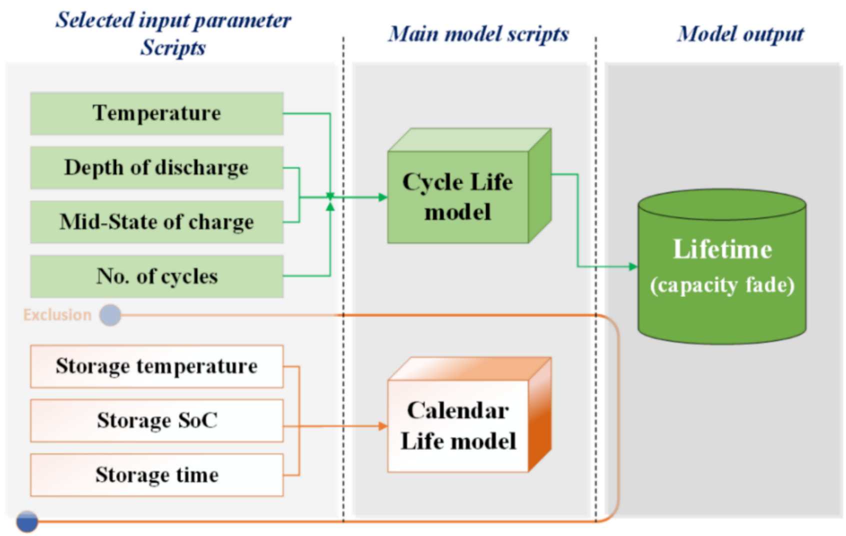
State-of-the-Art SOH Prediction Models

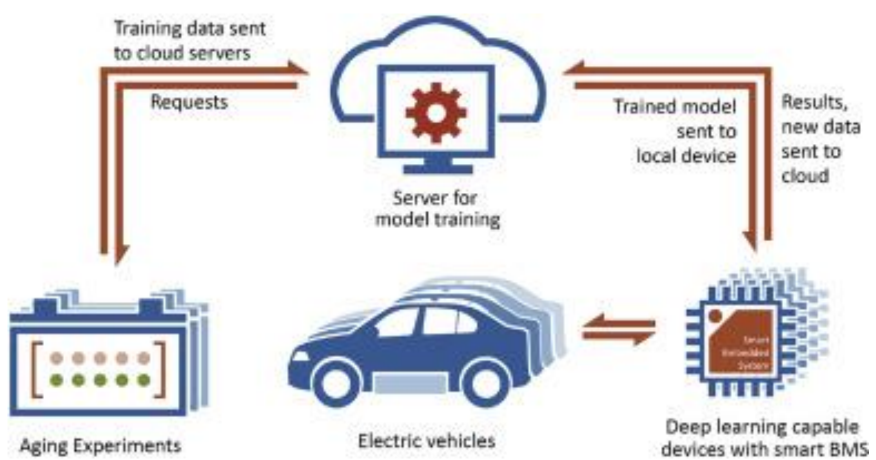


Real-Time Data Acquisition
Machine Learning Models
Data-Driven Approaches
Battery Management Systems (BMS)
SOC Control Algorithms
Advanced Control Algorithms
Model Predictive Control (MPC)

Machine Learning Models for Lifetime Prediction

Machine learning models, including Support Vector Machines, Random Forests, and Neural Networks **increasingly combined with hybrid physics-informed approaches**, are commonly used for battery lifetime prediction due to their ability to analyze complex relationships in large datasets without explicit programming.





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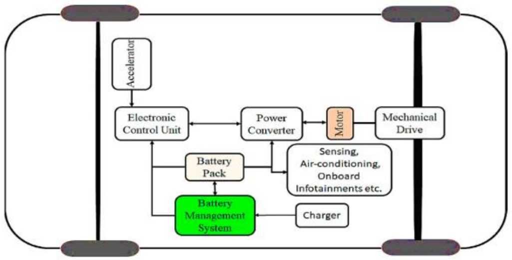

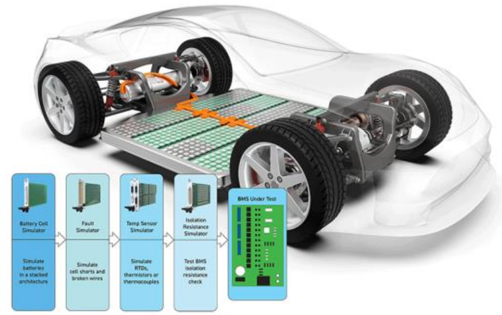

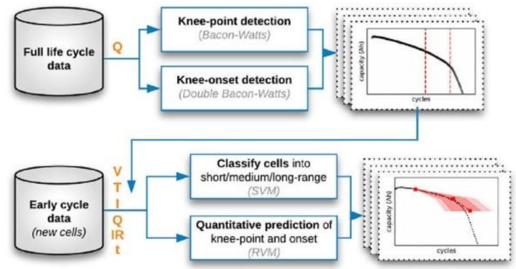

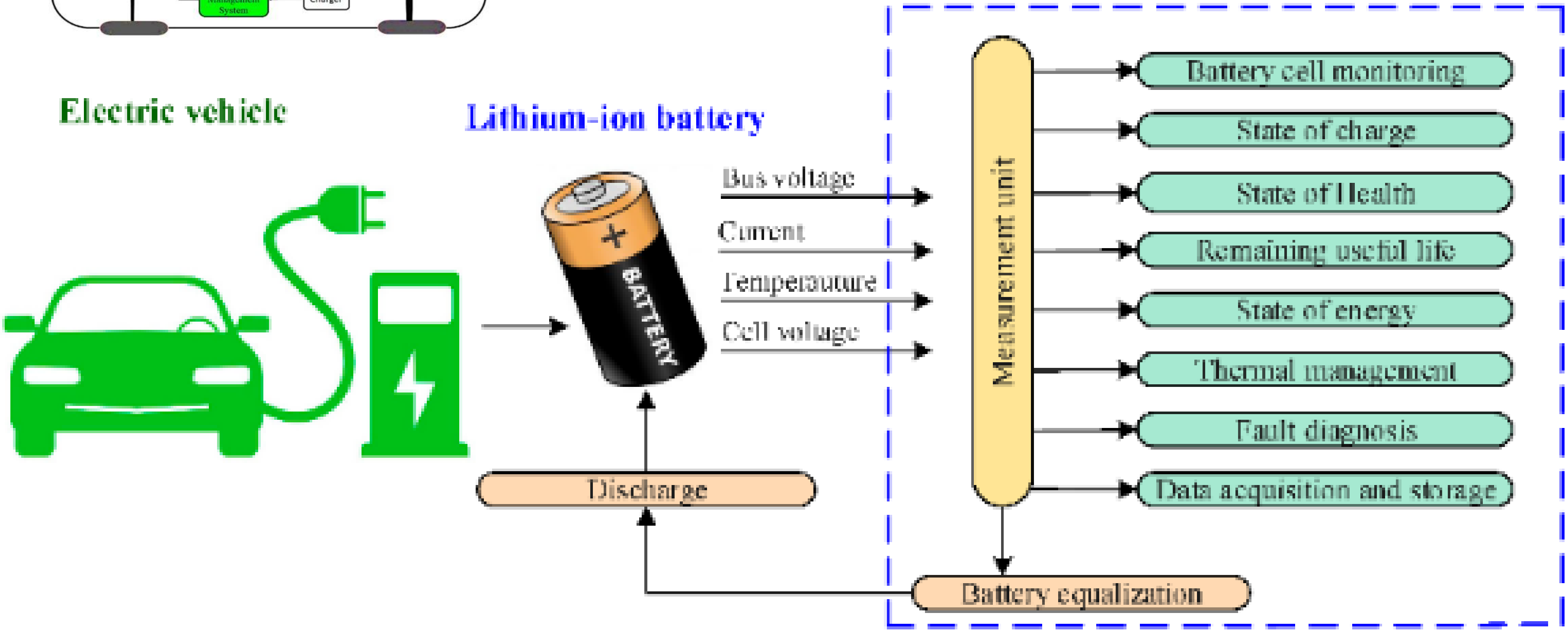

- Diverse aging mechanisms like SEI formation, lithium plating, and electrode degradation impact battery performance over time.
- Lithium-ion battery aging involves electrochemical, thermal, and mechanical factors.
- State-of-the-art prediction models, including Machine Learning and Data-driven approaches, relying on real-time data and advanced analytics, contribute to enhanced prediction accuracy and offer tools for anticipating battery degradation.
- Mitigation strategies, such as advanced battery management systems, thermal management, control algorithms, and innovative materials, are crucial for extending battery life and optimizing performance.
- Continued research and development are vital for advancements in electric vehicle technology and sustainable energy solutions.

III. TEACHING FOCUS

Matlab/Simulink

Predict Battery State of Charge Using Machine Learning

R2025a

This example shows how to train a Gaussian process regression (GPR) model to predict the state of charge of a battery in automotive engineering.

Battery state of charge (SOC) is the level of charge of an electric battery relative to its capacity measured as a percentage. SOC is critical information for a vehicle energy management system, and must be accurately estimated to ensure reliable and affordable electrified vehicles (xEV). However, due to the nonlinear temperature, health, and SOC-dependent behavior of Li-ion batteries, SOC estimation is a significant automotive engineering challenge. Traditional approaches to this problem, such as electrochemical models, usually require precise parameters and knowledge of the battery composition, as well as its physical response. In contrast, using a machine learning model is a data-driven approach that requires minimal knowledge of the battery or its nonlinear behavior [1].

This example uses:

Statistics and Machine Learning Toolbox

Parallel Computing Toolbox

Open in MATLAB Online

Copy Command

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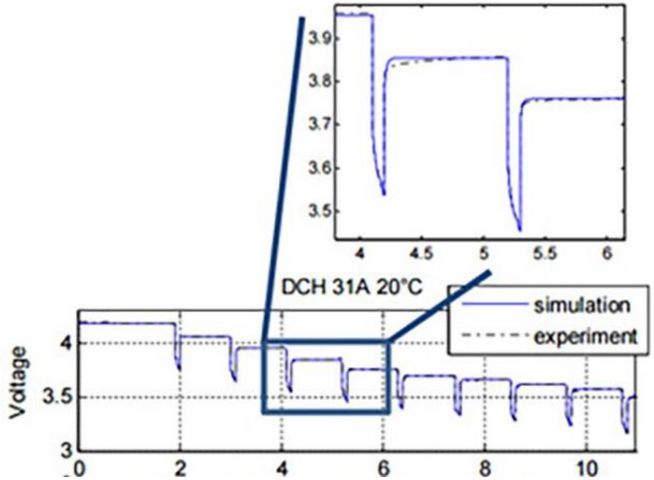
Battery Modeling

What Is Battery Modeling?

Battery models have become an indispensable tool for the design of battery-powered systems. Their uses include battery characterization, state-of-charge (SOC) and state-of-health (SOH) estimation, algorithm development, system-level optimization, and real-time simulation for battery management system design.

Battery Characterization

The first step in the development of an accurate battery model is to build and parameterize an equivalent circuit t reflects the battery's nonlinear behavior and dependencies on temperature, SOC, SOH, and current. These dependencies are unique to each battery's chemistry and need to be determined using measurements performec battery cells of exactly the same type as those for which the controller is being designed. Example battery model available for download from MATLAB Central.



https://www.mathworks.com/discovery/battery-models.html

SOC Estimation

One common application of battery models is to develop algorithms for SOC estimation. Open-circuit voltage (OC measurement and current integration (coulomb counting) may give reasonable estimates for SOC. However, to estimate the SOC in modern battery chemistries that have flat OCV-SOC discharge signatures, you need to use a different approach, such as Kalman filtering.

Degradation

Batteries degrade over time due to their calendar life and charge-discharge cycles, showing a gradual loss in reser capacity and an increase in internal resistance. The battery management system (BMS) needs to adapt to these changes for effective control of the battery. Battery models can help you develop a BMS that accounts for degradation.

Real-Time Simulation

Hardware-in-the-loop testing of BMS is another common application of battery models. A battery model built for system-level design can be reused for real-time simulation.

For more information on battery modeling, see the examples, webinars, and conference papers below, which feature MATLAB® and Simulink® products.

Examples and How To

- Battery Management System Development in Simulink (16:03) - Video
- Lithium Battery Model with Thermal Effects for System-Level Analysis (24:05) - Video
- Automating Battery Model Parameter Estimation using Experimental Data (25:28) - Video
- Real-Time Simulation of Battery Packs Using Multicore Computers (22:57) - Video
- Hardware-in-the-Loop (HIL) Testing of Battery Management System (BMS) using Simulink Real-Time and

mathworks.com/videos/how-to-develop-battery-management-systems-in-simulink-part-1-bms-overview-1574416523692.html

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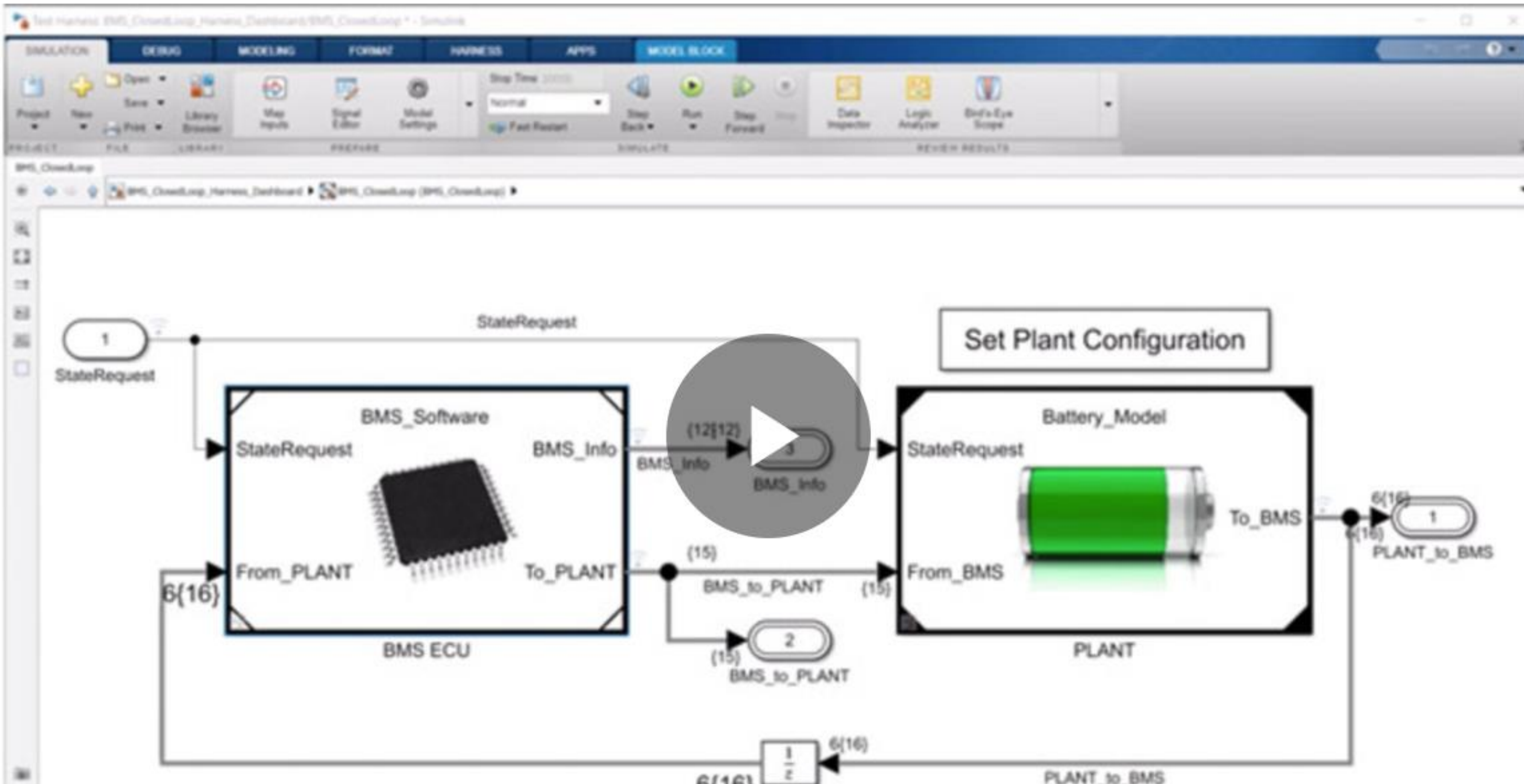


Battery Lifetime Analysis and Simulation Toolsuite (Blast-Lite)

NREL / BLAST-Lite Public

Code | Issues 1 | Pull requests | Actions | Projects | Security | Insights

main | 4 Branches | 6 Tags | Go to file | Code

pauljgasper Merge branch 'main' of https://github.com/NREL/BLAST-Lite bae8c71 · 4 months ago 121 Commits

MATLAB BLAST-Lite	reorganize code, python to the fore	last year
assets	update readme, assets	6 months ago
blast	Fix temperature normalization in J. Energy Stor. paper models	5 months ago
docs	fix a single character bug, new example, update version	last year
examples	LFP-Gr EV data and model calibration	4 months ago
.gitignore	Update documentation for all functions	last year
.readthedocs.yml	Update readthedocs.yml	last year
LICENSE	Progress - pip install and docs	last year
NOTICE	Progress - pip install and docs	last year
README.md	Update README.md	4 months ago

pauljgasper Update examples after some bug fixes b05b1ab · 5 months ago

Preview Code Blame 630 lines (630 loc) · 614 KB Raw

Battery life model library

Example notebook demonstrating how to use the battery life models in Python.

First examples use the Kokam NMC111|Gr 75Ah battery life model. The battery modeled here is a high-power cell with long cycle life. Because nominal cell resistance is low, the relative change of resistance at end-of-life is quite high compared to other cell designs (~300% increase in cell resistance at 80% capacity if not more). Fade rates can be changed in the code to accomodate other cell models. Documentation is provided in the life model class. See https://ieeexplore.ieee.org/abstract/document/7963578 for the aging test details and results used to parameterize this model.

Conferences > 2017 American Control Confere...

Life prediction model for grid-connected Li-ion battery energy storage system

Publisher: IEEE Cite This PDF

Kandler Smith ; Aron Saxon ; Matthew Keyser ; Blake Lundstrom ; Ziwei Cao ; Albert Roc **All Authors**

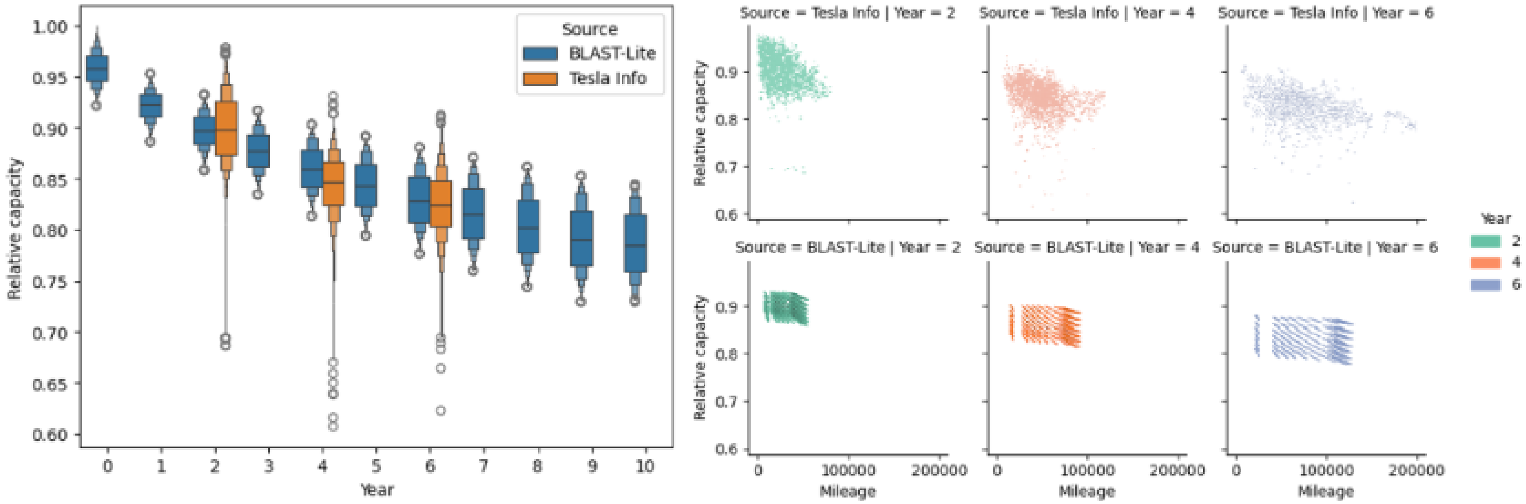
Simulating real-world battery use cases

Battery degradation is a complex interplay between battery-specific degradation behaviors, battery operating strategy and controls, and environmental conditions. BLAST-Lite provides a simplified set of tools to enable exploration of battery degradation versus all of these parameters, and has pre-built tools to help evaluate the life of applications like electric vehicles and stationary energy storage systems with reasonable assumptions.

Electric vehicles

Electric vehicle simulations are conducted after generating realistic state-of-charge profiles using NREL's FASTSim vehicle simulation tool. The state-of-charge profile for an 'average' week of vehicle use can then be scaled according to annual vehicle miles traveled (VMT), using U.S. Department of Transportation data (documented here) to estimate the distribution of annual VMT across the U.S. population, utilizing the `scale_vehicle_profile_to_annual_efcs` function.

For example, the Panasonic NCA-Gr 18650 battery model can be compared to real world Tesla Model 3 Long Range vehicle data (extracted from https://tesla-info.com/ YouTube videos), which used Panasonic NCA-Gr 21700 batteries from their first model year in 2018 through at least 2022. Both the distribution of annual VMT and degradation model variability need to be accounted for to match the observed distributions of capacity fade and miles driven.



Stationary storage

Stationary storage battery systems vary substantially in their design, operation, and application. Specifically, the application can have huge impacts on battery lifetime, as operations like peak shaving or backup-power have completely different battery use than operations like PV load-firming or electric vehicle charging station support. Here, we have compiled a wide variety of stationary storage system battery applications.

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Key Challenges in Teaching ML-Based Storage Control

- Students often **lack programming experience** (Python, MATLAB) and have **limited understanding** of basic **AI/ML** methods
- **Limited Simulink modeling experience** → slows project progress
- **Software license issues** restrict access to key tools
- Very **diverse student backgrounds** → hard to equalize knowledge
- **No dedicated battery laboratory** for hands-on practice
- Reliance on **public datasets** → not scalable to real applications
- **Local industry link is weak** (factories without research centers)

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Needs and Gaps Identified

- Access to **modern battery labs,** measurement, characterization, life testing
- **HIL simulation platforms** to bridge theory and practice
- Better **industrial collaboration** for real data and case studies
- Infrastructure: **storage & computing capacity** for large datasets
- Need for **system-level modeling skills** (currently lacking in preliminary courses)
- Students have **no exposure to HIL methods**
- Teaching goal is to provide **practical, scalable skills** beyond theory

IV. STUDENT PROJECT EXAMPLE

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Oussama MOUHIB
Vehicle Engineering MSc
Battery Management System Design for Electric Vehicles (December, 2023)

Project Focus

compare **classical vs. AI-based approaches** to SoC estimation

Challenge: balance accuracy, computational load, and real-time constraints

Tools: MATLAB/Simulink, machine learning (neural networks, Kalman filter models)

Student's activities

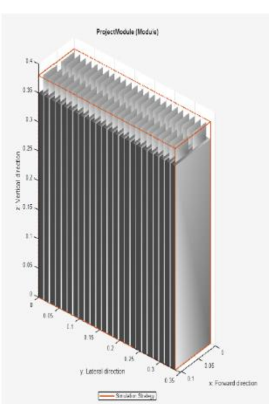
Conducted **literature review** on BMS architectures and SoC estimation methods

Built **battery models** (electrochemical, equivalent circuit, data-driven) and tested them

Implemented **simulation framework** for EV scenarios in MATLAB/Simulink

Developed and trained **ML-based SoC estimators**

Performed **comparative analysis** of accuracy, computational efficiency, and feasibility for real-time EV operation criteria



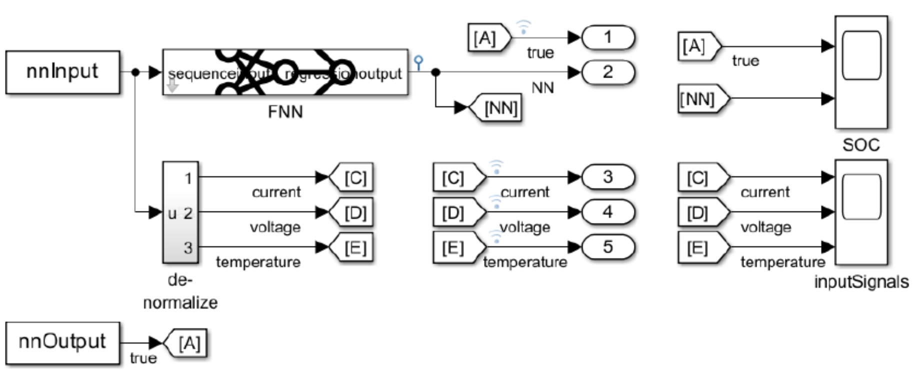


Figure 32: Simulink Model to Predict SOC using Feedforward Neural Network.

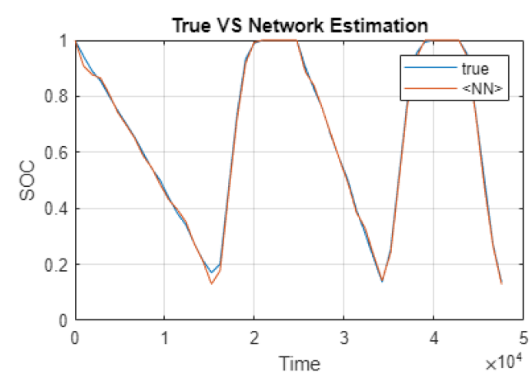


Figure 34: Visualizing the outputs (True SOC vs NN SOC).

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the project work's **comparative analysis table** on the implemented methods highlighting:

Aspect	Kalman Filter Model	Neural Network Model
Estimation Technique	Recursive mathematical updates	Supervised learning with feedforward architecture
Handling of non-linearities	Moderate	Excellent
Computational Complexity	Low	High
Real-Time Performance	Good for steady-state and moderately dynamic cases	High, even in dynamic and noisy conditions
Accuracy	Good under steady conditions, less accurate for rapid changes	Superior accuracy overall
Ease of Implementation	Straightforward requires system equations	Requires training, dataset preparation, and tuning
Robustness	Sensitive to model	Robust to non-linear and

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V. FUTURE OUTLOOK

Teaching aspect of pw

demonstrates to students why ML is needed beyond traditional methods
Students learn battery modelling & AI integration → skills directly applicable in automotive R&D
Project bridges theory (SoC methods) with practical EV BMS design

Employability

Graduates can work in automotive companies (EV development, BMS design, embedded systems)

Skills are transferable

to other fields such as renewable energy, energy storage, and grid applications

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AI in Teaching Storage Control

- AI as a **supportive teaching tool could** help students understand SOC/SOH estimation beyond classical models
- Provides adaptive feedback and personalized learning
- Use of **virtual labs with AI support**
- Safe training environment (no real batteries needed)
- Students can test BMS algorithms and ML models interactively
- Teaching impact goal: students learn **how AI complements engineering methods**

Outlook for Research & Education

- Extend scope from EV batteries → BESS & energy communities
- AI for battery selection, sizing, and lifetime optimization
- AI for renewable integration and distributed storage control
- Education will prepare graduates:

    to work in automotive EV sector (AI-driven BMS, control)
    to join renewable energy & grid storage companies
    to continue at PhD level and research institutes

Hungarian & EU Battery Context

Hungary: major EU battery hub (CATL, SK On, Samsung SDI, etc.)

Samsung SDI's 2024 revenue ≈ €4.6 B (4th largest company in Hungary by revenue in 2024, 96% export-based) → but **–21% drop** vs. 2023

Challenge: strong manufacturing capacity, but little domestic R&D → risk of "production hub without innovation"+ environmental controversies

Europe: multiple bankruptcies (Northvolt, Britishvolt, AMTE) show that *funding alone is not enough*

- not isolated cases,similar bankruptcies show structural weaknesses in Europe

Source: Márton Czirfusz (2023): The Battery Boom in Hungary: Companies of the Value Chain, Outlook for Workers, and Trade Unions.

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Lessons & Outlook

- **Quebec – Northvolt case**

€270 M public investment lost, project collapsed → company spread too thin, weak foundations

Key lessons:
Factories ≠ innovation → need R&D and skilled engineers
Protectionism & weak cooperation undermine EU competitiveness
Training in ML-based storage control is essential for Europe's battery future

- **Switzerland – SCB AG**: first solid-state battery gigafactory **co-located with R&D** → continuous feedback loop between production & innovation

Thank you for your attention!

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