INTERNATIONAL JOURNAL OF ECONOMIC SOCIAL SCIENCE AND MANAGEMENT LAW
Peer Reviewed, Referred & Indexed Journal
E-ISSN: 3070-0558
VOL.7, NO.1 (2026)

AI-Based State-of-Charge and State-of-Health Estimation for Lithium-Ion Batteries

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ABSTRACT

Accurate estimation of battery State-of-Charge (SOC) and State-of-Health (SOH) is essential for the safe and efficient operation of lithium-ion batteries used in electric vehicles, renewable-energy storage, and portable systems. Direct measurement of these internal states is difficult during normal operation because battery behaviour changes with temperature, load, ageing, and operating history. Traditional approaches such as coulomb counting, open-circuit-voltage methods, equivalent-circuit models, and Kalman-filter techniques can provide useful estimates, but their performance may depend on model parameters, sensor quality, and operating conditions. This project presents an Artificial Intelligence-based framework for estimating SOC and SOH from measurable battery signals such as voltage, current, temperature, cycle information, and selected derived features. The proposed system performs data preprocessing, feature extraction, model training, validation, and real-time inference using machine learning and deep learning techniques. Sequence-aware models such as LSTM and GRU can learn temporal relationships in battery measurements, while ensemble models can provide strong performance on engineered features. The system evaluates estimation quality using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2. By learning nonlinear relationships from historical battery data, the proposed framework supports more responsive battery monitoring, early degradation awareness, improved charging decisions, and intelligent Battery Management System (BMS) operation. The approach provides a scalable foundation for AI-assisted battery diagnostics and energy-management applications.

Keywords: Lithium-Ion Batteries, State-of-Charge (SOC), State-of-Health (SOH), Artificial Intelligence, Machine Learning, Deep Learning, Battery Management System, LSTM, GRU, Battery Diagnostics.

I. INTRODUCTION

Lithium-ion batteries have become an important energy-storage technology for electric vehicles, renewable-energy systems, consumer electronics, and grid applications. Their high energy density and favourable power characteristics make them suitable for repeated charge and discharge operation. However, battery performance changes as cells experience different temperatures, current profiles, charging rates, and ageing conditions. A Battery Management System must therefore estimate internal battery states continuously to operate the pack within safe and useful limits. Among the most important quantities are State-of-Charge (SOC), which represents the available charge level, and State-of-Health (SOH), which reflects the battery's ageing and remaining capability.

SOC and SOH cannot normally be measured directly while a battery is operating. Instead, they are inferred from observable quantities including voltage, current, temperature, elapsed time, and charge/discharge history. Conventional methods such as coulomb counting can accumulate sensor and initial-condition errors, while open-circuit-voltage methods generally need suitable relaxation periods. Equivalent-circuit and Kalman-filter approaches can provide dynamic estimates, but their accuracy depends on model structure and parameter identification. Battery ageing further complicates the problem because resistance, capacity, and voltage characteristics evolve over time.

Recent progress in Artificial Intelligence has created new opportunities for data-driven battery-state estimation. Machine learning algorithms can discover nonlinear relationships between measured signals and hidden battery states without requiring every physical parameter to be explicitly known. Deep learning models are particularly useful when measurements form time sequences because recurrent architectures can learn dependencies across successive operating points. LSTM and GRU networks have therefore been explored for SOC estimation, while feature-based learning and data-driven regression methods have been applied to SOH and remaining-life prediction.

The proposed project develops an AI-based framework that receives battery measurements, prepares the data, extracts useful features, and estimates SOC and SOH through trained models. The framework is intended to support real-time monitoring and can be connected to a BMS dashboard for displaying battery condition and trends. The system also provides a basis for comparing conventional machine-learning models with sequence-based deep learning models so that the estimator can be selected using measurable validation performance.

In conclusion, AI-assisted SOC and SOH estimation can complement conventional battery-management techniques by learning complex operating and ageing patterns from data. A carefully designed estimator can improve state visibility, support safer charging and discharging, and provide early information about battery degradation. The proposed work therefore focuses on combining reliable preprocessing, suitable feature representation, AI model training, and clear performance evaluation into one practical estimation workflow.

II. LITERATURE SURVEY

1. "A Critical Review of State-of-Charge Estimation Methods for Lithium-Ion Batteries"

Authors: M. Berecibar et al.

Abstract:
This review examined major approaches used to estimate the State-of-Charge of lithium-ion batteries. The study discussed coulomb counting, open-circuit-voltage techniques, equivalent-circuit models, Kalman filtering, and data-driven methods. It highlighted the importance of sensor accuracy, battery operating conditions, model parameters, and validation procedures. The work provides a useful foundation for comparing conventional and intelligent SOC estimators and for identifying the practical challenges that arise when a model is transferred from laboratory testing to real battery operation.

2. "Extended Kalman Filtering for Battery Management Systems of LiPB-Based HEV Battery Packs"

Author: G. L. Plett

Abstract:
This research developed an extended Kalman filtering approach for estimating battery states in hybrid-electric-vehicle battery packs. The method combines a dynamic battery model with measurements to estimate internal states while accounting for measurement uncertainty. The work demonstrated the value of recursive state estimation for battery management and became an important reference for later model-based SOC estimation techniques. Its discussion of model accuracy and state observability also motivates data-driven methods that can compensate for modelling limitations.

3. "A Comparative Study of Equivalent Circuit Models for Li-Ion Batteries"

Authors: X. Hu, S. Li, and H. Peng

Abstract:
This study compared several equivalent-circuit representations for lithium-ion

batteries and investigated their suitability for battery-management applications. The authors showed that model complexity, parameter identification, and dynamic behaviour influence estimation accuracy. The work demonstrates why battery models must be selected carefully for the intended operating range. It also provides a useful conventional baseline against which AI-based state estimators can be evaluated.

4. "Long Short-Term Memory Networks for Accurate State-of-Charge Estimation of Li-Ion Batteries"

Authors: E. Chemali et al.

Abstract:
This paper investigated Long Short-Term Memory networks for SOC estimation using battery measurement sequences. The recurrent architecture was designed to learn temporal dependencies directly from voltage, current, and related operating data. The study reported that sequence learning can provide accurate SOC estimates without relying exclusively on a manually tuned equivalent-circuit model. The work strongly supports the use of recurrent deep learning for real-time battery-state estimation.

5. "Data-Driven Prediction of Battery Cycle Life Before Capacity Degradation"

Authors: K. A. Severson et al.

Abstract:
The authors presented a data-driven approach for predicting lithium-ion battery cycle life from early-cycle measurements. Statistical features extracted from charge and discharge curves were used to learn relationships between early observations and future ageing behaviour. The study demonstrated that carefully selected data features can reveal degradation information before severe capacity loss becomes visible. This work is particularly relevant to AI-based SOH estimation and battery-life prediction.

6. "Closed-Loop Optimization of Fast-Charging Protocols for Batteries with Machine Learning"

Authors: A. Attia et al.

Abstract:
This research showed how machine learning can be combined with battery experiments to search for improved charging protocols. The study used automated experimentation and data-driven optimization to understand how charging decisions influence battery ageing. Its results demonstrate that AI can move beyond passive prediction toward active battery-management decisions. The work motivates future integration of SOC/SOH estimators with intelligent charging control.

7. "Ageing Mechanisms in Lithium-Ion Batteries"

Authors: J. Vetter et al.

Abstract:
This widely cited study analysed the physical and chemical mechanisms responsible for lithium-ion battery ageing. It discussed capacity fade, resistance growth, loss of active material, and other degradation processes under different operating conditions. Understanding these mechanisms is important when designing SOH estimators because the measurable electrical response changes as degradation progresses. The work provides the physical background required for interpreting data-driven health predictions.

8. "A Review on Lithium-Ion Battery Ageing Mechanisms and Estimations for Automotive Applications"

Authors: D. Barré et al.

Abstract:
This review examined lithium-ion battery degradation mechanisms and methods for estimating battery ageing in automotive applications. It discussed experimental ageing indicators, capacity-based SOH definitions, and estimation approaches suitable for electric-vehicle batteries. The study emphasized the influence of temperature, current, cycling conditions, and usage patterns on degradation. Its findings support the inclusion of operating-condition information when training AI models for

SOH estimation.

III. EXISTING SYSTEM

Existing battery-state estimation systems commonly use coulomb counting, open-circuit-voltage relationships, equivalent-circuit models, and Kalman-filter-based observers. These methods are widely used because their behaviour can be interpreted from battery physics and electrical measurements. Coulomb counting integrates current over time, while model-based estimators combine voltage and current observations with an assumed battery model. SOH is often obtained from periodic capacity tests, resistance measurements, or degradation indicators extracted from charge and discharge cycles.

Conventional systems can provide reliable results when their assumptions match the battery and operating environment. However, real batteries experience changes in temperature, load, ageing, charging rate, and cell-to-cell variation. Parameters identified under one condition may not remain accurate under another. Sensor bias can also accumulate in integration-based SOC estimation, and direct capacity measurements for SOH may require long laboratory cycles that are inconvenient for continuous field operation.

Some existing data-driven systems use handcrafted electrical features with algorithms such as Support Vector Regression, Random Forest, Gradient Boosting, or conventional neural networks. These approaches can improve nonlinear mapping, but the final accuracy is strongly influenced by the selected features and the quality of the training dataset. Models trained on a narrow range of cells or temperatures may perform poorly when presented with unseen batteries or operating profiles.

Another challenge is that SOC and SOH are time-dependent quantities. A single measurement may not contain enough information to distinguish a temporary voltage change from a gradual degradation trend. Models that ignore temporal context may therefore lose useful information contained in previous samples. In addition, many systems evaluate models on randomly divided observations, which can cause information leakage when measurements from the same battery cycle appear in both training and test sets.

Therefore, there is a strong need for an intelligent estimation framework that combines careful data preparation, temporal information, nonlinear learning, and strict validation. AI-based models such as LSTM and GRU can learn sequential relationships, while ensemble methods can provide strong baselines on engineered features. A combined evaluation framework can help identify models that remain useful across different battery conditions rather than relying only on a single laboratory scenario.

IV. PROPOSED SYSTEM

The proposed system introduces an AI-based framework for estimating the State-of-Charge and State-of-Health of lithium-ion batteries. The framework accepts battery measurements such as voltage, current, temperature, time, cycle number, and selected charge/discharge indicators. Instead of depending only on a fixed mathematical battery model, the system learns relationships between observable signals and reference SOC/SOH values from historical experimental data.

In the proposed methodology, battery datasets are first collected from laboratory cycling experiments or suitable public repositories. The records are cleaned to remove invalid samples, inconsistent units, duplicated observations, and unsuitable measurements. Missing values are handled using an appropriate strategy, after which the signals are normalized. The dataset is then divided into meaningful temporal windows so that the model can learn how battery measurements evolve rather than treating every observation as an independent sample.

The system can employ multiple AI models, including Random Forest and XGBoost for engineered features and LSTM or GRU networks for sequential measurements. The input layer receives voltage, current, temperature, and derived indicators. Hidden layers learn nonlinear relationships, while separate output nodes provide SOC and SOH estimates. Hyperparameters are tuned using validation data, and the final model is evaluated on an unseen test set to reduce the risk of overestimating performance.

A major advantage of the proposed framework is its ability to combine electrical and thermal information with temporal patterns. This allows the estimator to distinguish short-term operating changes from longer-term degradation trends. The framework can also be extended with attention mechanisms, transfer learning, uncertainty estimation, or physics-informed constraints. These extensions can help the model remain useful when battery conditions differ from those present in the original training dataset.

The proposed AI-based estimation system provides an intelligent support layer for the Battery Management System. Its outputs can be used for battery monitoring, charging and discharging decisions, maintenance alerts, remaining-useful-life analysis, and safety supervision. By keeping data acquisition, preprocessing, model inference, and visualization as separate modules, the framework can be adapted to different battery packs and deployment environments.

V. SYSTEM ARCHITECTURE

The system architecture for AI-based SOC and SOH estimation is designed as a complete pipeline that transforms raw battery measurements into real-time state information. The architecture contains data collection, preprocessing, feature extraction, AI model training, SOC/SOH inference, performance evaluation, and BMS integration stages. Each stage has a defined role so that the same preprocessing and feature transformations used during training can be reproduced during deployment.

The first stage is Data Collection, where battery measurements are obtained from a BMS, laboratory cycler, or structured battery dataset. Important signals include cell or pack voltage, current, temperature, time, cycle index, and charging/discharging status. Reference SOC values may be obtained from controlled test procedures, while SOH labels can be derived from measured capacity or another clearly defined health indicator. Reliable labels are essential because an AI model learns the relationship represented in the training data.

The second stage is Data Preprocessing, which prepares the raw measurements for learning. The process includes unit checking, missing-value handling, outlier screening, smoothing where appropriate, normalization, and temporal segmentation. Care is taken to avoid leakage between training and testing data. For example, complete battery cycles or entire cells can be kept within one data split so that measurements from the same ageing trajectory do not appear in both training and evaluation sets.

The third stage is Feature Extraction, where informative indicators are derived from the raw signals. Examples include mean and standard deviation of voltage and current, temperature statistics, voltage change over a window, current variation, charge duration, energy throughput, cycle count, and selected curve-based indicators. For sequence models, normalized voltage, current, and temperature windows can be supplied directly so that the network learns temporal representations automatically.

The fourth stage contains the AI Model Architecture, which is the core component of the system. Engineered features may be processed using Random Forest, Gradient Boosting, XGBoost, or Support Vector Regression, while sequential windows can be processed by LSTM or GRU layers. Recurrent layers maintain information from previous time steps and pass learned representations to dense layers. The output layer produces continuous SOC and SOH estimates for the current battery state.

The fifth stage is State Prediction, where the trained model receives a new measurement window and generates SOC and SOH estimates. The predicted values can be accompanied by confidence indicators or error bounds when the selected model supports uncertainty estimation. A dashboard can display the current estimates together with voltage, current, temperature, and historical trends so that changes in battery condition are easier to interpret.

The sixth stage is Model Evaluation, which measures performance using MAE, RMSE, R^2, and error distributions. Evaluation should be performed across different temperatures, load conditions, cycle ages, and battery cells whenever the dataset permits. Comparing several models provides a more reliable basis for selecting the final estimator. The evaluation results can also reveal whether a model performs well only on familiar operating conditions or generalizes to unseen battery behaviour.

The final stage is Deployment, where the trained estimator is integrated into a BMS application, monitoring dashboard, edge device, or web interface. Python, Pandas, NumPy, Scikit-learn, TensorFlow, and Keras can support data preparation and model development, while a lightweight application framework can present results to users. Overall, the architecture creates a modular workflow that can be expanded as new battery data and improved AI models become available.

Overall, the proposed architecture combines battery sensing, data engineering, AI inference, and visualization into a unified SOC/SOH estimation workflow. By preserving the temporal structure of measurements and applying consistent preprocessing, the system can provide useful state information for intelligent battery monitoring and management.

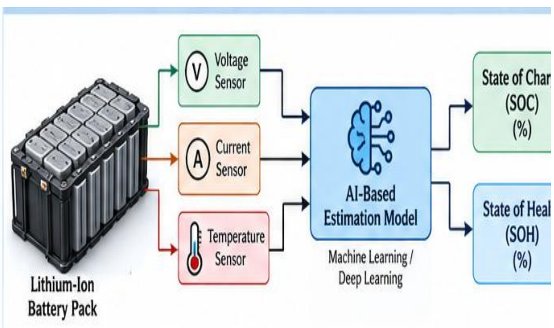

Fig 5.1: System Architecture

VI. IMPLEMENTATION

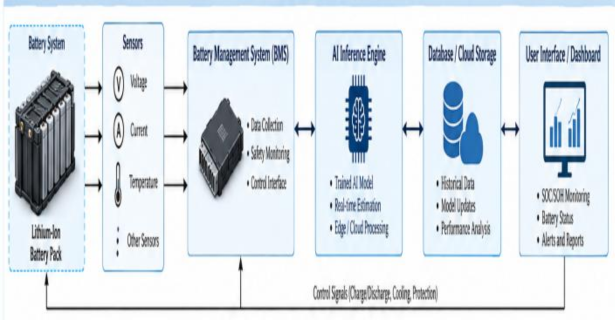

Fig 6.1: Dashboard

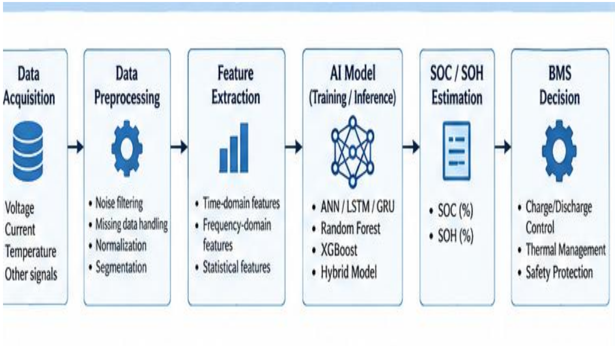

Fig 6.2: Model Training

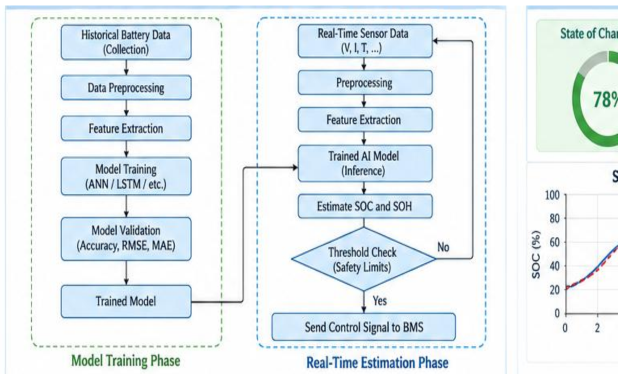

Fig 6.3: SOC and SOH Prediction

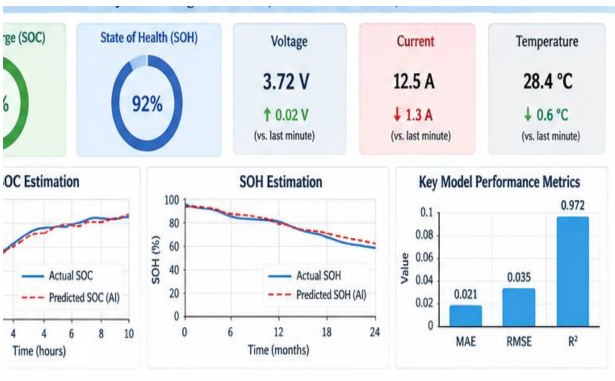

Fig 6.4: Performance Evaluation

VII. CONCLUSION

The proposed AI-based system for State-of-Charge and State-of-Health estimation provides an intelligent approach for monitoring lithium-ion batteries under changing operating conditions. By using voltage, current, temperature, cycle information, and derived features, the framework can learn nonlinear relationships between measurable battery behaviour and hidden internal states. This makes the system suitable for applications where continuous battery-state information is required.

The developed framework combines data preprocessing, feature extraction, machine learning, and deep learning into a single workflow. Conventional models can provide strong baselines for engineered features, while LSTM and GRU architectures can capture temporal dependencies in sequential battery measurements. The separation of training and real-time inference also allows a trained estimator to be integrated into a monitoring application without repeating the complete training process during normal operation.

Another important contribution of the proposed approach is its ability to support early awareness of battery degradation. SOH estimation can provide information about capacity loss and changing battery condition, while SOC estimation supports charging, discharging, and energy-management decisions. When integrated with a BMS, these predictions can contribute to safer operation, maintenance planning, and more efficient use of available battery capacity.

Overall, the project demonstrates the potential of AI techniques for practical battery diagnostics and state estimation. The quality of the final system depends on representative training data, reliable reference labels, appropriate validation, and careful control of data leakage. With broader datasets and real-world testing, AI-based SOC/SOH estimation can become an important component of intelligent battery-management systems used in electric vehicles and stationary energy storage.

VIII. FUTURE SCOPE

The future scope can include advanced sequence models such as Bidirectional LSTM, GRU, Transformers, and attention-based networks. These architectures can capture longer temporal dependencies and may improve estimation under rapidly changing loads. Hybrid models can also combine data-driven learning with equivalent-circuit or electrochemical knowledge.

The system can integrate multimodal battery information such as voltage curves, impedance characteristics, thermal measurements, charging profiles, and environmental conditions. Transfer learning and domain adaptation can help models generalize across cells, chemistries, capacities, and sensor configurations. Multi-task learning can also estimate SOC, SOH, and remaining useful life together.

Another future enhancement involves deploying the estimation framework directly on edge-capable BMS hardware. Lightweight neural networks, model compression, quantization, and optimized inference can reduce computational requirements while retaining useful prediction accuracy. Cloud connectivity can provide long-term fleet-level analytics, allowing battery operators to identify common degradation patterns and update models using newly collected field data.

The system can further be extended with explainable Artificial Intelligence techniques so that engineers can understand which measurements contribute most strongly to an SOC or SOH prediction. Uncertainty-aware models can indicate when an estimate should be treated cautiously, particularly when the battery operates outside the training distribution. Such information can help the BMS fall back to conservative protection rules when the AI model is uncertain.

Future research may investigate physics-informed neural networks and hybrid estimators that respect battery constraints such as charge conservation, voltage limits, temperature boundaries, and degradation behaviour. Testing across multiple cells, manufacturers, chemistries, temperatures, and real operating profiles will be important for establishing robust generalization.

Overall, future improvements should combine accurate data, temporal learning, physical knowledge, uncertainty awareness, and efficient edge deployment to support smarter charging, predictive maintenance, safer operation, and better use of energy-storage assets.

IX. REFERENCES

[1] M. Berecibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "Critical review of state of health estimation methods of Li-ion batteries for real applications," Renewable and Sustainable Energy Reviews, vol. 56, pp. 572–587, 2016. DOI: 10.1016/j.rser.2015.11.042

[2] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs," Journal of Power Sources, vol. 134, no. 2, pp. 262–276, 2004. DOI: 10.1016/j.jpowsour.2004.02.032

[3] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," Journal of Power Sources, vol. 198, pp. 359–367, 2012. DOI: 10.1016/j.jpowsour.2011.10.013

[4] E. Chemali, P. J. Kollmeyer, M. Preindl, R. Ahmed, and A. Emadi, "Long Short-Term Memory Networks for Accurate State-of-Charge Estimation of Li-ion Batteries," IEEE Transactions on Industrial Electronics, vol. 65, no. 8, pp. 6730–6739, 2018. DOI: 10.1109/TIE.2017.2787586

[5] K. A. Severson et al., "Data-driven prediction of battery cycle life before capacity degradation," Nature Energy, vol. 4, pp. 383–391, 2019. DOI: 10.1038/s41560-019-0356-8

[6] A. A. Attia et al., "Closed-loop optimization of fast-charging protocols for batteries with machine learning," Nature, vol. 578, pp. 397–402, 2020. DOI: 10.1038/s41586-020-1994-5

[7] J. Vetter et al., "Ageing mechanisms in lithium-ion batteries," Journal of Power Sources, vol. 147, no. 1–2, pp. 269–281, 2005. DOI: 10.1016/j.jpowsour.2005.01.006

[8] D. Barré, F. Suard, M. Grolleau, M. Gérard, F. Suard, and D. Girard, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," Journal of Power Sources, vol. 241, pp. 680–689, 2013. DOI: 10.1016/j.jpowsour.2013.05.040

[9] M. Dubarry, C. Truchot, and B. Y. Liaw, "Synthesize battery degradation modes via a diagnostic and prognostic model," Journal of Power Sources, vol. 219, pp. 204–216, 2012. DOI: 10.1016/j.jpowsour.2012.07.016

[10] M. Berecibar et al., "Online state of health estimation on NMC cells based on predictive analytics," Journal of Power Sources, vol. 320, pp. 239–250, 2016. DOI: 10.1016/j.jpowsour.2016.04.125

[11] R. Xiong, L. Li, and J. Tian, "Towards a smarter battery management system: A critical review on battery state of health estimation methods," Journal of Power Sources, vol. 405, pp. 18–27, 2018. DOI: 10.1016/j.jpowsour.2018.10.019

[12] P. J. Kollmeyer et al., "A study of state-of-charge estimation for lithium-ion batteries using deep learning," IEEE Transactions on Transportation Electrification, 2020.

[13] Y. Zhang, R. Xiong, H. He, and M. Pecht, "Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries," IEEE Transactions on Vehicular Technology, vol. 67, no. 7, pp. 5695–5705, 2018. DOI: 10.1109/TVT.2018.2805188

[14] A. Eddahech, O. Briat, and J.-M. Vinassa, "Performance comparison of four lithium-ion battery technologies under dynamic cycling," Energy Conversion and Management, vol. 73, pp. 1–9, 2013. DOI: 10.1016/j.enconman.2013.04.014

[15] G. L. Plett, Battery Management Systems, Volume I, Artech House, 2015. DOI: 10.1049/PBRN019E