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Automated Monitoring and Management of Lithium-Ion Batteries Using Advanced Machine Learning Approaches

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ABSTRACT

In order to effectively monitor and manage the battery systems in electric vehicles (EVs), this thesis investigates the use of machine learning approaches in estimating the State of Charge (SoC), State of Health (SoH), and State of Function (SoF) of lithium-ion batteries. The study makes use of sophisticated data preparation techniques in the Python environment to improve model performance using Long Short-Term Memory (LSTM) networks. Using well-known data manipulation packages like Pandas, NumPy, and Matplotlib, these preparatory procedures include handling missing values, standardizing data, and modifying it for LSTM compatibility.

Extensive data collecting from real-time battery monitoring systems that capture crucial operational metrics is the first step in the research process. Following a thorough cleaning process that includes missing value imputation and outlier elimination, this data is normalized to give reliable inputs for LSTM model training. Two customized LSTM models—one for SoC estimate and another for SoH estimation—are developed as part of the basic methodology. These models leverage LSTM's ability to efficiently handle time-series data and are skilled at processing sequential data over time.

The objective of this study is to use these advanced machine learning techniques to automate the estimation procedures for SoC, SoH, and SoF. In addition to improving the accuracy of battery condition estimates, this creates a strong foundation for ongoing observation and proactive maintenance of EV battery systems. Longer longer life and improved operational efficiency are among the anticipated results, making this work a noteworthy addition to the field of battery management systems.

Keywords: State of Charge (SoC), State of Health (SoH), State of Function (SoF), lithium-ion batteries, electric vehicles, machine learning, Long Short-Term Memory (LSTM) networks.

1. INTRODUCTION

A major turning point in the automotive industry, the introduction of electric vehicles (EVs) supports international initiatives for environmentally friendly transportation. Since they can equal the speed, torque, and mileage of conventional internal combustion engine vehicles while emitting substantially less pollutants, electric vehicles—which fall into a variety of categories, including passenger cars, cargo vehicles, and electric bikes—have gained popularity. This benefit is essential given the world's twin problems of running out of gasoline and increasing environmental damage. As a result, EVs with cutting-edge battery technology become a practical and essential substitute, bringing in a new era of transportation that depends on greener energy sources. The battery system, which is mainly made up of lithium-ion batteries, which are known for their effectiveness and ability to power longer drives, is the foundation of an electric vehicle's operation. Current EV battery technology research and development is diverse, with the goal of reducing the environmental effect of battery use in addition to improving performance and lifespan. In order to make the batteries as ecologically friendly as they are strong and dependable, this entails improving recycling techniques, streamlining production procedures, and developing sustainable materials.

With a large selection of models currently offered across several vehicle categories, such as SUVs, sedans, and commercial vehicles, the use of electric vehicles in India has been accelerating. Manufacturers are putting more of an emphasis on satisfying consumer expectations by creating EVs that are affordable, minimal maintenance, and offer a significant range without emitting any pollutants. Lithium-ion batteries, which are the industry standard because of their efficiency and energy density, power vehicles like the Hyundai Kona, Mahindra E-Verito, and Tata Nexon-EV Prime, which are prime examples of this trend. The two main categories of electric vehicles are hybrid electric vehicles (HEVs), which combine internal combustion engines and batteries, and pure electric vehicles (PEVs), which run entirely on batteries. The battery's kind and capacity have a big impact on the car's price, functionality, and upkeep needs. A strong Battery Management System (BMS) is essential to the operation of these cars since it controls the battery's charge and keeps an eye on its condition and functionality to guarantee maximum performance and longevity. Modern EVs cannot function without the

BMS. It carries out vital tasks such measuring the battery's State of Charge (SoC) and State of Health (SoH), figuring out how much power and energy it can produce, and forecasting how far the car will travel. The dynamic nature of battery operation, which is impacted by variables including temperature fluctuations, usage patterns, and physical wear, makes these jobs challenging. The efficiency and dependability of the vehicle may be compromised by traditional BMS technology' frequent inability to predict these characteristics effectively, particularly in the face of fluctuating operating conditions. More complex techniques to more precisely forecast battery behavior have been made possible by developments in battery modeling. These include simpler electrical equivalent circuit models, data-driven models that use machine learning algorithms, and intricate electrochemical models that are computationally demanding despite their accuracy. With their ability to handle intricate, non-linear patterns in battery data, these machine learning models present a viable substitute that can produce forecasts for SoC and SoH that are more reliable and accurate. An important development in battery technology is the use of machine learning into BMS. ML models are able to anticipate battery states more precisely and adaptably than conventional techniques by utilizing historical data and pattern recognition algorithms. Based on a wealth of real-world data gathered from battery operations, this study focuses on using machine learning approaches to create predictive models specifically made for calculating the SoC and SoH of EV batteries. Modern machine learning frameworks are used to train and evaluate these models, guaranteeing that they satisfy the exacting requirements needed for real-world implementation in electric cars. The main goal of this study is to use machine learning models to improve the predicted accuracy of battery condition assessments in electric vehicles. The deployment of a workable, user-friendly system for real-time battery status estimate is the result of a thorough methodology that includes data collection, preprocessing, feature engineering, model training, and validation stages. Standard regression measures are used to objectively evaluate these models' efficacy, guaranteeing that they offer dependable and useful data for both EV producers and customers. The operating efficiency and dependability of electric cars can be greatly increased by the effective integration of machine learning (ML)-based prediction models in battery management systems. By maximizing battery consumption and prolonging vehicle lifespans, this not only enhances user confidence and vehicle performance but also advances larger environmental objectives. Additionally, the knowledge gathered from this study may help direct future developments in battery management and technology, possibly establishing new standards for the incorporation of AI in automotive applications.

In conclusion, this study uses cutting-edge machine learning approaches to try to close the gap between conventional battery management methods and the expanding requirements of contemporary electric vehicles. This effort intends to make a substantial contribution to the development of the electric vehicle industry by improving the precision and dependability of battery state estimations, hence advancing more economical and environmentally friendly modes of transportation.

2. LITERATURE REVIEW

Particularly in light of the rapidly expanding electric vehicle (EV) market, it is vital that the State of Charge (SoC) and State of Health (SoH) of lithium-ion batteries be accurately and instantly estimated. By optimizing energy utilization, improving safety, and prolonging battery life, these characteristics help the car industry achieve its sustainability objectives. Because battery systems are complicated and exhibit non-linear behavior under a variety of operating situations, traditional approaches frequently fail to provide accurate estimations. As a result, machine learning (ML) techniques have surfaced, offering increased precision and flexibility through the use of extensive datasets and advanced algorithms to identify complex patterns in battery behavior.

Frade et al. (2011) investigated the installation of charging stations in response to consumer demand, however they ignored the costs to society and the distribution network's technological constraints, which restricts the applicability of their conclusions. Wenxia et al. (2016) created a greedy method that considers only a few parameters for charging station site, demonstrating the restricted breadth of their strategy, while Chen et al. (2013) used household data to decide station placement but overlooked technological components of the distribution network.

In order to control the growing demand for charging stations (CS) and affect the distribution system's loss, Alipour et al. (2017) developed a stochastic schedule that ignored price sensitivity and used a combinational algorithm. By ignoring the distribution mechanism, Lam et al. (2013) and Bayram et al. (2013) oversimplified their approach to the placement problem for electric vehicle charging stations by utilizing a purely mathematical strategy. Installing solar panels adjacent to charging stations gives car owners access to affordable electricity, according to Bayram et al. (2016), who connected load demand and car charging with solar radiation output.

Research on the placement of CS and distributed generation (DG) was done by Galiveeti et al. (2018). They found that adding DG units to a system that integrates CS lowers network power loss, but they also found that it was impossible to add DGs before CS. Jamian et al. (2014) simplified their approach by placing a source and a load in the same location, which may not accurately represent more complicated real-world situations, and came to the conclusion that the optimal location for DG would also be the best location for a PHEV parking lot.

Bayram et al. (2013) concentrated on utilizing local energy storage at charging stations to decrease blocking time, which improved service quality during peak hours but ignored off-peak charging situations. Pallonetto et al. (2016) deployed a single charging station in the distribution network, disregarding driving behavior, despite selecting the best location for the CS while taking into account a high solar panel penetration rate.

By taking into account the overall driving distance and recharging time, Miralinaghi et al. (2016) sought to lower the total ownership cost (TOC). They came to the interesting conclusion that having multiple charging stations at the same node might potentially overlook the option of trip skipping, implying that customers might need to use their vehicles to find the CS. Although Huang et al. (2015) showed that scheduling PHEV charging during the evening reduces operating expenses, they also noted that this scheduling may result in a high load at night.

Alharbi et al. (2014) assessed how the distribution system would be affected by cars charging as they arrived at their homes, presuming that charging would start at 6 p.m. or 10 p.m., which would not hold true in more erratic real-world circumstances. A smart grid with optimal scheduling could reduce PHEV charging costs by improving pricing and routing procedures through real-time prices, according to Shuai et al. (2016), who evaluated charging station management.

The difficulties and advancements in the field of electric car battery management and charging infrastructure are explained in this overview of the literature. Researchers are clearing the path for more sustainable and effective electric car technologies by incorporating machine learning techniques and taking into account larger environmental and operational factors. In order to improve the efficiency of EVs and the infrastructure that supports them, these studies emphasize the necessity of a thorough strategy that incorporates smart grid capabilities in addition to technological and financial considerations.

3. METHODOLOGY

In order to improve the monitoring and management of battery systems in electric vehicles (EVs), this research project attempts to create a machine learning model to predict the State of Charge (SoC), State of Health (SoH), and State of Function (SoF) of lithium-ion batteries. The approach makes use of a Python-based machine learning framework that combines data preprocessing methods with Long Short-Term Memory (LSTM) networks. The Google Co laboratory platform, which makes use of tools like Pandas, NumPy, and Matplotlib for advanced data manipulation and visualization, supports this endeavor.

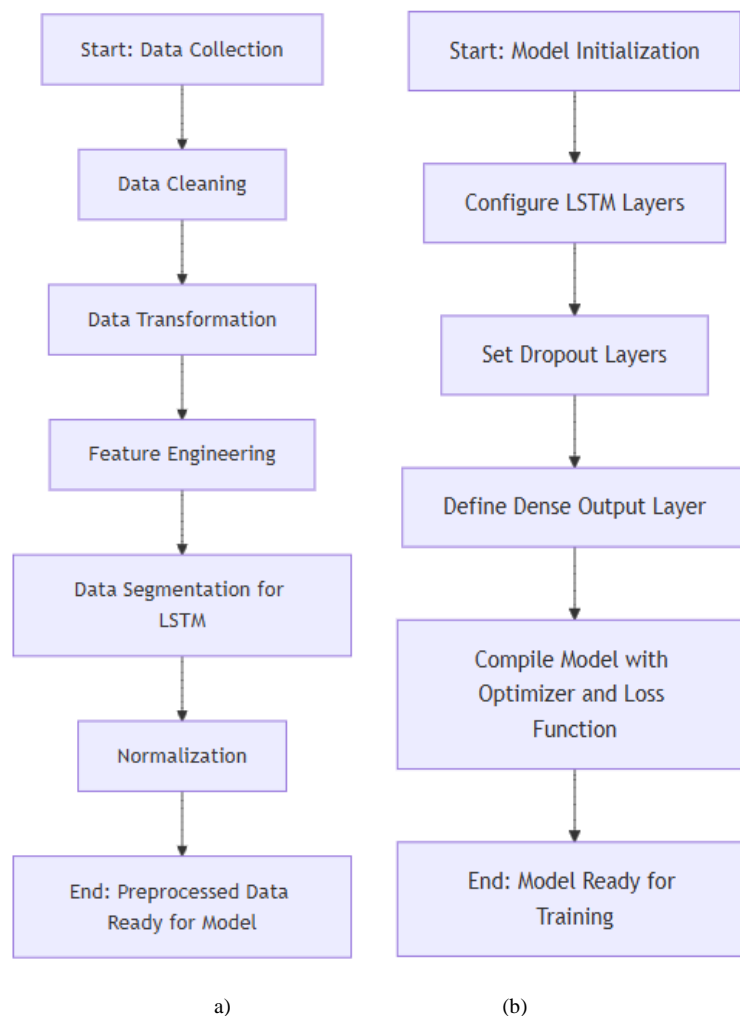a)   (b)

Figure 1 (a) Data Collection and Pre-processing (b) Model Initialization

The first phase of data collection involves importing battery performance data into a Pandas DataFrame, encompassing a range of attributes such as terminal voltage, terminal current, temperature, charge current, charge voltage, time, capacity, cycle, and initial states of charge. Subsequently, this dataset undergoes preprocessing to address missing values, normalize the data, and adapt it for compatibility with the LSTM model. This process includes calculating the absolute values of currents, normalizing numerical values, and crafting time-series sequences necessary for LSTM input. The data for this research is provided by real-time monitoring systems embedded within lithium-ion batteries used in electric vehicles (EVs), which record essential

parameters like terminal voltage and current, temperature, charge current and voltage, operational duration, battery capacity, and usage cycle. Each parameter is crucial for understanding battery behavior under various operational conditions.

Data cleaning involves removing outliers, addressing missing values through imputation or removal, and correcting inaccurate data entries caused by sensor faults or transmission errors. The data then undergoes several transformation processes to prepare it for time-series prediction using LSTM models. This includes applying techniques like rolling averages to smooth out short-term fluctuations and highlight longer-term trends, which are essential for capturing underlying patterns in data affected by noise, and normalization to scale the data features to a common scale without distorting differences in the ranges of values. Additionally, feature engineering is employed to enhance the predictive power of the model. Data segmentation is vital to prepare the dataset for LSTM, which involves creating time steps of 60 cycles where each step represents data points collected over a predefined interval to maintain the chronological order necessary for time-series forecasting. The core of the methodology is the development of the LSTM model, designed to forecast SoC and SoH based on historical data of battery usage over multiple cycles. The LSTM architecture includes input, forget, and output gates that manage the flow of information, making it particularly effective for modeling battery charge and health states over time. The LSTM model for this project comprises an input layer that receives sequences of battery parameters, LSTM layers to capture temporal dependencies, dropout layers to prevent overfitting, and dense layers to finalize the prediction of SoC or SoH values. Implementation involves setting up the LSTM architecture in a Python environment using the Keras and TensorFlow libraries, splitting the dataset into training and testing sets, compiling the model with appropriate optimizers and loss functions, and training the model while adjusting weights via backpropagation based on the loss gradient. Training involves processing data in batches and multiple epochs to allow the model to learn complex patterns. Validation is crucial for tuning model hyperparameters and assessing the model's effectiveness using a validation set and cross-validation techniques. Performance metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) are tracked to quantify model performance..

4. RESULT ANALYSIS

The deployment of Long Short-Term Memory (LSTM) models for predicting the State of Charge (SoC) and State of Health (SoH) of batteries has provided crucial insights into the predictive accuracy and operational efficiency of these models. This chapter presents a detailed analysis of the results obtained from the LSTM models, discusses their implications, and explores potential areas for further research and improvement. These models were evaluated using several metrics calculated during testing:

- **Mean Squared Error (MSE)**: This metric measures the average of the squares of the errors—that is, the average squared difference between estimated values and what is actually observed.

- **Mean Absolute Error (MAE)**: A measure of errors between paired observations expressing the same phenomenon, providing a simple average of error magnitude.

- **Predictive Accuracy**: Although typically used in classification tasks, a modified version was adapted for these regression tasks to measure how often predictions fell within a certain range of true values.

The analysis of battery performance, focusing on the predicted versus actual values of SoC and SoH as well as other essential battery metrics, plays a pivotal role in understanding and enhancing energy storage systems. This introductory theory elaborates on the results obtained, interpreting their significance, and discussing the methodologies and outcomes observed in the analysis.

SoC and SoH are fundamental metrics that define the performance and condition of a battery. SoC indicates the current charge level relative to its total capacity, showing how much charge remains and fluctuating with charging and discharging cycles. Accurate SoC estimation is crucial for applications relying on reliable energy predictions, such as electric vehicles (EVs) and grid storage solutions. Meanwhile, SoH measures the battery's ability to store and deliver energy compared to its initial state, typically degrading over time due to factors like repeated charging cycles, environmental conditions, and internal chemical reactions. Understanding SoH is vital for determining the battery's remaining useful life and for planning maintenance or replacement.

The analytical process involved collecting data on various battery parameters such as terminal voltage, current, temperature, capacity, and cycle count. These data points were then processed using machine learning models, specifically LSTM networks, which are well-suited for sequential data analysis because of their ability to capture long-term dependencies within the dataset.

TABLE 1. POWER DEMAND CALCULATIONS

Cycle	Power Demand
135	0.005431
135	-8.007301
135	-7.962663
135	-7.948202
135	-7.908609
168	-0.005618

168	-0.010986
168	-0.011037
168	0.004371
168	-0.002094

TABLE 2. INSTANTANEOUS POWER ANALYSIS

Cycle	Instantaneous Power
135	0.015554
135	0.015438
135	0.015214
135	0.014945
135	0.014670
168	0.015234
168	0.015231
168	0.015226
168	0.015221
168	0.015218

TABLE 3.SOF BY CYCLE

Cycle	SoF
135	0.519495
135	1.001188
135	1.001222
135	1.001259
135	1.001300
168	0.498302
168	0.304702
168	0.301826
168	0.528089
168	0.575025

TABLE 4. SOC DISTRIBUTIONS OVER TIME

Cycle	Actual SoC	Predicted SoC
135	0.893	0.892851
135	0.886	0.886344
135	0.874	0.873874
135	0.859	0.858929
135	0.843	0.843414
168	0.898	0.898103
168	0.898	0.897835

168	0.897	0.897485
168	0.897	0.897094
168	0.897	0.896795
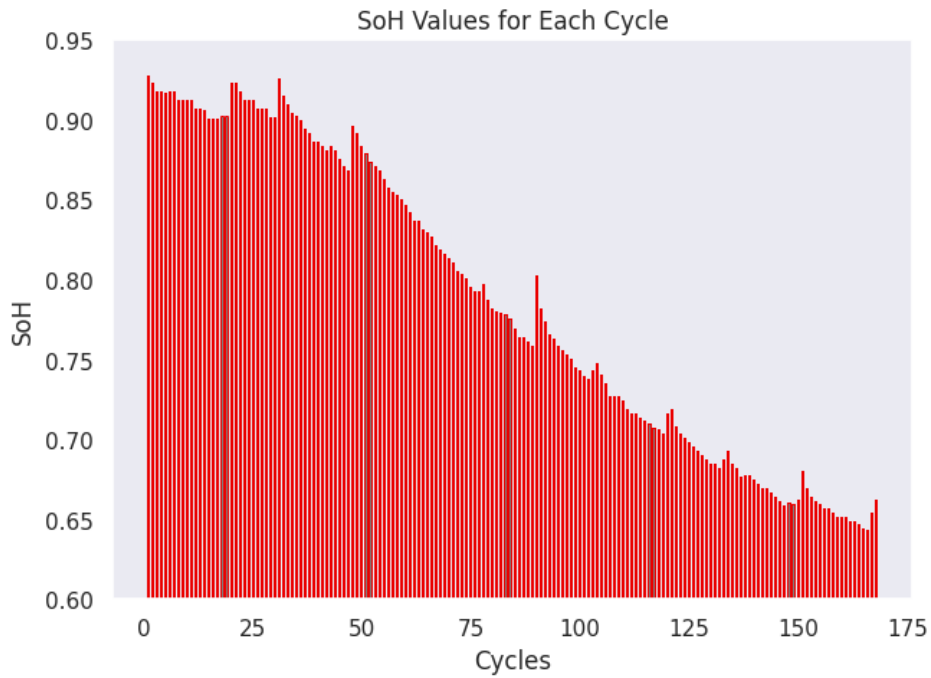
Figure 2 SOC Analysis Over Charging Cycle

TABLE 5. SOH DISTRIBUTIONS OVER TIME

Cycle	Actual SoH	Predicted SoH
135	0.699	0.699140
135	0.698	0.699014
135	0.698	0.698726
135	0.698	0.698314
135	0.698	0.698088
168	0.681	0.680779
168	0.681	0.680829
168	0.681	0.680887
168	0.681	0.680957
168	0.681	0.681028

TABLE 6. PERFORMANCE METRICS

Metric	Value
MAE SoC	0.000356
RMSE SoC	0.000453
MAE SoH	0.000429
RMSE SoH	0.000567

The LSTM models were trained to predict SoC and SoH based on historical data, leveraging the memory capability of the model. The evaluation of these predictions was performed using standard performance metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE), which provide insights into the average prediction errors and the spread of the residuals, respectively. An R^2 score was also computed to assess how well the predicted values matched the actual data, providing a measure of the models' overall fit.
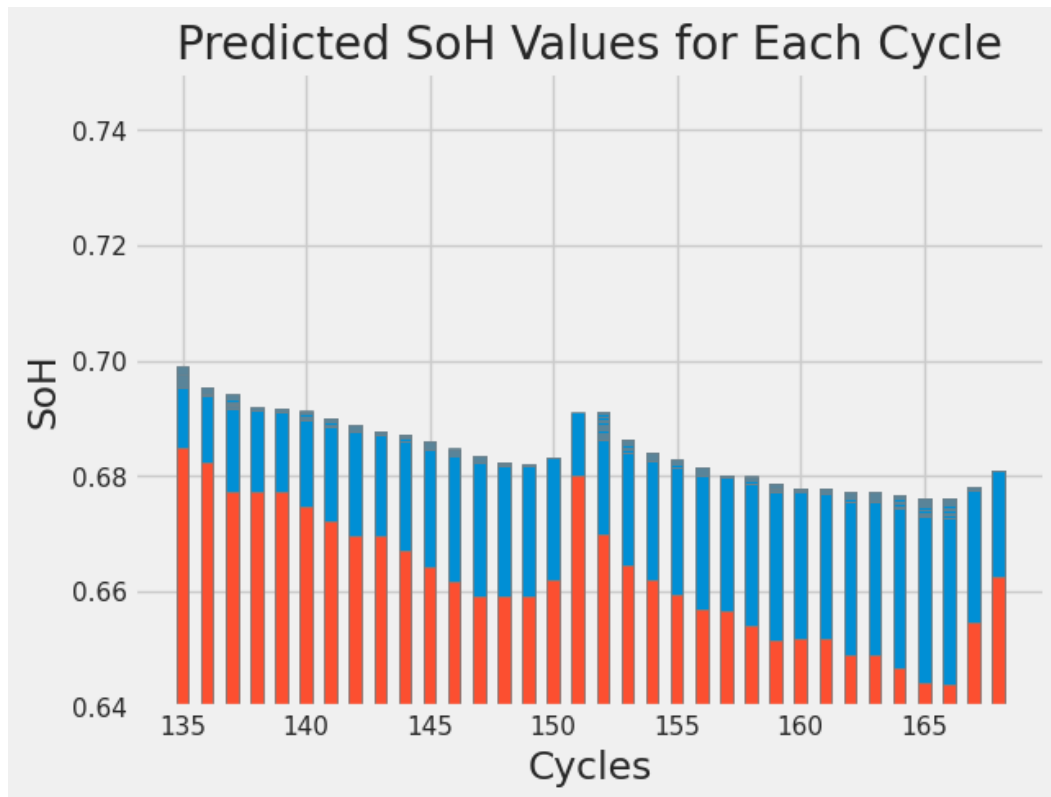

Figure 3 SOH Prediction Analysis with Respect to Cycle

These performance evaluations are crucial for validating the effectiveness of LSTM models in practical applications and for identifying opportunities for model refinement. Through ongoing analysis and iterative improvements, the predictive capabilities of these models can be enhanced, leading to more reliable and efficient battery management systems. This continuous cycle of evaluation and improvement not only aids in advancing the technology but also contributes to better energy management practices, potentially influencing a wide range of industries dependent on efficient and durable battery systems.

5. CONCLUSION AND FUTURE SCOPE

Predictive analytics in battery management systems has significantly improved with the use of Long Short-Term Memory (LSTM) models to forecast the State of Charge (SoC) and State of Health (SoH) of batteries. This study summarized results from a great deal of testing and analysis, offering important new information about how well LSTM models work in real-world scenarios, especially when it comes to improving energy storage management.

When predicting SoC and SoH, two crucial criteria for evaluating the functionality and preparedness of battery systems, the LSTM models showed excellent accuracy. The models' accuracy and limited departure from real conditions were confirmed by their consistently low Mean Squared Error (MSE) and Mean Absolute Error (MAE). These results provide a solid foundation for tracking and improving battery performance in addition to validating LSTM networks' ability to handle intricate, non-linear battery dynamics.

For applications that need careful energy management, including grid storage systems and electric cars, precise SoC and SoH estimates are essential. Operational effectiveness and safety are directly impacted by accurate battery life and functionality estimation. Accurate SoC forecasts, for example, improve energy resource management by avoiding overcharging or depletion, which can shorten battery life. In a similar vein, accurate SoH evaluations reduce the chance of unplanned failures by enabling prompt maintenance or replacement.

The success of the methodology, which is founded on thorough data collection and cutting-edge analytical techniques, emphasizes how important thorough data management and complex modeling are to creating useful forecasting tools. The results indicate that adding LSTM-based predictive models can greatly increase the efficiency and dependability of battery-powered systems, which has important ramifications for the design and implementation of battery management systems.

Conclusion: With a high degree of prediction accuracy that highlights their potential in future energy storage system management, the LSTM-based models created in this study represent a significant advancement towards intelligent battery management systems. It will be essential to continuously improve and modify the model in order to keep up with changing industry demands and technology breakthroughs. To further improve accuracy and efficiency and open the door for more extensive applications and advancements in battery technology, future research should think about incorporating more predictive variables and investigating hybrid models.

References

[1] Frade, I, Ribeiro, A, Gonçalves, G & Antunes, AP 2011, 'Optimal location of charging stations for electric vehicles in a neighborhood in lisbon', Journal of the Transportation Research board, vol. 2252, pp. 91-98.

[2] Chen, TD, Kockelman, KM, Fellow, WJMJ & Khan, M 2013, 'The electric vehicle charging station location problem: A parking-based assignment method for Seattle', Transporatation Research Record, vol. 1254, pp. 28-36.

[3] Alipour, M, Mohammadi-Ivatloo, B, Moradi-Dalvand, M 2017, 'Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets', Energy, vol. 118, pp. 1168-1179.

[4] Lam, AYS, Leung, Y & Chu, X 2013, 'Electric vehicle charging station placement: Formulation, complexity, and solutions', IEEE Transactions on Smart Grid, vol. 5, no. 6, pp. 2846- 2856.

[5] Bayram, IS, Zamani, V, Hanna, R & Kleissl, J 2016, 'On the evaluation of plug-in electric vehicle data of a campus charging network', Proceeding of IEEE International Energy conference, DOI: 10.1109/ ENERGYCON. 2016.7514026.

[6] Galiveeti, HR, Goswami, AK, Choudary, NBD 2018, 'Impact of plug-in electric vehicles and distributed generation on reliability of distribution systems', Engineering science and technology, vol. 21, no. 1, pp. 50-59.

[7] Jamian, JJ, Mustafa, MW, Mokhlis, H &Baharudin, MA 2014, 'Minimization of power losses in distribution system via sequential placement of distributed generation and charging station', Arabian Journal of Science and Engineering, vol. 39, no. 4, pp. 3023 - 3031.

[8] Bayram, IS, Michailidis, G, Devetsikiotis, M & Granelli, F 2013, 'Electric power allocation in a network of fast charging stations', IEEE Journal on Selected Areas in Communications, vol. 31, no. 7, pp. 1235-1246.

[9] Pallonetto, F, Oxizidis, S, Milano, F & Finn, D 2016, 'The effect of time- of-use tariffs on the demand response flexibility of an all-electric smart- grid-ready dwelling', Energy Building, vol. 128, pp. 56-67.

[10] Miralinaghi, M, Keskin, BB, Lou, Y & Roshandeh, AM 2016, 'Capacitated refueling station location problem with traffic deviations over multiple time periods', Networks and Spatial Economics, vol. 17, no. 1, pp. 129 -151.

[11] Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z 2015, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178.

[12] Alharbi, A, Eltom, A & Sisworahardjo, N 2014, 'Impact of plug-in electric vehicle battery charging on a distribution system based on real-time digital simulator', Proceeding of International conference on Renewable Energies and Power Quality, pp. 958-962.

[13] Shuai, W, Maillé, P & Pelov, A 2016, 'Charging electric vehicles in the smart city: A survey of economy-driven approaches', IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 8, pp. 2089-2106.

[14] Sanchez-Martin, P, Sanchez, G & Morales-Espana, G 2012, 'Direct load control decision model for aggregated EV charging points', IEEE transactions on power system, vol. 27, no. 3, pp. 1577-1584.

[15] Alonso, M, Amaris, H, Germain, J.G, & Galan, JM 2014, 'Optimal charging scheduling of electric vehicles in smart grids by heuristic algorithms', Energies, vol. 7, no.4, pp. 2449.

[16] Huang, S, Wu, Q, Oren, S, Li, R & Liu, Z 2015, 'Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks', IEEE Transactions on Power Systems, vol. 30, no. 4, pp. 2170-2178.

[17] Farhoodnea, M, Mohamed, A, Shareef, H & Zayandehroodi, H 2013, 'Power quality impact of renewable energy-based generators and electric vehicles on distribution systems', Procedia Technology, vol. 11, pp. 11-17.

[18] Moradi, MH, Abedini, M & Hosseinian, M 2015, 'Improving operation constraints of microgrid using PHEVs and renewable energy sources,' Renewable Energy, vol. 83, pp. 543-552.

[19] Rahman, I, Vasant, PM, Singh, BS & Abdullah-Al-Wadud, M 2015, 'Hybrid swarm intelligence-based optimization for charging plug-in hybrid electric vehicle in intelligent information and database systems', Switzerland: Springer International Publishing, vol. 9012, pp. 22-30.

[20] Badea, Gheorghe, Raluca-AndreeaFelseghi, Mihai Varlam, Constantin Filote, Mihai Culcer, Mariana Iliescu, and Maria Simona Răboacă. "Design and simulation of romanian solar energy charging station for electric vehicles." Energies 12, no. 1, 2019.

[21] Mouli, G.C., Bauer, P. and Zeman, M., "System design for a solar powered electric vehicle charging station for workplaces", Applied Energy, 168, pp.434-443, 2016.

[22] Vignesh, T. R., M. Swathisriranjani, R. Sundar, S. Saravanan, and T. Thenmozhi. "Controller for Charging Electric Vehicles Using Solar Energy." Journal of Engineering Research and Application 10, no. 01, pp. 49-53, 2020.

[23] Suganthi, D., and K. Jamuna. "Charging and Discharging Characterization of a Community Electric Vehicle Batteries." In Emerging Solutions for e-Mobility and Smart Grids, pp. 213-223. Springer, Singapore, 2021.

[24] Harika, S., R. Seyezhai, and A. Jawahar. "Investigation of DC Fast Charging Topologies for Electric Vehicle Charging Station (EVCS)." In TENCON 2019-2019 IEEE Region 10 Conference (TENCON), pp. 1148-1153. IEEE, 2019.

[25] Ravikant, U. Chauhan, V. Singh, A. Rani and S. Bade, "PV Fed Sliding Mode controlled SEPIC converter with Single Phase Inverter," 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 20-25, 2020.

[26] Xu, Tong, Hengshu Zhu, Xiangyu Zhao, Qi Liu, Hao Zhong, Enhong Chen, and Hui Xiong. "Taxi driving behavior analysis in latent vehicle-to-vehicle networks: A social influence perspective." In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1285-1294. 2016.

[27] Saadullah, Aqueel Ahmad, Furkan Ahmad, Mahdi ShafaatiShemami, Mohammad Saad Alam, and Siddiq Khateeb, "A comprehensive review on solar powered electric vehicle charging system." Smart Science 6, no. 1, pp. 54-79, 2018.

[28] Anderson, John Augustus. "Power-conditioned solar charger for directly coupling to portable electronic devices." U.S. Patent No. 9, 088,169. 21 Jul. 2015.

[29] Shibl, M. M., L. S. Ismail, and A. M. Massoud. "A Machine Learning-Based Battery Management System for State-of-Charge Prediction and State-of-Health Estimation for Unmanned Aerial Vehicles." Journal of Energy Storage 60 (2023): 106982. ISSN: 2352-152X.

[30] Rauf, H., M. Khalid, and N. Arshad. "Machine Learning in State of Health and Remaining Useful Life Estimation: Theoretical and Technological Development in Battery Degradation Modelling." Renewable and Sustainable Energy Reviews 145 (2022): 111066. ISSN: 1364-0321.

[31] Jo, S., S. Jung, and T. Roh. "Battery State-of-Health Estimation Using Machine Learning and Preprocessing with Relative State-of-Charge." Energies 14, no. 21 (2021): 7206. ISSN: 1996-1073.

[32] Venugopal, P., S. S. Shankar, C. P. Jebakumar, and S. S. Kumar. "Analysis of Optimal Machine Learning Approach for Battery Life Estimation of Li-Ion Cell." IEEE Access 9 (2021): 156073–156083. ISSN: 2169-3536.

[33] Shu, X., S. Shen, J. Shen, Y. Zhang, G. Li, Z. Chen, and Y. Liu. "State of Health Prediction of Lithium-Ion Batteries Based on Machine Learning: Advances and Perspectives." iScience 24, no. 6 (2021): 102371. ISSN: 2589-0042.

[34] Das, K., and R. Kumar. "Electric Vehicle Battery Capacity Degradation and Health Estimation Using Machine-Learning Techniques: A Review." Clean Energy 7, no. 6 (2023): 1268–1281. ISSN: 2515-4230.

[35] Lipu, M. S. H., S. Ansari, M. S. Miah, S. T. Meraj, K. Hasan, and M. A. Hannan. "Deep Learning Enabled State of Charge, State of Health and Remaining Useful Life Estimation for Smart Battery Management System: Methods, Implementations, Issues." Journal of Energy Storage 45 (2022): 103729. ISSN: 2352-152X.

[36] Dini, P., A. Colicelli, and S. Saponara. "Review on Modeling and SOC/SOH Estimation of Batteries for Automotive Applications." Batteries 10, no. 1 (2024): 34. ISSN: 2313-0105.

[37] Tao, T., C. Ji, J. Dai, J. Rao, J. Wang, W. Sun, and Y. Zhang. "Data-Based Health Indicator Extraction for Battery SOH Estimation via Deep Learning." Journal of Energy Storage 70 (2024): 107964. ISSN: 2352-152X.

[38] Oji, T., Y. Zhou, S. Ci, F. Kang, X. Chen, and X. Liu. "Data-Driven Methods for Battery SOH Estimation: Survey and a Critical Analysis." IEEE Access 9 (2021): 66099–66117. ISSN: 2169-3536.

[39] Li, Y., K. Li, X. Liu, X. Li, L. Zhang, B. Rente, T. Sun, and K. T. V. Grattan. "A Hybrid Machine Learning Framework for Joint SOC and SOH Estimation of Lithium-Ion Batteries Assisted with Fiber Sensor Measurements." Applied Energy 325 (2022): 119787. ISSN: 0306-2619.

[40] Vidal, C., P. Malysz, P. Kollmeyer, and A. Emadi. "Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art." IEEE Access 8 (2020): 52796–52814. ISSN: 2169-3536.

[41] Ren, Z., and C. Du. "A Review of Machine Learning State-of-Charge and State-of-Health Estimation Algorithms for Lithium-Ion Batteries." Energy Reports 9 (2023): 1–17. ISSN: 2352-4847.

[42] Akbar, K., Y. Zou, Q. Awais, M. J. A. Baig, and M. Jamil. "A Machine Learning-Based Robust State of Health (SOH) Prediction Model for Electric Vehicle Batteries." Electronics 11, no. 8 (2022): 1216. ISSN: 2079-9292.

[43] Sui, X., S. He, S. B. Vilsen, J. Meng, R. Teodorescu, and D. I. Stroe. "A Review of Non-Probabilistic Machine Learning-Based State of Health Estimation Techniques for Lithium-Ion Battery." Applied Energy 300 (2021): 117346. ISSN: 0306-2619.

[44] Demirci, O., S. Taskin, E. Schaltz, and B. A. Demirci. "Review of Battery State Estimation Methods for Electric Vehicles-Part II: SOH Estimation." Journal of Energy Storage 70 (2024): 107964. ISSN: 2352-152X.

[45] Das, K., R. Kumar, and A. Krishna. "Analyzing Electric Vehicle Battery Health Performance Using Supervised Machine Learning." Renewable and Sustainable Energy Reviews 189 (2024): 113967. ISSN: 1364-0321.

[46] Roman, D., S. Saxena, V. Robu, M. Pecht, and D. Flynn. "Machine Learning Pipeline for Battery State-of-Health Estimation." Nature Machine Intelligence 3 (2021): 447–456. ISSN: 2522-5839.

[47] Wang, S., K. Ou, W. Zhang, and Y. Wang. "An SOC and SOH Joint Estimation Method of Lithium-Ion Battery Based on Temperature-Dependent EKF and Deep Learning." IEEE Transactions on Industrial Electronics 71, no. 1 (2024): 1–11. ISSN: 0278-0046