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Machine Learning for State of Charge Estimation in Battery Management System

B. Madhavi[1], Dr. G. Indira Kishore[2], Dr. V. Manoj[3], J. Divya[4]

[1] Electrical Engineering Department, GMR Institute of Technology, Rajam, India
[2]Assistant professor, Electrical Engineering Department, GMR Institute of Technology, Rajam, India
[3] Senior Assistant Professor, Electrical Engineering Department, GMR Institute of Technology, Rajam, India
[4] Electrical Engineering Department, GMR Institute of Technology, Rajam, India

ABSTRACT:

SoC estimation is a particularly crucial task in battery management, especially for electric vehicles. State of Charge (SoC) estimation plays a key role in battery management systems, which serves as the basis for judging how much remaining energy there still be in a battery at any given time. Precise Operationality accuracy of SoC estimation is important for better battery performance, longer lifetime, and safety in many applications such as EVs or renewable energy storage. Traditional techniques have used Coulomb counting and voltage-based methods, which may be limited by problems such as sensor drift and battery degradation. More recently, data-driven and adaptive methods are coming into focus. Machine learning models, for instance, can learn evolving behaviour from operations data. This will account for issues like temperature changes, varying use-cycles, and degradation. The integration of an understanding of battery physics and data-driven methods provides a strategy to develop models that capture the fundamentals as well as complexities of how batteries operate. Future iterations could look toward models that self-correct, adjusting in real time for batteries that age or operate in new environments. This continuous improvement of SoC estimation could lead to more dependable and effective battery systems for today's fast-rising energy applications.

Keywords: State of charge (SOC), Battery management system (BMS), Support vector regression (SVR), Long short-term memory (LSTM), Machine learning.

1. Introduction:

1.1 Importance of battery management system:

Battery Management Systems (BMS) are the main control units that keep an eye on, regulate, and improve the performance of rechargeable batteries in electric vehicles (EVs), hybrid cars, and stationary energy storage systems. Their main goals are to make sure the battery is safe to use, improve its performance, and make it last longer. The BMS keeps an eye on the State of Charge (SOC), which shows how much energy is left in the battery compared to its maximum capacity.

1.2 Limitations of Conventional Estimation Techniques:

Although they are straightforward, traditional SOC estimate methods like Coulomb counting and the Open Circuit Voltage (OCV) method have serious shortcomings. For on-board devices that run continuously, the OCV approach is unsuitable since it requires the battery to remain at rest in to detect voltage accurately. Contrarily, coulomb counting integrates the charge/discharge current across time, which can lead to an accumulation of noise and sensor drift and, over extended periods of time, increase estimation errors. By using battery models and dynamic corrections, model-based filtering techniques like the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) increase accuracy.

1.3 Machine Learning for SoC Estimation:

That's where machine learning (ML) truly shines. Unlike traditional physics-based methods, machine learning does not rely on rigorous formulas; instead, it learns directly from data, such as previous performance or experimental results. This enables it to detect subtle, complicated trends in battery behaviour and adjust as conditions change. Machine learning (ML) has fast become vital in battery management systems (BMS), particularly for assessing state of charge (SoC). Initially, ML approaches like fuzzy logic and neuro-fuzzy systems were effective in dealing with the unpredictable, nonlinear characteristics of batteries.

1.4) Problem Statement:

Both renewable energy systems and electric vehicles (EVs) depend on lithium-ion batteries. For the battery to operate safely and effectively, it is essential to estimate its State of Charge (SOC), which is its "fuel gauge." Conventional techniques such as Kalman filters, open-circuit voltage (OCV), and Coulomb counting have drawbacks, including complex modelling, accumulated errors, and rest time requirements. Machine learning (ML) approaches like Support Vector Regression (SVR), Neural Networks (NN), and Recurrent Neural Networks (RNN) have been investigated as solutions to these problems.

2. Literature Review:

Lithium-ion batteries used in energy storage systems and electric cars depend on accurate State of Charge (SOC) estimation for longevity, performance, and safety. Numerous methods, from contemporary data-driven approaches to traditional electrochemical models, have been developed over time to predict SOC. Among the most basic methods are conventional estimation techniques like Coulomb counting and the Open Circuit Voltage (OCV) method.

2.1 Research Gaps:

- **Model Dependency:** The intricate physical models used by current SOC estimation techniques alter with temperature and battery aging.
- **Poor Generalization:** Conventional machine learning models, such as SVR and ANN, only work well with particular datasets and are ineffective when used in novel driving scenarios.

2.2 Research Objectives:

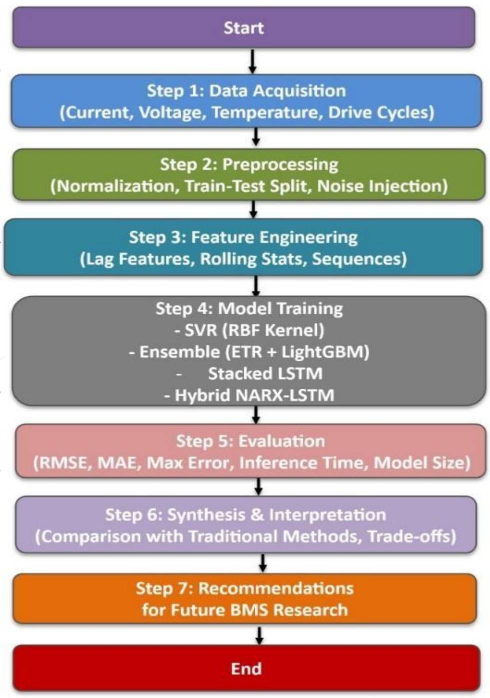
- To review and analyse existing machine learning techniques used for State of Charge (SoC) Estimation in lithium-ion battery systems.
- To identify the limitations of traditional SoC estimation methods such as Kalman filters, Coulomb counting, and model-based approaches.

3. Methodology:

3.1 Model of Support Vector Regression (SVR):

The Support Vector Regression (SVR) algorithm estimates the State of Charge (SoC) of a lithium-ion battery by learning the nonlinear relationship between measurable electrical parameters and the actual SoC. The general procedure involves data collection, model training, and SoC prediction.

1. **Data Acquisition**: The input dataset is formed using measurable battery parameters such as voltage (V), current (I), temperature (T), and time (t) obtained during charge–discharge cycles. The corresponding reference SoC values are determined using a reliable method (e.g., Coulomb counting or experimental calibration).
2. **Model Training:** SVR maps the nonlinear input–output relationship using a kernel function, typically the Radial Basis Function (RBF). The model learns from training data to minimize the prediction error within a defined tolerance margin (ε).
3. **SoC Prediction:** Once trained, the SVR model predicts the SoC for new input conditions. The method captures nonlinear behaviour, reduces sensitivity to measurement noise, and ensures accurate estimation under dynamic load variations.



$$SOC_{est} = \sum_{i=1}^{N} (\alpha_i - \alpha^*_i)\, K(x_i, x) + b$$

$$K(x_i, x) = \exp(-\gamma |x_i - x|^2)$$

3.2) Long Short-Term Memory (LSTM) Network:

The Long Short-Term Memory (LSTM) network, a type of recurrent neural network (RNN), is widely used for SoC estimation due to its capability to learn temporal dependencies and nonlinear relationships in sequential battery data. Unlike static models, LSTM effectively captures the dynamic behaviour of lithium-ion batteries under varying load conditions.

1. **Data Preparation:** Time-series data of battery parameters such as voltage (V), current (I), temperature (T), and charge/discharge time (t) are collected. These parameters are pre-processed— normalized and segmented into sequences—so that the model can learn temporal patterns corresponding to SoC variations.
2. **Model Architecture and Training:** The LSTM model consists of multiple layers of memory cells, each containing input, forget, and output gates that control the flow of information through time steps. This structure allows the network to retain important historical information and discard irrelevant data.

$SOC\mathrm{est}(t) = Wy \cdot ht + by$

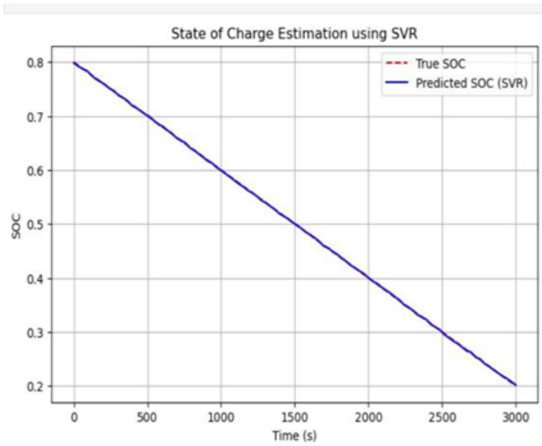
$ht = ot.\ \tanh(Ct)\ ,\ Ct = ft.\ Ct{-}1 + it.\ \tilde{C}t$

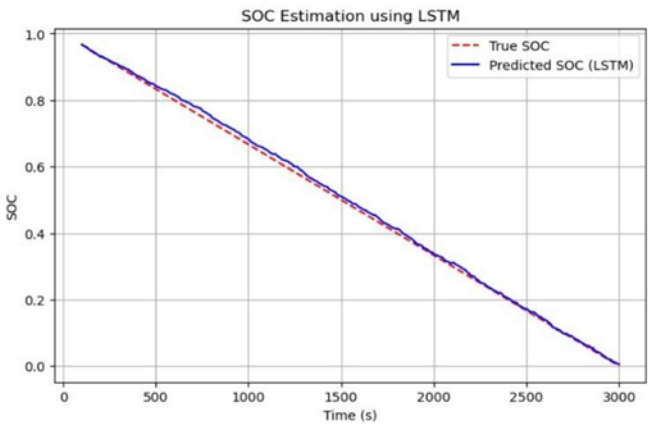
SoC Prediction: After training, the model can predict SoC in real time using recent voltage, current, and temperature sequences as input.

4. Results and Discussion:

Through the capture of nonlinear relationships between voltage, current, and temperature, SVR efficiently estimates the State of Charge (SOC). It exhibits little sensitivity to changes in parameters

and maintains accuracy and robustness under a range of load conditions. The reliability of SVR for SOC estimation is confirmed by studies that report low RMSE and MAE values. By identifying long- term dependencies in time-series battery data, LSTM networks perform better than other models. They offer precise, real-time SOC tracking and are highly adaptive to changes in load and temperature. Electric vehicles and energy storage systems benefit greatly from LSTM's ability to capture dynamic battery behaviour and provide smoother, more accurate predictions. SVR and LSTM both perform better than conventional SOC estimation techniques overall.





5. Conclusion:

For determining the State of Charge (SOC) of lithium-ion batteries, machine learning techniques like Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) networks provide a number of benefits. These data-driven models successfully handle nonlinear and time-varying battery behavior, in contrast to conventional methods like Kalman filters or Coulomb counting, which have the drawbacks of error accumulation and reliance on exact parameters. Accurate real-time SOC tracking under fluctuating loads and temperatures is made possible by LSTM networks, which are particularly capable of capturing temporal dependencies in time-series data.

References:

1. J Antón, J. C. Á., Nieto, P. J. G., Viejo, C. B., & Vilán, J. a. V. (2013). Support vector machines used to estimate the battery state of charge. *IEEE Transactions on Power Electronics*, *28*(12), 5919– 5926. https://doi.org/10.1109/tpel.2013.2243918
2. Yang, F., Song, X., Xu, F., & Tsui, K. (2019). State-of-Charge estimation of Lithium-Ion batteries via Long Short-Term memory network. *IEEE Access*, *7*, 53792–53799. https://doi.org/10.1109/access.2019.2912803
3. Firke, R., & Gupta, M. K. (2024). Long Short-Term Memory Approach to Predict Battery SOC. *Journal of Renewable Energies*, *27*(2). https://doi.org/10.54966/jreen.v27i2.1311
4. Zhao, F., Guo, Y., & Chen, B. (2024). A review of Lithium-Ion Battery state of charge estimation methods based on machine learning. *World Electric Vehicle Journal*, *15*(4), 131. https://doi.org/10.3390/wevj15040131
5. Wang, Y., Shao, N., Chen, G., Hsu, W., & Wu, S. (2022). State-of-Charge estimation for Lithium- Ion batteries using residual convolutional neural networks. *Sensors*, *22*(16), 6303. https://doi.org/10.3390/s22166303

6. Rout, S., Samal, S. K., & Mahapatro, S. R. (2024). Estimation of SOC for Li-ion battery- powered three-wheeled electric vehicle using machine learning methods. *Engineering Research Express*. https://doi.org/10.1088/2631-8695/ad8063