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State of Charge (SOC) Optimization Algorithm in Electrical Vehicles

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ABSTRACT:

Knowing how much charge is left in the battery of an electric vehicle — also called State of Charge (SOC) — is very important for safety, performance, and battery life time, particularly in fast charging. The old ways of estimating the SOC are slow and usually get it wrong when the data is considered noisy or missing. So, people are now using smarter tools to get better results, faster, with machine learning and artificial intelligence methods, such as LSTM networks, transformer models, and optimization methods like Dung Beetle Optimizer. Also, some of these models reduce the time to measure data from the battery by only considering the most important signals, known as feature selection. These new models are tested with real data from batteries and the results are amazing — they get faster, more accurate, and more reliable SOC estimates. This helps make electric vehicles safer, improves battery performance, and supports smarter charging systems.

KEYWORDS: State of Charge (SOC), Electric Vehicles (EVs), Machine Learning, Soc estimation Fast Charging, Battery Management System (BMS).

1.INTRODUCTION

The green and clean movement has accelerated with great force, propelling Electric Vehicles (EVs) to the forefront as one of the most promising solutions to future mobility. The battery is the heart of every Electric Vehicle since it is the primary source of energy. The reliability, efficiency, and performance of the vehicle also largely depend on the management of the battery and one of the most important features is the State of Charge (SoC), which is the amount of energy left in the battery and is usually represented as a percentage of the total capacity.

Accurate estimation and optimisation of SoC are very important. Failure to control SoC accurately can lead to deep discharge or overcharging of the battery, which leads to a reduction in its lifespan and safety. On the part of the user, inaccurate SoC estimation can lead to unnecessary restriction of the driving range of the vehicle or worst still, loss of power while stranded. SoC optimisation algorithms have therefore been at the forefront of EVs today.

SoC is not easily **adjustable.** Batteries are non-linear reactants and temperature, age, and other driving conditions worsen the situation. Underestimation of SoC will make the driver feel like he has less power left than he really does with possible wastage while overestimation will lead to sudden loss of power or battery ageing. To facilitate the solution of all these challenges, researchers and engineers developed sophisticated algorithms that would enhance the accuracy and speed of SoC estimation when compared to real-time situations.

These two types of algorithms fulfill two different roles: optimisation and estimation. In the estimation process Coulomb counting, Kalman filters, fuzzy logic systems, and even different types of AI techniques are used. For example, Coulomb counting measures the amount of current flowing into and out of the battery but can carry errors forward in time. Model-based techniques such as Kalman filters can improve accuracy by having a battery model process sensor data. In the case of AI-based techniques, the method learns from terabytes of data to discern the highly complex behaviour of batteries in a wide variety of scenarios. From the optimisation perspective these algorithms run in the Battery Management System (BMS) so as to optimise the use of the energy when accelerating, cruising or braking using regenerative breaking. For example, when using regenerative breaking, when breaking the system should keep the recovered energy at bay, that is, it should not allow the breaking energy to charge the battery. SoC optimisation divides the power between the battery and engine in hybrid cars which saves fuel and minimises emissions. A correct SoC also helps a big bit regarding estimating the range. Knowing more or less how much distance left on the existing charge goes a long way in alleviating range anxiety, one of the biggest issues of EV-owning. It also helps in predicting the times at which the car will need to be charged, especially as smart grids and V2G technology becomes more common, where the EV ends up supplying the grid with energy during peak hours of demand. The other important aspect is safety aspect. Misuse of SoC leads to overheating, thermal runaway and fire. Optimization places the battery within the safety margin, thereby ensuring the safety of the vehicle and the occupants.

So in summary SoC optimisation algorithms play an important role in the development of EV technology. They help in increasing the life of the battery, increase the performance of the battery, increase the safety of the battery and give the driver confidence in the vehicle. As AI and machine learning develops, SoC optimisation is likely to be even more intelligent and predictive, and will be the future of electric vehicles in a more efficient, safe and sustainable manner.

2. STATE OF CHARGE

State of Charge (SoC) is the percentage of energy that is left in a battery in comparison to the total energy that the battery can hold.SoC is usually expressed in percentage (%)100% means the battery is charged and 0% means the battery is discharged.SoC serves the same purpose as a fuel gauge in a normal car, giving the customer an approximation of how much distance is left on the existing charge and helps the Battery Management System (BMS) to avoid overcharge or deep discharge of the battery. Since SoC cannot be measured directly, different approaches and equations are implemented to determine the SoC in terms of current, voltage, resistance and complex algorithms.

.Simple Definition Formula

$$\mathrm{SOC} = \frac{\mathrm{Cr}}{\mathrm{Ct}} \times 100\%$$

$\mathrm{C_t}$: Total rated capacity of the battery

2. Coulomb Counting Method

This is one of the most widely used equations to estimate

$$\mathrm{SOC(t)} = \mathrm{SOC(to)}\frac{1}{\mathrm{Cn}}\int_{\mathrm{tn}}^{\mathrm{t}} \mathrm{I}(\tau)\mathrm{d}\tau$$

$\mathrm{SOC(t_0)}$: Initial SoC at beginning time

$\mathrm{C_n}$: Nominal battery capacity (Ah)

$\mathrm{I}(\tau)$: Battery current (positive on discharge, negative on charge)

3. KEY TECHNIQUES

3.1 SIMPLE / TRADITIONAL METHODS:

Coulomb counting — principle and fiction:

Coulomb counting is nothing more than a count of electric charge. If the battery has a nominal capacity (in ampere-hours), and you know the instantaneous current into(negative sign) or out of (positive sign) the battery, then the change in storedcharge from time to is the time integral of current. In continuous form this is written as

$$.\mathrm{SOC(t)} = \mathrm{SOC(t_0)} - \frac{1}{\mathrm{C_{nom}}}\int_{\mathrm{t_0}}^{\mathrm{t}} \mathrm{I}(\tau)\mathrm{d}\tau$$

$$\mathrm{SOC(K)} = \mathrm{SOC[K-1]} - \frac{\mathrm{I[K]}.\,\underline{\Delta}\mathrm{t}}{\mathrm{C_{nom}}}$$

$$\mathrm{SOC(K)} = \mathrm{SOC[K-1]} - \frac{\mathrm{\eta I[K]}.\,\underline{\Delta}\mathrm{t}}{\mathrm{C_{eff}(T, age)}}$$

The appeal of Coulomb counting is that it’ s simple and can be done in real time: give me continuous SoC estimates to drive my dashboard, range estimate, charge control, etc.

But tiny systematic errors - a tiny offset in a current sensor, the quantization of ADC measurements, timing jitter, self discharge errors, leakage currents, coulombic efficiency variations with varying currents and temperatures, etc., conspire to induce large SoC drifts over timescales of hours or days.

To make Coulomb counting practical in the real world you need to (a) use a low-offset accurate accurate current sensing method, (b) sample and integrate at a suitable rate with anti-aliasing filtering, (c) use temperature- and health-dependent capacity correction, and (d) periodically re-calibrate against an independent reference (e.g. OCV or a known complete charge event).

Open-CircuitVoltage (OCV lookup) - idea and limitations:

A cell’ s open-circuit voltage, measured after the terminal polarization has relaxed, has a general SoC dependence based on cell chemistry and temperature. In a well-characterized OCV–SoC measurement, slow charge or discharge steps repeated with waiting periods long enough for the cell to rest create a lookup table or continuous curve that can be used to estimate SoC from a relaxed-measured voltage.

The typical lithium-ion standard OCV curve is nonlinear: it is relatively steep in the near-empty and full states (meaning voltage is relatively more sensitive to SoC in those states) and relatively flat in the middle range (which means that the sensitivity of voltage and accuracy in the mid-SoC range is poor).

OCV is drift-free from integration because of its character as an instantaneous mapping, but it has serious practical drawbacks. A real OCV measurement requires the cell to be in repose (zero net current) and polarization effects to stabilize; the resting time needed needed varies depending on cell size and history of recent current, from minutes to hours. Hysteresis exists: OCV at a given SoC following discharge might be slightly varying from that following charge because of internal polarization and electrochemical path dependence. Battery aging and temperature change the OCV-SoH relationship, so only a single stored curve is applicable to the tested temperature and State of Health (SoH). In practice the OCV method is optimally applied as an offline calibration or for sporadic correction when the pack is known to be at rest (e.g. overnight or after prolonged idling).

Implementation considerations and best practice (narrative).

Used effectively these old tricks need to be focussed on a number of issues in several areas.

Offset and temperature drift need to be cancelled or measured (this is usually done with current sensing - ie differential amplifiers with shunt resisters but Hall sensing is also used).

High frequency noise needs to be removed prior to integration by signal conditioning.

The sampling resolution needs to be high enough to capture the dynamics of the system being modelled; poor sampling will lead to increased numerical integration errors, but over sampling will place a computational burden and increase the likelihood of noise.

Aging and temperature capacity corrections - the manufacturers capacity is only a starting point and should be compared against OCV or full charge events periodically to ensure long term accuracy.

OCV curves: Draw the curves for the various cell types over the temperature range of interest in characterisation. retain OCV – SoC curves indexed by temperature as lookup tables or fit function (usually splines or low order polynomials) for interpolation.

3.2 OBSERVER AND FILTER BASED SOC ESTIMATION TECHNIQUES:

Estimation of the State of Charge (SoC) is required to be sufficiently accurate for safe and effective use of batteries in electric vehicles. Observer and filter based techniques are efficient techniques used for estimating the SoC as integration of battery modelling and real-time measurement information gives an optimal trade-off between robustness, accuracy and adaptability for different operating conditions.Sense and compensate for hysteresis: prefer to correct OCV following prolonged rest periods due to hysteresis. Do not correct OCV during transient temperature states.

Example operating profile: On-drive BMS in an EV would typically perform Coulomb counting and recalculated SoC every second or faster with the effective capacity and efficiency term temperature compensated. At night when current in the pack falls below a certain threshold for a prolonged rest period, the BMS records the pack OCV, reads from the temperature-matched OCV – SoC curve and corrects the cumulative SoC estimate towards the OCV-based value. This regular simple re-anchoring mechanism ensures the dash display current without placing a heavy computation burden on the system or placing a burdensome test regime on the manufacturer..

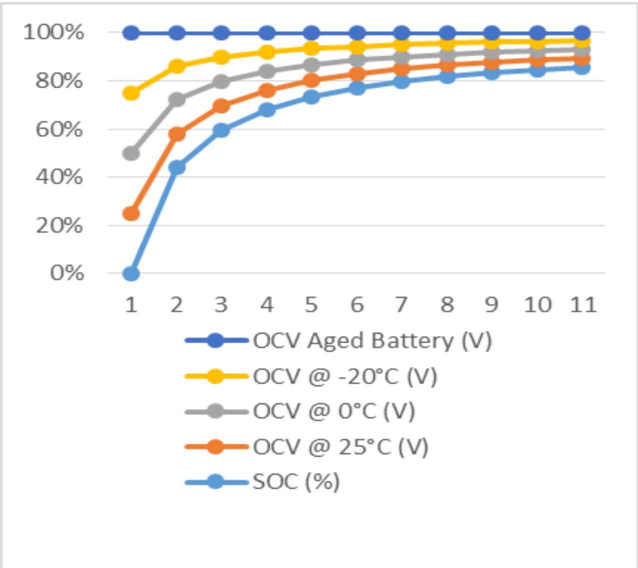

Fig2.1: Coulomb counting & Open-Circuit Voltage

The predicted internal states, including SoC, are supplied by the battery model. The observer/filter compares these state predictions with measurements. The filter corrects the measured state, in this case SoC, to account for any discrepancy between prediction and measurement. This closed loop correction mechanism means that these techniques are able to cope with sensor noise, uncertainties and dynamic operating conditions efficiently.

Extended Kalman Filter (EKF): EKF is an extension of classical Kalman Filter to nonlinear systems by linearising the battery model about the current operating point. It is a compromise between accurate but computationally expensive solution and is one of the most viable real time solutions.

Unscented Kalman Filter (UKF): UKF is better than EKF because it is a deterministic sampling strategy (sigma points) to deal with nonlinearities. More accurate estimation (especially in case of dynamic load change) at the expence of more computations in.ParticleFilter(PF)is an approximation of SoC probability distribution by a set High computational cost which may make it unuseable in real time constrained application.

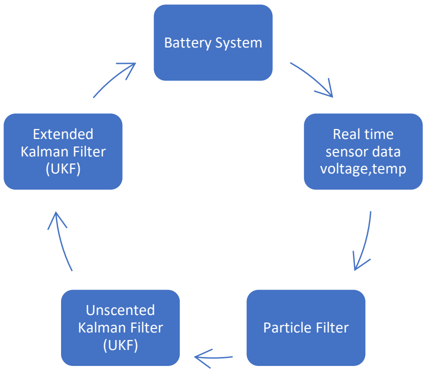

Fig2.1: Filter Based Battery Soc Estimation

Advantages and Limitations: The power of such methods is their capacity to suppress noise and enhance estimation robustness. UKF and PF, especially, can achieve SoC estimation error low in single digits, which is very useful in prolonging battery life and enhancing safety. This comes at a price, however, of higher computational load, with PF as the most computationally intensive

3.3 PARAMETER-IDENTIFICATION AND OPTIMIZATION HYBRID METHODS FOR SOC ESTIMATION:

It is crucial to estimate the SoC of the batteries correctly in order to make practical BMS feasible, especially for electric vehicles. Even model-based methods as the Extended Kalman Filter and other filters work fine, their performance decreases when the batteries' parameters (internal resistance, capacity, time constants, etc.) change due to aging or the temperature conditions. To overcome this problem, the hybrid methods which combines the parameter-identification with the optimization methods are used.

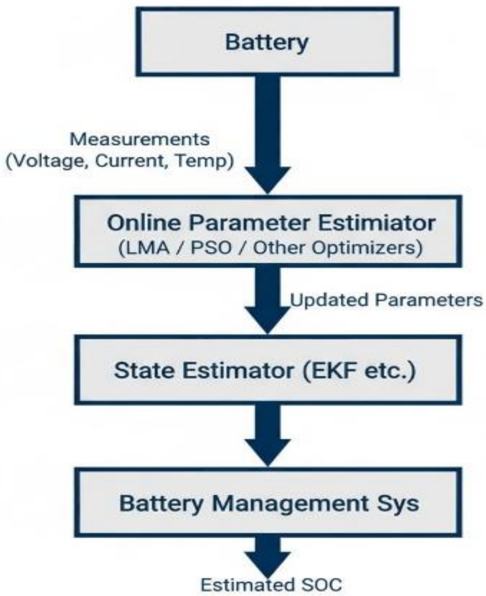

Fig 3.1: Hybrid State of charge (soc) Estimation Framework.

Working Principle: In these kinds of hybrid methods, the filters like EKF are not used separately. These filters are used in combination with estimation algorithms or optimization methods which update the parameters of fig3.1 represents the battery model in real time. For example: EKF combined with online parameter estimators like the Levenberg –Marquardt Algorithm (LMA) helps to accurately estimate the nonlinear parameters of the battery model. Particle Swarm Optimization (PSO)-aided filters enhance the tuning of the parameters by using the bio-inspired optimization to make the filter adaptive to new operating conditions. This kind of continuous tuning guarantees that the mathematical model of the battery is always accurate. The effects of aging, load change and temperature variations are always compensated.

The greatest advantage of using parameter-identification hybrids is that they can maintain high accuracy in the long term. As the filter works with current and realistic model parameters in the continuous operation, the soc estimation is guaranteed to be accurate in the whole life time of the battery. So, they are very well positioned for actual electric vehicle application where the batteries are constantly stressed and aged. But with that accuracy comes the disadvantage of increased complexity. They require more computational resources, strong algorithms and a huge amount of training or identification data. In addition, real-time optimization may be hard to accomplish when the vehicle is running under rapidly changing conditions

3.4 MODEL PREDICTIVE CONTROL (MPC) AND OPTIMAL CONTROL FOR CHARGING BATTERIES:

As the number of electric vehicles is rising drastically, charging strategies have become an important research topic. Conventional charging schemes, e.g., CC/CV, are easy to implement, but they will cause high heat, unbalanced charging and aging of batteries in the long run. To overcome the above disadvantages, advanced control strategies such as Model Predictive Control (MPC) are used. MPC-based charging methods use mathematical models to predict the future behavior of the battery and compute an optimal charging path considering charging rate, battery life and safety.

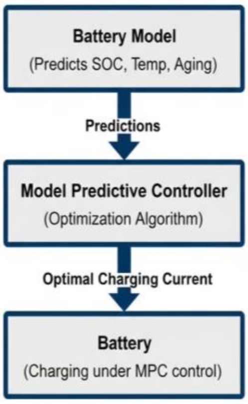

Fig4.1: Model predictive control for Battery charging.

Working Principle: The essence of MPC for battery charging is to estimate future battery states, such as SoC, temperature and internal stresses by using a predictive model. In every time step, the controller decides on the best charging current profile by solving an optimization problem. The charging path is built to satisfy some constraints, including.Reach the desired Soc in a given time, limit the temperature rise to prevent thermal stress, and reduce the effects of degradation mechanisms that shorten the battery's life. This results in what is now referred to as "health-aware fast charging". Unlike traditional approaches, MPC explicitly recognizes the tradeoff between fast charging and long-term battery reliability as shown in Fig 4.1

Benefits and Disadvantages of MPC charging method is it is possible to extend battery life while still allowing fast charging. MPC considers the thermal and electrochemical limits to prevent over stressing the battery and encourage safe operation. Also it allows for different user profiles to be supported by MPC, e.g. one could configure that speed is an important attribute for emergency charging, whereas longevity is an important attribute for regular charging. However method also has some down sides. MPC requires an accurate predictive model of the battery, which could be challenging due to the nonlinear electrochemical behavior. Additionally an optimization problem to be solved in real time requires more computing power, making the Battery Management System BMS more costly and complex. Nevertheless given all the constraints, the benefits in terms of battery performance and health make MPC a very promising approach for future generation charging systems.

3.5 DATA-DRIVEN AND MACHINE LEARNING TECHNIQUES FOR SOC ESTIMATION:

In past years data-driven approaches based on machine learning (ML) have emerged as strong tools for State of Charge (SoC) estimation of batteries. Unlike traditional model-based approaches which are heavily dependent on electrochemical models and parameter estimation, ML methods learn from data itself. Machine learning algorithms learn very non-linear relationships from past records of measurements from batteries such as current, voltage, temperature, and cycling history which cannot be represented by physical equations.

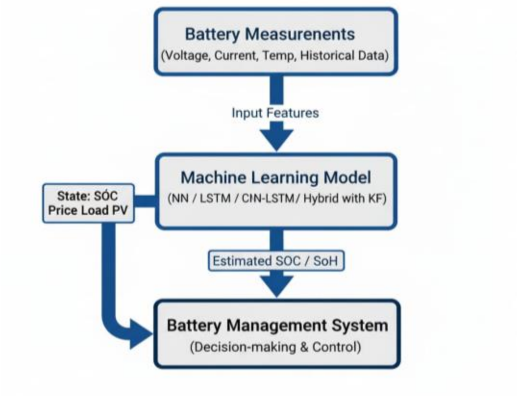

Fig5.1: Machine Learning- Based Battery Management System

Working Principle: Fig5.1is represents the Machine learning techniques work by projecting input features (live sensor measurements) onto output states like SoC, State of Health (SoH), or even future trend of degradations. Different types of algorithms are used depending on the problem complexity: Feed-forward neural networks can be used to approximate fixed nonlinear mappings between inputs and outputs. RNN, such as LSTM and GRU, are well adapted to sequential data since they are able to learn temporal relationships and discover how current SoC is affected by historical charging and discharge cycles.Hybrids of CNN and LSTM are both spatial feature extraction and temporal learning, so they are suitable for extracting latent patterns from voluminous sensor data Hybrids of neural network and Kalman filter combine the learning capability of ML with classical state estimators stability, yielding more accurate predictions using using these architecture, not only do ML-based methods enable accurate SoC estimation, but they also help predict battery degradation, enabling predictive maintenance and extending battery life.

Benefits of ML-based methods lie in their ability to model the strong nonlinear effects such as temperature, changes in internal resistance, and aging on capacity for each cell. With adequate and representative training data, they outperform conventional methods by learning to perform better in situations where physical R can. However, there are also potential disadvantages with these approaches. Their success depends on having adequate diversity and quality of the training data. Without adequate data or data that can represent the operating context, the model will be unable to generalize and will produce poor estimates in situations they have not seen before. Like deep learning approaches, neural networks also require significant amounts of computational power to train and deploy, which makes them impractical for real-time execution on embedded systems.

3.6 REINFORCEMENT LEARNING AND CHARGING SCHEDULING FOR OPTIMAL CHARGING:

As the number of electric vehicles (EVs) increases, there is a huge increase in the demand for smart charging techniques. Conventional charging mechanisms for EVs are user initiated or based on a schedule, which results in high electricity charges, increased battery wear and significant impact on the power grid. Reinforcement Learning (RL) which is an area of research in artificial intelligence, is now a powerful framework to optimize charging plans. RL algorithms learn the policy for making decisions by interacting with an environment and receiving feedback in the form of a reward or penalty. RL is therefore well suited for a dynamic and stochastic charging environment where electricity prices, amount of renewable energy available and capacities of the power grid change over time.

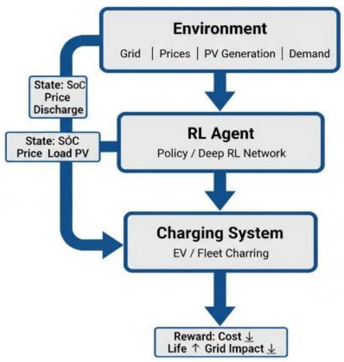

Fig6.1: RL-Based EV Charging System.

Working Principle: In an RL-based charging system, Fig6.1 represents the electric vehicle or fleet in considered as an agent that acts in an environment constituted by the power grid, charging facilities and user demand constraints. The agent observes the system state, such as the current SoC of the battery, electricity price, grid load, availability of renewable energy, and then selects an action. The action may be when to charge, how much power to consume, or whether to discharge energy back to the grid in a vehicle-to-grid (V2G) mode. The environment measures this selected action and returns a reward signal as a function of the goals to reduce charging cost, reduce peak demand, maximize battery life, or the efficient use of renewable energy. The RL agent learns an optimal charging policy through interactions and balances these conflicting objectives. Many recent works have explored using deep reinforcement learning (DRL) where neural networks are used to represent approximations of decision-making policies such that high-dimensional, abstract state spaces can be managed.

Applications and Strengths:

Reinforcement learning has strengths for both individual EVs and large fleets of charging. For individual vehicles, RL can schedule charging when called, based on electricity prices, real-time renewable generation, and driver demand. At the fleet level, RL can enable coordinated charging to alleviate grid congestion and improve load balancing, while integrating distributed energy resources such as solar photovoltaics (PV). Because of RL's flexibility to varying and dynamic conditions, it is most suitable for use on the smart grid where real-time optimization is key.

Benefits and Limitations of RL Charging Optimization with Rewards: Optimization of charging with RL charging is beneficial, but not without challenges. An appropriate reward function must be carefully designed, or suboptimal--and potentially dangerous--charging schemes can result. RL algorithms require large quantities of training data or simulated worlds to learn successful policies that don't embody real-world conditions. Computational complexity also limits real-time applications, particularly for deep RL methods using large neural networks. But recent advances are mitigating these problems with model-based RL, transfer learning, and hybrid methods combining RL and optimization/control theory

4. Results and Discussions

Category	Technique	Examples	Core Principle	Primary Advantage	Primary Limitation
Traditional / Simple	**Coulomb Counting (CC)**	—	Time integration of instantaneous current.	Ease of use, real-time continuous estimation.	Severe drift due to accumulated systematic errors (sensor offset, efficiency, self-discharge).
	Open-Circuit Voltage (OCV)	—	Mapping rested cell voltage to SoC using lookup tables.	Free from integration error drift, useful for recalibration.	Needs long rest time, hysteresis-sensitive, low sensitivity in mid-SoC range.
Model-Based Filtering	**Kalman Family Filters**	Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Particle Filter (PF)	Combining an analytical battery model and real-time measurement for closed-loop state estimation.	Attenuation of noise, greater robustness, high precision (particularly UKF/PF).	Greater computational burden (PF most compute-intensive), precision decreases as model parameters drift.
Hybrid (Filtering + Parameter ID)	**Adaptive Filters**	EKF with Levenberg–Marquardt Algorithm (LMA), PSO-supported filters	Real-time updating of battery model parameters (resistance, capacity) alongside state estimation.	Ensures long-term accuracy, adapts to aging and temperature variations.	High computational demand; requires complex algorithms and data for real-time optimization.
Optimal Control	**Model Predictive Control (MPC)**	—	Application of a predictive model to compute an optimal future charging current profile under constraints (temperature, desired SoC, degradation).	"Health-aware fast charging," extends battery life while minimizing stress.	Needs accurate predictive model and high computational resources for real-time optimization.
Data-Driven / ML	**Neural Network-Based Models**	RNN, LSTM, GRU, Neural Network–Kalman Filter Hybrids	Learning nonlinear relationships between sensor data (V, I, T) and battery states (SoC, SoH) from training data.	Captures strong nonlinear effects (aging, temperature), excellent predictive capability.	Heavy dependence on training data quality/diversity, computationally expensive to train and deploy.

Category	Technique	Examples	Core Principle	Primary Advantage	Primary Limitation
Decision / Scheduling	**Reinforcement Learning (RL)**	RL, Deep RL	Agent learns optimal charge/discharge policy by interacting with a dynamic environment (grid, prices, demand) to maximize reward.	Adaptive scheduling for cost/grid/longevity objectives; well-suited for dynamic environments (V2G, smart grid).	Requires massive training data/simulation; designing effective reward functions is challenging; high computational cost.

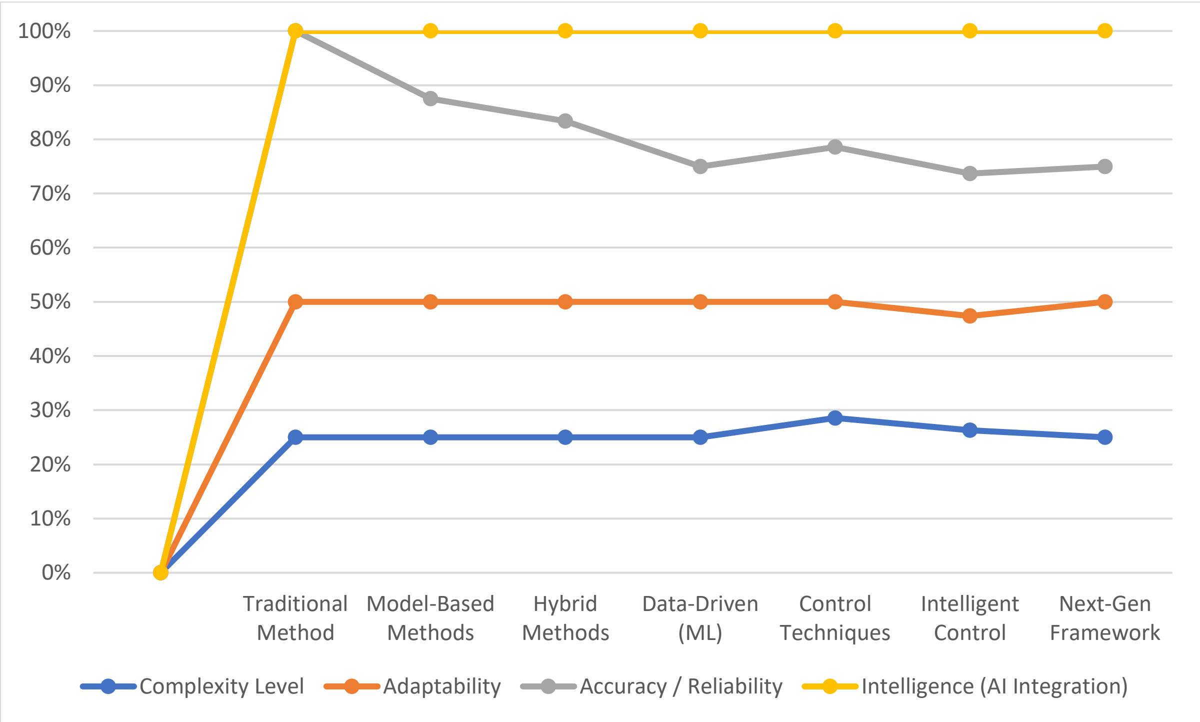

Fig: Comparative Analysis of Estimation/control Methods

5. Conclusions

One of the developments away from simple, inaccurate Coulomb Counting to very sophisticated, predictive intelligence is the evolution of Battery Management Systems (BMS). Most notable of these innovations is the progression from simple models updated in real-time (Observer/Filter-Based) to Hybrid Approaches that are dynamically compensating the model trying to account for battery aging and temperature drift.

Simultaneously, Data-Driven (ML) approaches present a robust alternative by acquiring complex battery performance from actual operating data. Under under charging, the focus is on "health-aware" control through Model Predictive Control (MPC) and Reinforcement Learning (RL) for preserving speed without compromising safety or longevity.

The Blended Framework is the total solution that combines the strength of model-based methods and flexibility of data-driven learning into a strategic blend. Such a combination is required for accurate State of Charge (SoC) estimation and optimal, safe control in the complex, dynamic environment of next-generation electric vehicles.

6.References

1. X. Zhang, Z. Li, D. Zhou, and M. Chen, "State-of-Charge Estimation for Lead-Acid Battery Using Isolation Forest Algorithm and Long Short Term Memory Network With Attention Mechanism," School of Information Science and Engineering, Dalian Polytechnic University, Dalian 116000, China, Accessed: Oct. 21, 2025.
2. C. Bourelly, M. Vitelli, F. Milano, M. Molinara, F. Fontanella, and L. Ferrigno, "EIS-Based S0C Estimation: A Novel Measurement Method for Optimizing Accuracy and Measurement Time," IEEE, Accessed: Oct. 21, 2025.

3. S. H. Lee, "Optimal Allocation of BESS to Maximize Efficiency Under Constrained SOC in Parallel Inverter-Based Scaled-Up Slack Bus," IEEE, Accessed: Oct. 21, 2025.
4. K. Qian, R. Fachrizal, J. Munkhammar, T. Ebel, and R. C. Adam, "The Impact of Considering State-of-Charge-Dependent Maximum Charging Powers on the Optimal Electric Vehicle Charging Scheduling," IEEE, Accessed: Oct. 21, 2025.
5. M. Yılmaz, E. Çınar, and A. Yazıcı, "A Transformer-Based Model for State of Charge Estimation of Electric Vehicle Batteries," Department of Computer Engineering, Eskişehir Osmangazi University, Eskişehir, Türkiye, Accessed: Oct. 21, 2025.
6. W. Ding, F. Zou, J. Liu, and C. Zhang, "State of Charge Prediction for Electric Loader Battery Based on Extreme Learning Machine," School of Electronics, Electrical, and Physics, Fujian University of Technology, Fuzhou 350118,China, Accessed: Oct. 21, 2025.
7. F. Ahmed, K. Abualsaud, and A. M. Massoud, "On Equivalent Circuit Model-Based State-of-Charge Estimation for Lithium-Ion Batteries in Electric Vehicles," IEEE, Accessed: Oct. 21, 2025.
8. V. Selvaraj, I. Vairavasundaram, D. O. Pranav, S. Shukla, and B. Ashok, "Implementation of Discrete Wavelet Combined Bayesian-Optimized Gaussian Process Regression-Based SOC Prediction of EV Battery," School of Electrical Engineering, Vellore Institute of Technology, Vellore 632014, India, Accessed: Oct. 21, 2025.
9. H. Xu, Q. Xu, F. Duanmu, J. Shen, L. Jin, B. Gou, F. Wu, and W. Zhang, "State-of-Charge Estimation of Lithium-Ion Batteries Based on EKF Integrated With PSO-LSTM for Electric Vehicles," Accessed: Oct. 21, 2025.
10. S. Guo and X. Meng, "Optimal Resequencing of Connected and Autonomous Electric Vehicles in Battery SOC-Aware Platooning," Accessed: Oct. 21, 2025.
11. J. Sarda, H. Patel, Y. Popat, K. L. Hui, and M. Sain, "Review of Management System and State-of-Charge Estimation Methods for Electric Vehicles," Accessed: Oct. 21, 2025.
12. V. Behnamgol, M. Asadi, M. A. A. Mohamed, S. S. Aphale, and M. F. Niri, "Comprehensive Review of Lithium-Ion Battery State of Charge Estimation by Sliding Mode Observers," Accessed: Oct. 21, 2025.
13. H. Li, H. Jia, P. Xiao, H. Jiang, and Y. Chen, "Research Progress on State of Charge Estimation Methods for Power Batteries in New Energy Intelligent Connected Vehicles," Accessed: Oct. 21, 2025.
14. M. I. Al-Hiyali, R. Kannan, and H. Shutari, "Optimizing State of Charge Estimation in Lithium–Ion Batteries via Wavelet Denoising and Regression-Based Machine Learning Approaches," Accessed: Oct. 21, 2025.
15. R. Issa et al., "A Data-Driven Digital Twin of Electric Vehicle Li-Ion Battery State-of-Charge Estimation Enabled by Driving Behavior Application Programming Interfaces," Accessed: Oct. 21, 2025.
16. H. Bouchareb, K. Saqli, N. K. M’sirdi, and M. O. Bentaie, "Lithium-Ion Battery Health Management and State of Charge (SOC) Estimation Using Adaptive Modelling Techniques," Accessed: Oct. 21, 2025.
17. X. Wang et al., "Lithium Battery SoC Estimation Based on Improved Iterated Extended Kalman Filter," Accessed: Oct. 21, 2025.
18. B. Sungur and A. Kaleli, "State of Charge Estimation for Lithium-Ion Batteries Using Optimized Model Based on Optimal HPPC Conditions Created Using Taguchi Method and Multi-Objective Optimization," Accessed: Oct. 21, 2025.
19. D. P. Pau and A. Aniballi, "Tiny Machine Learning Battery State-of-Charge Estimation Hardware Accelerated," Accessed: Oct. 21, 2025.
20. Benallal, N. Cheggaga, A. Hebib, and A. Ilinca, "LSTM-Based State-of-Charge Estimation and User Interface Development for Lithium-Ion Battery Management," Accessed: Oct. 21, 2025.
21. R. Carrera, L. Quiroz, C. Guevara, and P. Acosta-Vargas, "State-of-Charge Estimation of Medium- and High-Voltage Batteries Using LSTM Neural Networks Optimized with Genetic Algorithms," Accessed: Oct. 21, 2025.
22. X. Zuo et al., "State of Charge Estimation for Sodium-Ion Batteries Based on LSTM Network and Unscented Kalman Filter," Accessed: Oct. 21, 2025.
23. T. Xia et al., "Research on Estimation Optimization of State of Charge of Lithium-Ion Batteries Based on Kalman Filter Algorithm," Accessed: Oct. 21, 2025.
24. L. V. A. Mouodo and P. J. Axaopoulos, "Optimization and Estimation of the State of Charge of Lithium-Ion Batteries for Electric Vehicles," Accessed: Oct. 21, 2025.
25. Z. R. Yuan, K. F. Huang, C. H. Xu, J. C. Zou, and J. Yan, "Bayesian Optimization-Based State-of-Charge Estimation with Temperature Drift Compensation for Lithium-Ion Batteries," Accessed: Oct. 21, 2025.

26. C. G. Manriquez-Padilla et al., "State of Charge Estimation Model Based on Genetic Algorithms and Multivariate Linear Regression with Applications in Electric Vehicles," Accessed: Oct. 21, 2025.
27. S. Peng et al., "State-of-Charge Estimation of Lithium-Ion Batteries Based on Dual-Coefficient Tracking Improved Square-Root Unscented Kalman Filter," Accessed: Oct. 21, 2025.
28. Q. Huang et al., "State of Charge Estimation in Batteries for Electric Vehicle Based on Levenberg–Marquardt Algorithm and Kalman Filter," Accessed: Oct. 21, 2025.
29. Y. Zeng, Y. Li, and T. Yang, "State of Charge Estimation for Lithium-Ion Battery Based on Unscented Kalman Filter and Long Short-Term Memory Neural Network," Accessed: Oct. 21, 2025.
30. S. M. Shahriar et al., "State of Charge Estimation for Electric Vehicle Battery Management Systems Using the Hybrid Recurrent Learning Approach with Explainable Artificial Intelligence," Accessed: Oct. 21, 2025.
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