0International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 03 March-2026 | Impact Factor: 3.5

Battery State of Charge (SOC) Estimation Techniques for Lithium-ION Batteries in Electric Vehicles

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How to Cite this Article:

Shete, R., Tagirisa, S., Betallu, S., Mathurkar, S. & Kamble, S. (2026). Battery State of Charge (Soc) Estimation Techniques for Lithium-Ion Batteries in Electric Vehicles. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(03). https://doi.org/10.55041/ijcope.v2i3.114

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ABSTRACT

Electric cars are spreading fast, so smart systems to track battery charge have become essential. Getting the charge level right helps prevent damage from too much charging or draining, while also making batteries last longer. Still, lithium-ion cells behave unpredictably - changing with temperature, age, and usage - which complicates accurate readings. Because of this, figuring out exact levels demands more than basic methods. Six recent approaches to estimate charge are examined here, each shaped by current studies. What emerges is not a single fix but varied paths through shifting chemical responses. A look at different ways to manage battery charging starts with physical devices using fuzzy logic, built into circuits that run on STM32 chips and respond instantly to sensor readings. Moving away from hardware, some systems rely on patterns found in data, like the Tsetlin Machine, which shows how it reaches conclusions while still predicting well - key when mistakes could be dangerous. Comparisons show how basic techniques stack up: counting charge flow, measuring voltage when idle, and refining estimates with Kalman math, each tested inside simplified electrical designs. Temperature shifts and wear over time affect voltage behaviour, making fixed assumptions less reliable as batteries age. Instead of preset rules, certain algorithms learn from examples; SVR and tree models test how stable predictions stay when conditions change. Wrapping up, the study dives into a combined Dual Extended Kalman Filter setup that tracks both system states and internal values at once. Instead of treating methods separately, it blends insights from physical tests, simulation models, and pattern- based approaches - giving a clear path through different SoC estimation options depending on how electric vehicles are used.

Keywords: Lithium-Ion Battery, State of Charge (SoC), Electric Vehicles, Fuzzy Logic, Machine Learning, Kalman Filter, Battery Management System (BMS), Equivalent Circuit Model (ECM).

INTRODUCTION

Electric cars are changing how we think about driving, pushed by worries over pollution and a push for cleaner power sources. Though they pack plenty of punch, lithium-ion batteries rely completely on careful oversight to work right. Their performance hinges on something called a Battery Management System, which keeps everything in check behind the scenes. Without it, risks rise fast - overheating, sudden drops in output, even breakdowns. This system watches every little detail, acting like a guard that never sleeps, making sure each bit of stored energy counts.

What drives the BMS to work properly is figuring out the State of Charge, or SoC. Think of SoC like how much juice is left in the tank - just like a gas meter in regular cars with engines. But here is the catch: you cannot just peek inside a battery to see how full it is. Instead, engineers rely on clues such as voltage at the terminals, how hard the battery is working, and how warm the cells are. These signals help piece together an estimate, since there is no dipstick for electrons. Finding this value is not straightforward since lithium-ion batteries behave in unpredictable ways. What you measure connects to SoC through shifting internal resistance, effects from delayed voltage responses, how heat changes reactions inside, also gradual loss of ability to hold charge over time.

Simple methods like adding up current flow work okay at first yet drift off track because tiny mistakes pile up without any way to fix themselves. Starting with voltage checks when idle gives good results though it needs the power source to sit still long enough to settle, something that rarely happens when vehicles keep moving and recharging on the go. Because of these hurdles new approaches began appearing through ongoing study and testing.Starting off, this piece breaks down six fresh studies on SoC estimation. From a gear-focused angle, one looks at how fuzzy logic handles charging plus state tracking [1]. Shifting gears, other dives into clear-box AI using the Tsetlin Machine setup [2]. Instead of black boxes, it spells out decisions step by step. Basic techniques like counting charge flow, open- circuit voltage checks, and Kalman filters get lined up side by side [3]. On top of that, changes in voltage readings due to heat and battery wear come under close inspection [4]. One study checks how different supervised machine learning models work for regression tasks [5]; then introduces a combined filtering method that estimates both system states and parameters at once [6]. Mixing these angles gives a full picture of today's top methods used to estimate battery charge in electric cars.

LITERATURE REVIEW

Starting with simple hardware checks, today's methods for guessing battery charge now lean on smart software tricks instead. One after another, this part walks through half a dozen key studies just as they appeared.

Fuzzy Logic and Hardware-Integrated Systems [1]

One early study tackles problem in making lithium-ion batteries run efficiently, stay safe, while lasting longer - this through a fuzzy logic setup that improves how charge levels are judged and charging is adjusted. Battery behaviour tends to shift unpredictably, something standard techniques fail at handling well. Instead of relying on fixed models, the approach in source [1] uses physical components designed around fuzzy reasoning to deal with unclear patterns during live operation.

Built around an STM32 chip, the setup uses a BMS to handle live readings from various sensors. Instead of lumping measurements together, each signal gets its own moment to matter. One cell after another, four lithium batteries at 3.7 volts feed info through divided circuits. Watched closely, their voltages avoid dangerous peaks thanks to a dedicated sensor. Charge flow moves under scrutiny via a separate monitor keeping cycles stable. Heat matters too - so an LM35 chip tracks warmth changes across operation. Rather than stick to fixed rules, charging shifts dynamically between steady current and steady voltage modes. This shift helps dodge overheating along with energy overload risks. Testing happened two ways: on actual circuit boards and inside Proteus software models. Results showed the smart logic behind the scenes could sort battery fullness clearly - not just roughly - into three buckets: empty, middle, full. Outdated guesswork fades when patterns adapt mid-run based on what the system sees happening. Precision climbs without leaning on older, clunkier techniques

Explainable Data-Driven Models [2]

When machines learn to guess battery levels, understanding their reasoning matters most - especially in electric vehicles where safety is key. Instead of hiding decisions inside complex math, one study uses a Tsetlin Machine, which shows its work plainly. This method leans on basic true-or-false rules to make choices, keeping results accurate while staying clear. What sets it apart? It does not trade clarity for performance but holds both in step.

From cold mornings to mild afternoons, tests ran on a Panasonic battery pack under shifting temps. Instead of blending methods blindly, one model stood near the front runners. Errors stayed small - just past three hundredths in root mean deviation. Voltage pulled more weight than any other clue when guessing charge levels. Heat mattered less than expected once data flowed through circuits. While others chewed power just explaining choices, this system kept rules clear and demands light. Sharp answers came fast, even without heavy number crunching behind them.

Comparison of Coulomb Counting, OCV, and Kalman Filter [3]

One study checks how well Coulomb Counting does, alongside OCV and the Kalman Filter. Different setups were tested using basic, Thevenin, and adjusted Thevenin structures. Instead of treating voltage in a flat way, the Thevenin version uses an RC loop to mimic real shifts better.

One thing stood out. Though straightforward, Coulomb Counting builds up mistakes over time - also fails to fix bad starting points. Waiting on idle periods slows down the OCV approach; it needs rest before measuring. What surprised some? The Kalman Filter adjusted wrong starts fast - just fifty seconds versus more than twenty-five minutes for older methods. When numbers mattered, lower MSE and RMSE scores showed its edge clearly, even when battery behaviour changed unexpectedly.

Sensitivity of OCV Test Conditions [4]

Looking at how voltage links to charge level, work in [4] checks how temp changes, battery wear, plus testing methods affect precision. With 18650 NMC cells in play, one method used small voltage steps - waiting three hours between points - while another relied on steady current readings instead.

Better results came through step-by-step testing, particularly when currents stayed under 0.25C. For NMC batteries, one flat stretch stands out - between 85% and 95% charge - where tiny voltage shifts cause large inaccuracies. After 350 charging rounds, mistakes in readings grew twice as big. Cold conditions made things worse; at just 5°C, errors climbed as high as 5%. Because of these shifts, voltage-based estimates must adjust themselves as temperature changes and batteries wear.

Analysis of Machine Learning Regression Models [5]

One study looked at different prediction methods like linear regression, k-nearest neighbours, decision trees for numbers, plus support vector machines. These tools learned patterns using data from more than seventeen thousand battery tests made by Panasonic. Each method handled the information in its own way. Some adjusted lines to fit trends. Others checked nearby results or split choices into branches. The training set came entirely from real-world cell performance under varied conditions. How each model responded shaped what kind of errors appeared later.

It turned out LR carried heavy bias because of its straight-line guesswork, whereas KNN stumbled when data spread unevenly. Following trends suited DTR well, though it wobbled wildly across different samples and demanded constant updates as the battery wore down. SVR stood out as the steadiest choice, splitting the difference between oversimplifying and overreacting. Even if SVR took more time predicting, thanks to tangled math inside, its knack for handling new situations smoothly made it fit well for live battery monitoring tasks.

Unified Dual Extended Kalman Filter Framework [6]

One approach, cited as [6], introduces a combined Dual Extended Kalman Filter method aimed at tracking both battery charge level and shifting internal traits at once. Running side by side, two filter units handle distinct roles within the setup. While the first one focuses on status measures like stored energy and voltage response, the second adjusts estimates of core elements such as resistance and capacitance values. Each part operates at the same time,yet targets different aspects of the overall model.

Using Panasonic NCR-style lithium-ion batteries, performance surpassed both basic EKF and charge tracking methods when loads changed fast or sensors gave noisy data. Instead of simple lines, a five-part curve shaped how voltage linked to stored energy, cutting mistakes down - error averaged just 0.0038, with typical deviation at 0.31%. Charge counting slowly drifted off target as time passed; meanwhile, the updated filter stayed close by adjusting for shifting parts and wrong starting guesses.

METHODOLOGY

The methodologies across the six references integrate hardware development, experimental testing, and advanced computational modelling.

Hardware Implementation and Simulation [1]

The approach in Source [1] relies on a working model built around an STM32 chip along with several sensing units. Temperature readings come from LM35 devices, while voltage checks happen through divider circuits, besides current tracking components feeding live input. This setup sorts battery charge status into three groups - called low, medium, or high- thanks to reasoning rules shaped by fuzzy logic. Power delivery shifts when a transistor triggers a relay, which turns a small motor on or off depending on preset limits. Testing happened inside Proteus, where results from actual circuit behaviour matched earlier predictions closely enough to confirm function.

Machine Learning and Data Preparation [2, 5]

Out there among studies, numbers two and five lean hard on data from Panasonic’s 18650PF lithium-ion cells. You will find endless test runs inside it - different driving patterns, a range of temps.

Starting off, the model pulls data like voltage alongside current, temperature, plus energy used measured in Watt-hours. To clean up sudden jumps in readings, researchers apply an RMS method specifically to voltage and current signals.

Running the models meant setting up tools in Python through Anaconda. Instead of sticking with raw numbers, the system turned data points into on-off signals - this happened either by slicing values at set levels or splitting them evenly across ranges. Such conversions allowed Tsetlin Automata to work with inputs properly.

Testing the model relied on common measures like MAE, alongside MAPE, plus RMSE to check how close predictions were. Accuracy got judged by these standard error markers instead of guesswork.

Battery Characterization and Recursive Filtering [3, 4, 6]

A solid start in building models helps make SoC estimates more reliable. Filtering steps come next, shaping raw data into clearer signals. Without these methods, accuracy slips fast. Each layer builds on the one before it. Strong design at the base means fewer errors later. Getting this part right matters most of all.

Starting at low heat, scientists checked open- circuit voltage on common lithium batteries. Five-degree marks guided the climate control during trials. Each step moved in 5 percent charge jumps. Three hours of quiet time passed before readings began. Tests ran across a range from cold to warm settings.

Guessing the numbers: Study [6] pulled info from HPPC tests to pin down values for a basic circuit model, trying different drain speeds - from slow (0.5C) to fast (6C).A loop within a loop - each step forward needs a fresh snapshot of how things change. Inside that rhythm, guesses meet adjustments, one after another. Math shapes shift when formulas redraw curves into straight lines on the fly. Every update lean on instant-by-instant slopes pulled from tangled relationships. Equations map motion through hidden gears turning beneath voltage and charge.

RESULTS AND DISCUSSION

Looking at all six studies together shows how each method for guessing battery charge level comes with its own mix of pros and cons. One after another, the models reveal differences in precision, how heavy they are on computing power, also how well they manage messy real- life factors like shaky sensor data or shifts in heat.

Comparison of Estimation Techniques

Table 1 provides a comparative overview of the techniques discussed, based on their performance, complexity, and application suitability.

Table 1: Comparative Overview of SoC Estimation Methods [1]-[6]

Techniques	**Approach types**	**Advantages**	**Limitation**
Fuzzy Logic	Intelligent Control	Robustness to non-linearity; no training data needed	Depends on expert rule design; less precise
Tsetlin Machine	Explainable ML	High interpretability; computationally efficient	Lower accuracy than deep learning (LSTM)
Coulomb Counting	Current Integration	Extremely low computational cost	Accumulates sensor error; no self-correction
OCV Method	Characterization	Very high accuracy in equilibrium states	Requires long rest periods for relaxation
Kalman Filter (EKF)	Recursive Filter	Self-correcting; effective for noisy data	Requires highly accurate battery models
SVR	ML Regression	Excellent generalization; noise robustness	High computational cost during prediction
DEKF	Dual Filter	Simultaneously estimates state and parameters	Simultaneously estimates state and parameters

Performance Metrics and Accuracy

Table 2 details the specific accuracy metrics reported for the most effective models across the references.

Table 2: Performance Metrics for Selected Models

Model	**Dataset / Chemistry**	**RMSE**	**MAE / MAPE**
Tsetlin Machine	Panasonic 18650PF	0.0389	0.0298 (MAE)
LSTM	Panasonic 18650PF	0.0223	0.0184 (MAE)
OCV (5th Order Fit)	Panasonic NCR	0.0038	0.31% (MAPE)
ANN / RF / SVM	Comparison	Variable	SHAP identifies voltage as key feature
DEKF	(Dynamic Load)	Lowest	Robust under sensor noise

Discussion on Influencing Factors

A closer look at data from the six sources shows key patterns about how well SoC methods work outside labs. What stands out is that accuracy often drops when moving from controlled setups to actual use. One factor behind this shift appears tied to temperature swings affecting sensor inputs. Though models perform tightly in simulations, road conditions add noise hard to predict. Where algorithms adapt slowly, errors pile up over time instead of correcting. In practice, even small calibration gaps widen during long drives

Starting off wrong? That changes everything. Methods such as Coulomb Counting fail right away if the starting point is inaccurate - so does relying on Open Circuit Voltage alone, according to Study [3]. But here's where things shift: recursive techniques, especially the Kalman Filter cited in references [3, 6], fix bad guesses fast. Within roughly fifty seconds of running, they align with reality. Meanwhile, voltage-driven approaches drag on, needing nearly half an hour - close to 1600 seconds - just to catch up. Speed matters, and that delay makes a difference.

When it gets colder, the battery's voltage signal shifts especially when charge is low. After 350 uses, wear inside the cell might make guesses twice as wrong. Study number four shows how much heat and time twist those readings. Simple systems relying on fixed charts will not keep up as electric cars age. Cold tricks the meter, old cells lie longer.

Starting with how machines learn, some methods hide their reasoning behind layers of mystery. Though certain studies prove systems such as Support Vector Regression and Decision Trees grasp battery behaviour well, others point out a flaw - they do not show how decisions are made. Enter the Tsetlin Machine, which balances clarity and performance by using readable rules instead of opaque logic.
This openness matters greatly when meeting strict safety demands in vehicles.

When a battery gets older or colder, its inner resistance grows. The method from Reference
[6] handles this well through the Dual Extended Kalman Filter. Instead of fixing values ahead of time, it adjusts SoC along with changing parts like R0, R1, and C1 on the fly. Because everything updates at once, precision stays high. Accuracy does not slip even under shifting conditions deep inside the cell.

One step at a time, research moves beyond basic merging techniques toward smarter, self- adjusting tools. Though physical setups using fuzzy reasoning hold up well in compact uses, thanks to their straightforward design, complex math behind the DEKF stands out when exact results matter most - especially under strict safety demands in vehicles.

Real-world use brings hurdles. Running these smart algorithms needs strong computing inside the vehicle. Though SVR [5] gives better outcomes, its demands grow when speed matters most - like sudden changes in electric car operation. Because of this, regular chips might fall short. Instead, faster processors or specific AI hardware could be necessary just to keep up. Even DEKF [6] fits this pattern, where accuracy comes at a cost. When things shift quickly on the road, only robust systems may respond fast enough.

CONCLUSION

Figuring out how much charge remains in lithium-ion batteries matters a lot when running electric cars safely and smoothly. Through careful study, six recent approaches were examined - one used fuzzy logic built into physical devices, another leaned on repeat- calculation filters, while some relied on smart number-crunching methods that make their reasoning visible. Starting off, studies show movement from basic approaches - Coulomb Counting and Open Circuit Voltage - to smarter, evolving systems. Even though straightforward math tricks [3, 6] save computing power, mistakes pile up over time because there is no way to fix them on the fly. Methods relying on OCV [3, 4] deliver solid precision; however, they demand extended idle phases, which limits their use during real-time driving unless boosted somehow.

Not far off the mark, newer ways to sort signals
- like the EKF and DEKF [6] - hold up well under pressure. Instead of buckling, they handle messy sensor data, wrong starting guesses, while tracking shifts in a battery’s inner traits on the fly. Throw heat changes and wear into the mix [4], then it becomes clear: models must shift just as the battery does, right through years of use. A fixed setup simply will not cut it when everything else keeps changing.

With machine learning, even though tools like Support Vector Regression and Decision Trees pack strong prediction skills, the rise of the Tsetlin Machine opens a clear route to systems we can understand. That openness matters when it comes to cars - opaque models often fail to pass strict safety rules.

Putting together precise predictions from model-based filters with flexible learning from data-driven approaches - while keeping results clear - points toward better Battery Management Systems ahead. When electric car makers adopt these improved ways to estimate charge, vehicles gain longer reach, batteries last longer, keep passengers safe. The next step lies in fitting such systems into energy-efficient hardware so ideas tested in labs become real parts under car hoods.

ACKNOWLEDGMENT

Gratitude goes out to the researchers behind the six core sources guiding this work. Because of their efforts in battery modelling, hardware tuning, and transparent machine learning, key understanding took shape here. Their contributions formed the backbone of what appears in these pages.

REFERENCES

[1] S. Kalpana Devi, B. V. Sai Thrinath, V. Kamatchi Kannan, R. Sankarganesh, N. Dharshini, and P. Ponmurugan, "Implementation of SoC Estimation and Charging Method Optimization of Lithium-Ion Battery for Electric Vehicle," in *Proc. 2nd International Conference on Electronic Circuits and Signalling Technologies (ICECST-2025) , IEEE, 2025, pp. 383-387.

[2] S. Ojukwu, S. Maheshwari, M. Mamlouk, V. Pickert, A. Yakovlev, and R. Shafik, "Explainable Data- driven Battery State of Charge Estimation," in *Proc. 2025 Energy Conversion Congress & Expo Europe (ECCE Europe) , IEEE, 2025, pp. 1-6.

[3] G. Fathoni, S. A. Widayat, P. A. Topan, A. Jalil, A. I. Cahyadi, and O. Wahyunggoro, "Comparison of State-of-Charge (SOC) estimation performance based on three popular methods: Coulomb counting, open circuit voltage, and Kalman filter," in *Proc. 2nd International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT), IEEE, 2017, pp. 70-74.

[4] A. Gismero, D.-I. Stroe, and E. Schaltz, "Comparative Study of State of Charge Estimation Under Different Open Circuit Voltage Test Conditions for Lithium-Ion Batteries," in Proc. 2020 IEEE, 2020, pp. 1767-1772.

[5] T. Bhardwaj, V. S. Kale, M. S. Ballal, and S. Khond, "Comparative Analysis of Machine Learning Models for Li-Ion Battery SoC Estimation," in Proc. 3rd International Conference on Smart Technologies for Power, Energy and Control (STPEC)*, IEEE, 2023, pp. 1-6.

[6] H. Pati, S. S. Ghose, A. A. Dash, M. Biswas, A. K. Sahu, and A. Ghosh, "A Unified EKF Framework for SOC and Parameter Estimation in NCR type Lithium-Ion Batteries: Modelling and Comparison with Coulomb Counting," in *Proc. 6th India Council International Subsections Conference (INDISCON), IEEE, 2025, pp. 1-6.