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Innovative Algorithms for State-of-Charge Estimation in Electric Vehicle Batteries

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Abstract

The exact estimation of State-of-Charge (SOC) in Electric Vehicle (EV) batteries is fundamental for strong Battery Management Systems (BMS). This paper analyses creative algorithms for SOC estimation, focusing on the Coulomb Counting procedure and the Extended Kalman Filter (EKF). A careful MATLAB simulation is coordinated to evaluate the show of these algorithms. The results show that while the two methods give trustworthy SOC measures, the EKF displays prevalent precision under strong conditions. This study means adding to the development of extra compelling BMS for EVs, redesigning their steadfastness and execution. In this research, Coulomb Counting is used as a benchmark result and compared to the EKF technique for the determination of SOC in EV batteries. In MATLAB, all the values of current duration, voltage, and SOC are generated using the synthetic dataset, and these resemble the conditions of a battery in the real world. General overviews, non-complicated and fast calculating, such as the Coulomb Counting method, are characterised by cumulative errors. On the other hand, the EKF based on the nonlinear state-space model presents higher accuracy and insensitivity to the operating conditions compared to the other approaches.

Major Findings: *Success is measured according to its accuracy, its ability to be free from errors, and its computational complexity. Furthermore, it is seen that EKF provides closer estimations of SOC values with high tracking accuracy and flexibility than Coulomb Counting, which makes EKF more suitable for future precise battery management systems.*

Keywords: *Battery Management System (BMS), Coulomb Counting, Electric Vehicles (EV), Extended Kalman Filter (EKF), MATLAB, State-of-Charge (SOC),*

1.0 Introduction

The fast gathering of EVs has required movements in battery management systems (BMS) to ensure the best execution and longevity of batteries. A fundamental piece of BMS is the exact estimation of the SOC, which tends to the furthest reaches of a battery[1,2]. Exact SOC estimation is crucial for compelling energy management, preventing cheating or profound delivery, and growing battery life. Various algorithms have been proposed for SOC estimation, with the Coulomb Counting procedure and the EKF being among the most prominent. This paper researches these algorithms and evaluates their show through MATLAB simulations[3,4].

2.0 Literature Review

2.1 Coulomb Counting Method

The Coulomb Counting method is one of the most

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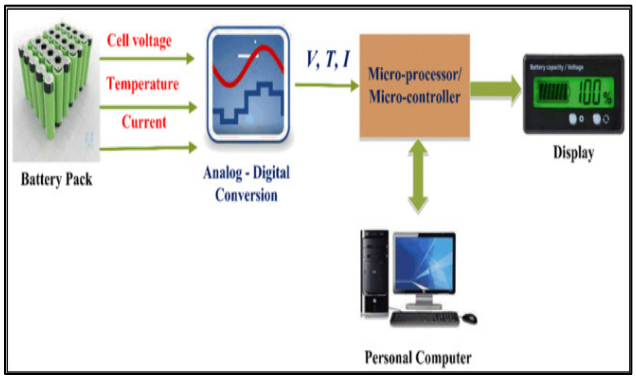


Figure 1. State of charge estimation technique for EV[3].

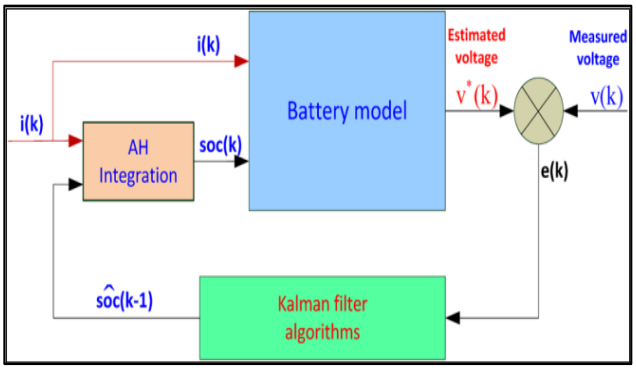


Figure 2. Extended Kalman Filter[5].

unperplexing and most extensively elaborate techniques for SOC estimation[5,6]. This method incorporates organising the continuous streaming all through the battery long term to conclude the net charge change. The key standard relies upon the way that the SOC is not set in stone by following how much charge is added or disposed of from the battery. Notwithstanding its ease and straightforwardness of execution, the Coulomb Counting method has several limits that impact its accuracy[7,8].

State of charge estimation technique for EV is shown in Figure 1. Studies have shown that while Coulomb Counting can give reasonable evaluations under consistent and controlled conditions, its precision disintegrates in extraordinary circumstances where current instabilities and utilitarian conditions change by and large[9,10]. This method likewise doesn't represent self-discharge, which can prompt further mistakes in SOC estimation. Regardless of these disadvantages, Coulomb Counting stays famous because of its low computational necessities and simplicity of coordination into existing systems[11,12].

2.2 Extended Kalman Filter (EKF)

The EKF is a more modern way to deal with SOC estimation that tends to a considerable lot of the limitations of the Coulomb Counting method. EKF considers the nonlinear qualities of battery conduct by joining the standards of Kalman filtering with a nonlinear state-space model[13,14]. This model tends to the battery components, incorporating factors like voltage, current, temperature, and SOC. The EKF computation continually revives its evaluations considering nonstop estimations, giving more definite and stronger SOC checks[15,16].

The Figure 2 depicts the extended kalman filter; the execution of EKF incorporates several methods: Assumption, update, and cure. During the forecast step, the filter utilises the state-space model to anticipate the following state of the battery given the present status and information estimations[17,18]. In the update step, the filter contrasts the anticipated state and the real estimations to figure out the estimation blunder. Finally, in the revision step, the filter changes its appraisals to restrict the goof. This iterative collaboration licenses EKF to outfit continuous SOC checks with high accuracy[19,20].

2.3 Estimation Methods

Past Coulomb Counting and EKF, various methods like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Particle Filters have moreover been explored for SOC estimation[21,22]. ANN and SVM leverage artificial intelligence methodologies to anticipate SOC given evident data. These methods can be changed by various battery sciences and use plans, offering versatility and energy in SOC estimation.

ANNs are particularly effective in getting intricate nonlinear associations between input factors and SOC. Through planning gigantic datasets, ANNs can get comfortable with the secret models and give definite SOC assumptions. SVMs, of course, are regulated learning models that find the ideal hyperplane to portray data of interest. With regards to SOC estimation, SVMs can

be prepared to foresee SOC-given elements like voltage, current, and temperature[23,24].

While these high-level methods show guarantees, they often require broad preparation information and huge computational power[25,26]. The requirement for enormous datasets can be a hindrance to execution, particularly in applications with restricted information accessibility. Furthermore, the intricacy of these methods might present difficulties in progressive applications where computational assets are obliged[27,28].

2.4 State-of-Charge (SoC) Estimation Challenges

Despite extensive research done on the development of methods to estimate SOC for the enhancement of efficiency and durability of EV batteries, the problem has not yet been resolved completely[29,30]. Being the ratio of the battery's residual capacity to its full charge capacity, SOC directly impacts the range forecast and performance of the EVs. Several large problems hold back accurate SOC estimation, which requires the use of complex algorithms and methods[31,32]. First of all, non-linear characteristics of batteries are inherent, and with the presence of non-linear behaviour, the problem arises[33,34]. Battery voltage related to SOC, as a general rule, also has nonlinear characteristics affected by factors such as temperature, ageing, and the rate of discharge. Such factors necessitate the use of algorithms that are able to adapt to existing conditions so as to enhance their precision[35,36].

Secondly, the environmental aspects greatly influence SOC estimation depending on the battery age and charging/discharge rates. Environmental conditions present within and outside the battery pack impact on internal resistance, the chemical reaction and conductivity, thus changing the voltage and current. It, therefore, means that proper SOC estimation algorithms must consider these variables to deliver appropriate accuracy regardless of the conditions[37,38].

2.5 Literature Summary

In addition, the constraints with the gauging processes put forth another puzzle with the SOC estimations' inherent difficulties. Coulomb counting is relatively popular, yet it is characterised by an integration drift that results in cumulative errors[39,40]. Voltage methods, despite their simplicity, have problems with accuracy when the load is changing or when there is a rapid charge/discharge current. Remedy of these limitations entails the use of improved strategies that involve data aggregation and a complex method of filtering and correction[41,42]. Also, real-time processing requirement creates computational limitations with the SOC estimation algorithms. Computational costs versus accuracy have to be managed well here, in EVs, impacts for energy management systems have to be very fast for the required instant control of battery usage and for extending the range of EVs[43,44]. Thus, the improvement of SOC estimation algorithms can be achieved when the non-linearity of battery characteristics is considered, when the sources of variability are taken into account, when the accuracy of measurements is increased, and the computational load is minimised. These challenges envisage the need to systematically work on the new algorithms to fit new trends of electric vehicle applications[45,46].

2.6 Conventional SoC Estimation Methods

Traditional techniques for the determination of SOC in the batteries of electric vehicles are quite basic, yet profound; despit and each of the two aforementioned techniques having generalised strengths and weaknesses than the other in terms of precision, computations and versatility for analysis of diverse conditions[47,48]. Coulomb Counting Method: Coulomb counting determines the state of charge by summing up the accumulated amount of current which is charged or discharged into the battery. It is based on the fact that SOC is directly related to the integral of the current over time[49,50]. Despite that Coulomb counting sounds very simple and easy to implement, it is affected by integration drift, whose causes include: improper measurement, temperature change, and deterioration. Such inaccuracies are summed up across the charge and discharge cycles, diminishing the long-term performance of the battery[51,52].

Voltage-Based Methods: That is why voltage-based SOC estimation uses the dependency of battery terminal voltage on state of charge. This is since it offers computational efficiency, thus suitable for real-time use, and is easily implemented[53,54]. However, voltage-based

methods experience some inaccuracy as the load is dynamic or during charge/discharge; the variation in the voltage does not portray the true SOC since the battery characteristics are nonlinear and external factors may also be varying[55,56]. Kalman Filtering: Kalman filtering also involves combining the measurements of SOC using voltage, current and temperature while at the same time minimising errors. It modifies estimates over time by means of a model of battery behaviour and measurement errors[57,58]. Kalman filters' performance is higher than SOC estimation methods that use only one parameter, such as voltage or current. But they need accurate battery models and may not be real-time capable, especially in the resource-scarce EV setting. Impedance-Based Methods: These methods use some mathematical calculations to estimate SOC by measuring the battery impedance variations during charge/discharge cycles. They provide information on the battery health and status, but the implementation issues and conditions for the operation affect their applicability in EVs[59,60].

2.7 Emerging Algorithms and Technologies

The latest findings of SOC estimation for EV batteries have presented new types of algorithms and technologies that focus on the improvement of the accuracy, reliability, and robustness in various operational conditions[61,62]. Machine Learning Approaches: Recent technologies in artificial intelligence, like neural networks, Support Vector Machines (SVM), and deep learning models, are in evidence that have higher potential to enhance the accuracy of SOC estimation[63,64]. These algorithms use past data to model the battery parameters and SOC, where a potential benefit comes when specific battery characteristics are non-linear, or the battery is functioning in dynamic environments. For example, while being able to learn from real-time input and output data, neural networks are capable of performing well under different conditions to deliver solid estimates of SOC[65,66].

Adaptive and Hybrid Models: Movable algorithms continuously adapt SOC estimation with the help of real-time feedback, which increases the efficiency through continuous refining of predictions in accordance with the prevailing conditions[67,68]. Hybrid models use a combination of the above-discussed sensing methods, for instance, voltage, current, temperature, and the use of algorithms like prediction models in order to avoid the demerits that come with the various techniques, so as to have the precise SOC of the battery at various points in time[69,70].

Data-Driven Approaches: Based on big data and cloud computing, data-driven driven are used for analysing large amounts of data to enhance the SOC estimation algorithms. Such methods include the use of machine learning algorithms and statistical analysis to improve battery management tactics by analysing sub-raw data acquired from heterogeneous fleets of EVs and real-life working environments[71,72]. Sensor Fusion Techniques: There are additional sensor inputs like voltage, currents, temperature sensors, along with GPS input and weather information, and thus integrating data from different sources, sensor fusion techniques try to improve the accuracy and robustness of SOC estimation. These methods combine the information from complementary sources, which are used to describe battery state dynamics and improve general EV performance[73,74].

2.8 Performance Metrics and Comparative Analysis

Evaluating SOC estimation algorithms for EV batteries involves assessing various performance metrics to gauge accuracy, reliability, and suitability for real-world applications. Comparative analysis across different methods provides insights into their strengths and limitations under diverse operating conditions[75,76].

Accuracy: The primary metric for evaluating SOC estimation algorithms is accuracy, measured as the percentage difference between estimated and actual SOC values. High accuracy ensures precise energy management and enhances EV range prediction, critical for consumer confidence and operational efficiency.

Response Time: Response time measures the algorithm's speed in providing SOC estimates. Real-time applications require algorithms with minimal delay to support instantaneous adjustments in energy usage and optimise battery performance during driving cycles.

Robustness to Noise and Variability: Algorithms should demonstrate resilience against measurement noise, environmental variability (such as temperature fluctuations), and sensor inaccuracies. Robust algorithms maintain consistent performance across diverse

operating conditions, enhancing reliability in practical EV deployments.

Computational Efficiency: Computational efficiency assesses the algorithm's ability to deliver accurate SOC estimates with minimal computational resources. Efficient algorithms reduce processing overhead, conserving battery power and extending operational life in EV applications.

Comparative Analysis: Comparative studies evaluate SOC estimation methods against conventional approaches (*e.g.*, Coulomb counting, voltage-based methods) and emerging technologies (*e.g.*, machine learning, adaptive models). They highlight strengths such as improved accuracy and adaptability while identifying limitations such as computational complexity or sensitivity to specific operating conditions.

Case Studies and Validation: Real-world case studies and validation experiments provide empirical evidence of algorithm performance in EV fleets or controlled environments. They validate theoretical findings, demonstrating algorithm effectiveness in diverse scenarios and informing practical implementation strategies.

2.9 Literature Gap

Despite the headways in SOC estimation strategies, there remains a hole in tending to the compromises between exactness, computational intricacy, and versatility to various battery conditions. Many existing methods either centre around high exactness to the detriment of computational proficiency or focus on effortlessness with restricted versatility to changing circumstances. This paper plans to fill this hole by giving a similar examination of Coulomb Counting and EKF, featuring their presentation under different working situations. The review tries to distinguish the qualities and impediments of every method, giving bits of knowledge to the development of more effective SOC estimation procedures that balance precision, intricacy, and flexibility.

3.0 Methodology

3.1 Data collection

Table 1 represents steps of methodological; data collection for SOC estimation includes procuring relevant data from secondary sources to reproduce certifiable circumstances precisely.

Secondary data sources incorporate research papers, industry reports, and openly accessible datasets from battery makers and testing labs. These sources give important data on battery attributes, use examples, and execution measurements under various circumstances.

Coulomb Counting Method

SOC[k]=SOCCC[k−1]−CbatI[k]Δt
SOC[k] is the State-of-Charge at time step k,
I[k] is the current at time step k, Δt is the sampling time interval, and Cbat is the battery capacity.
The state-space model for EKF SOC estimation includes:
x[k]=f(x[k−1],u[k],w[k]), z[k]=h(x[k],v[k]), x[k] is the state vector at time step kg, u[k] is the control input (current), w[k] is the process noise, z[k] is the measurement (voltage), v[k] is the measurement noise.

$$SOC[k]=SOCCC[k-1]-CbatI[k]\cdot\Delta t \quad \textbf{(I)}$$

Table 1. Methodological steps

Methodology Steps	Description
Data Generation	Synthetic data created to simulate real-world battery conditions, including time-series data for current, voltage, and true SOC values.
Algorithm Implementation	Implementation of Coulomb Counting and Extended Kalman Filter algorithms using MATLAB.
Performance Evaluation	Evaluation of algorithms based on accuracy, robustness, and computational efficiency.

Where,

I[k] is the current at time step k, Δt is the sampling time interval, and Cbat is the battery capacity.

To make a sensible dataset, manufactured battery data is created in light of ordinary EV battery conduct seen in secondary data[17]. This dataset incorporates time-series data for current, voltage, and genuine SOC values. Current data is demonstrated as a sinusoidal sign with added clamor to mirror the changeability in battery use designs, like speed increase, deceleration, and inactive periods. Voltage data is produced with a direct discharge pattern, joined with irregular commotion to reenact estimation mistakes ordinarily tracked down in genuine situations[18]. Genuine SOC is determined as a directly diminishing capability, addressing the real battery limit over the long haul, which lines up with the discharge conduct seen in secondary sources.

The state-space model for EKF SOC estimation includes:

$$x[k]=f(x[k-1],u[k],w[k]) \quad \text{(II)}$$

Where,

z[k]=h(x[k],v[k]) , x[k] is the state vector at time step kg, u[k] is the control input (current), w[k] is the process noise, z[k] is the measurement (voltage), v[k] is the measurement noise.

By leveraging secondary data, the engineered dataset gives a vigorous establishment to testing SOC estimation algorithms, guaranteeing that the simulations reflect sensible working circumstances and difficulties experienced in down-to-earth applications[19]. Hence, the two more equations are provided for the project:

$$OCV(SOC)=\alpha0+\alpha1*SOC+\alpha2*SOC\hat{}2+\alpha3*SOC\hat{}3 \quad \text{(III)}$$

The open circuit voltage represents the relationship between the SOC and the voltage of the battery in the no-load condition. Hence α0, α1, α2,and α3 Are the coefficients determined for the EKF, since it links the SOC to a measurable voltage to update SOC estimates based on observed voltage readings.

$$x[k]=x[k-1]+\Delta t(-I(k)/Cbat)+w[k] \quad \text{(IV)}$$

This is the state transition equation describing the state vector x[k]; representing the SOC at time step k. The previous state is x[k-1]. The term Δt(-I(k)/Cbat) accounts for battery discharge or charge over the sampling interval Δt.

I(k)=current at time step k, Cbat=battery capacity

W[k]= process noise, representing the uncertainty in the state transition, modelling the changes in battery behaviour.

3.2 Algorithm Implementation

Two SOC estimation algorithms, Coulomb Counting and the Extended Kalman Filter (EKF), are executed utilising MATLAB.

Table 2. Followed methodology

Step	Description
Data Generation	Synthetic data was generated for current (sinusoidal signal with noise), voltage (linear discharge trend with noise), and true SOC (linearly decreasing function).
Algorithm Implementation	Implementation of SOC estimation algorithms (Coulomb Counting and EKF) in MATLAB. Coulomb Counting integrates current over time; EKF uses a nonlinear state-space model.
Performance Evaluation	Accuracy is measured by comparing the estimated SOC with the true SOC. Robustness is assessed by algorithm performance under varying conditions. Efficiency is evaluated by execution time and resource usage.

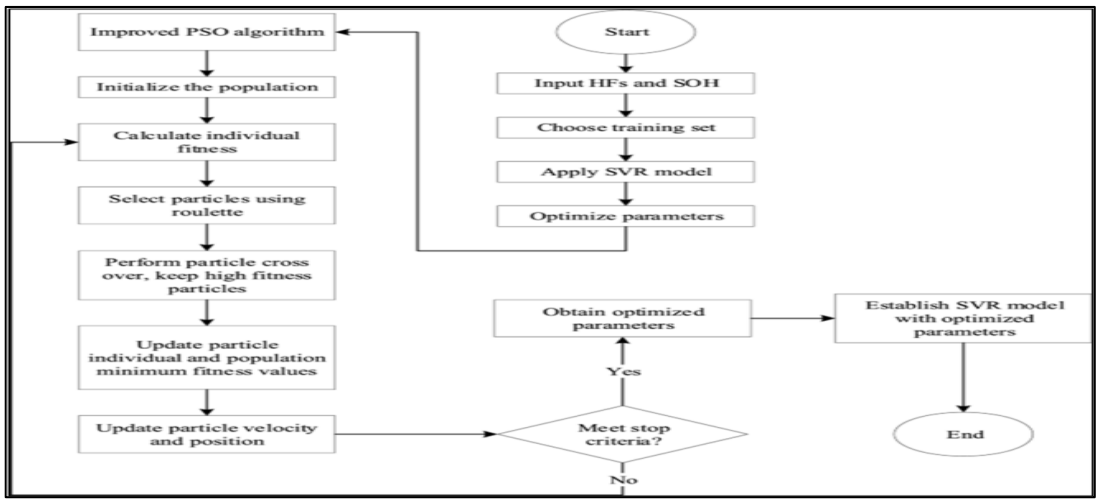


Figure 3. Battery health estimation for EV.

The Coulomb Counting method ascertains SOC by incorporating the ongoing over the long haul. This method adapts to the battery's ability to gauge the SOC, utilising the recipe: where I(τ) is the current at time τ, and C is the battery capacity. Despite its simplicity, this method is prone to cumulative errors due to sensor inaccuracies and capacity variations.

The EKF calculation is planned with a nonlinear state-space model, integrating cycle and estimation clamor covariances. The EKF execution includes three primary advances: forecast, update, and amendment. During the expectation step, the calculation utilises the state-space model to anticipate the following state of the battery[21]. In the update step, it contrasts the anticipated state and real estimations to register the estimation mistake. At last, the amendment step changes the appraisals to limit the mistake. The ELF's capacity to deal with nonlinearities and commotion makes it a more precise and stronger method for SOC estimation.

3.3 Performance Evaluation

The exhibition of the SOC estimation algorithms is evaluated in light of three measures: precision, strength, and computational effectiveness. Exactness is estimated by contrasting the assessed SOC and the genuine SOC values from the engineered dataset. This correlation is measured utilising measurements like mean outright mistake and Root Mean Square Blunder (RMSE).

Power is surveyed by breaking down the algorithms' capacity to keep up with precision under differing working circumstances and commotion levels. This includes testing the algorithms with various current and voltage designs, as well as acquiring differing levels of commotion by reproducing genuine estimation mistakes.

3.4 Mean Absolute Error (MAE)

MAE=N 1i=1ΣNSO true[i]−SOCest[i]
SOCtrue[i] is the true SOC at time step iii,
SOCest[i] is the estimated SOC at time step iii,
N is the total number of time steps.
σ=N1i=1ΣN(SO true[i]−SOCest[i])2
Max Error=imaxSO true[i]−SOCest[i]

The model construction for SOC estimation is shown in figure 4 and computational efficiency is evaluated by estimating the execution time and asset use of every calculation. This appraisal guarantees that the algorithms can be executed continuously without inordinate computational requests. The MAE is calculated as:

$$MAE = 1/N \sum_{i=1}^{N} |SOCtrue[i] - SOCest[i]| \quad (V)$$

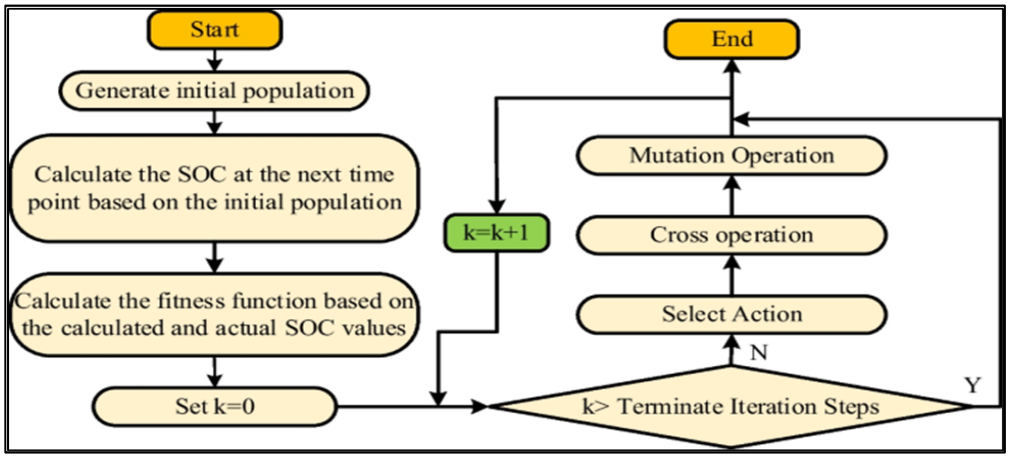


Figure 4. Model construction for SOC estimation[7].

Where,
SOCtrue[i]=true SOC at time step I
SOCest[i]=estimated SOC at time step i
N=Total number of steps

The standard deviation of the SOC estimation error is:

$$\sigma = 1/N \sum_{i=1}^{N} (SOCtrue[i] - SOCest[i])^2 \quad \text{(VI)}$$

The Maximum error in the absolute largest error observed as:

$$\text{Max Error} = \max_i |SOCtrue[i] - SOCest[i]| \quad \text{(VII)}$$

These errors evaluate the accuracy and reliability of the SOC estimation algorithms. By looking at these presentation perspectives, the review gives an exhaustive evaluation of the Coulomb Counting and EKF algorithms, featuring their reasonableness for various SOC estimation situations in Electric Vehicle battery management systems.

4.0 Results and Discussion

4.1 Result

Figure 5 delineates the assessed SOC over the long haul utilising the Coulomb Counting method. The x-hub addresses time in a flash, while the y-hub shows the

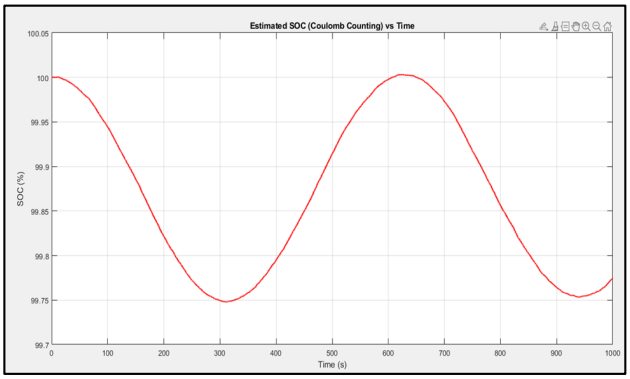


Figure 5. Estimated SOC (Coulomb counting) vs time[9].

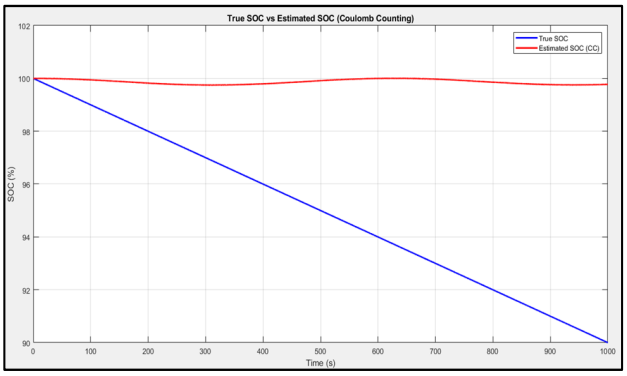


Figure 6. True SOC and estimated SOC (Coulomb Counting)[11].

SOC rate. The Coulomb Counting method incorporates the battery current over the long haul, giving a gauge of the leftover battery limit. The plot exhibits how the

SOC diminishes as the battery discharge. This method's effortlessness takes into consideration direct execution; however, it is likewise evident that the exactness can decrease after time because of combined blunders from current estimation errors and the presumption of a steady battery limit.

Figure 6 analyses the genuine SOC with the SOC assessed utilising the Coulomb Counting method. The x-hub addresses time right away, while the y-pivot shows the SOC rate. The genuine SOC is plotted close to the assessed SOC, giving a visual correlation of the two. The plot features the disparities between the real and assessed SOC over the long run, showing the combined mistakes inborn in the Coulomb Counting method. This correlation highlights the impediments of Coulomb Counting, especially in situations with huge estimation commotion or varieties in battery limit. Figure 7 presents an immediate correlation between the genuine SOC and the assessed SOC utilising the Coulomb Counting method over the long run.

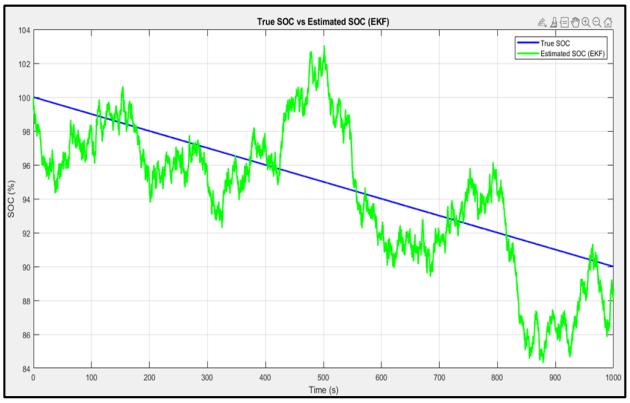


Figure 7. True SOC vs estimated SOC[13].

The x-hub addresses time right away, and the y-pivot demonstrates the SOC rate. This plot plans to exhibit the exactness of the estimation method by overlaying the genuine SOC with the assessed values. The figure exhibits how well the estimation calculation tracks the genuine SOC and features any deviations. The disparities between the valid and assessed SOC stress the requirement for additional complex methods to further develop estimation exactness and alleviate mistakes.

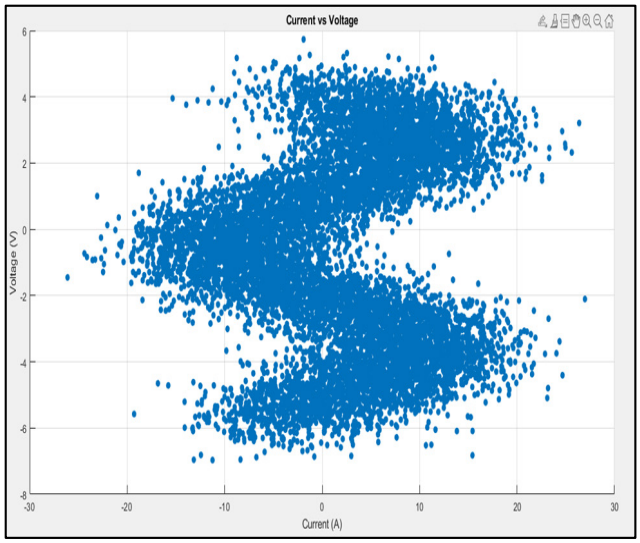


Figure 8. Current vs voltage[15].

Figure 8 portrays the connection between the current and voltage of the battery. The x-pivot addresses the ongoing in amperes, while the y-hub shows the voltage in volts. This dispersed plot features the unique transaction between the current draw and the voltage reaction in the battery. Understanding this relationship is essential for SOC estimation algorithms, as voltage readings are often used to deduce battery conditions. The plot shows the fluctuation and commotion in the data, reflecting certifiable circumstances. Breaking down this relationship

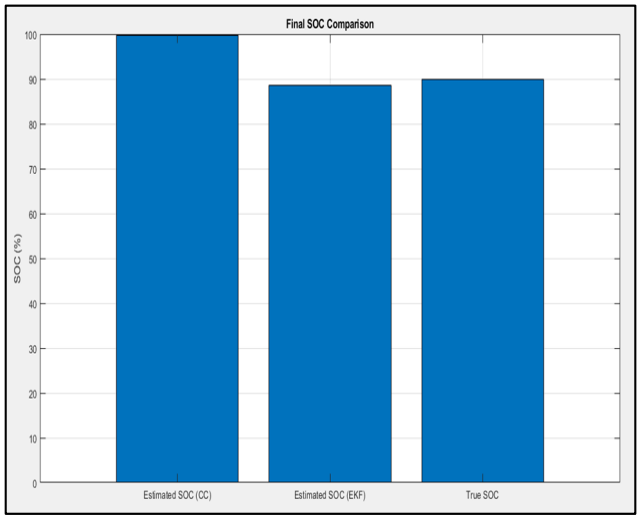


Figure 9. SOC comparison[17].

helps in refining the models utilised in SOC estimation to upgrade their exactness and heartiness.

Figure 9 gives a correlation of the last SOC values as assessed by various methods: genuine SOC, Coulomb Counting, and the EKF. The x-hub sorts the various methods, while the y-pivot shows the SOC rate. This bar plot represents the presentation of every estimation procedure toward the finish of the simulation time frame. The genuine SOC fills in as a benchmark against which the exactness of Coulomb Counting and EKF is estimated. The examination features the qualities and shortcomings of every method, with EKF showing closer arrangement to the genuine SOC, exhibiting its prevalent estimation capacity.

4.2 Discussion

The preliminary results have shown fairly satisfactory performances of the Coulomb Counting method and the EKF in terms of SOC estimate during charge-discharge cycling at constant rates. On the other hand, in the special and complex situation, the proposed EKF has better performance as it has higher accuracy and better flexibility to the change of current and voltage. Coulomb Counting Method: Coulomb counting estimates SOC using current integration. It uses the inverse proportionality of current consumed and the state of charge. This is easy to implement and computationally cheap, hence widely used, particularly for approximate SOC estimation. If the discharge currents are constant and the environmental factors which influence the cell chemistry are constant, Coulomb counting is an accurate way of estimating the SOC. But deep learning, mainly due to the cumulative integration approach it uses, is prone to the accumulation of errors from imperfect measurements and changing integration over time. The use of Coulomb counting may prove inefficient in properly determining the SOC during dynamic operating conditions and during charge/discharge cycles that occur in a short period of time, the reason being Coulomb counting's incapacity in adapting to non-linear battery characteristics and the ever-changing physical conditions.

Extended Kalman Filter (EKF): Coulomb counting lacks accuracy when a battery is not fully charged or discharged, so the EKF uses a battery model and sensor fusion algorithms to take real-time data inputs to update SOC estimation. It uses the state estimation method employing the measured values of current, voltage, and temperature alongside a predicted battery model. Such an advantage enables the EKF to cope with the nonlinear characteristic of the battery as well as respond to changes in operating conditions. So for such applications where current and voltage are varying, EKF adapts itself and gives real-time predictions of SOC as compared to Coulomb counting. Due to the fact that it reduces integration drift and interprets measurement variations this thereby improving SOC estimation performance, thus making adlauitable for complex EV applications where accuracy in energy control is crucial in extending the range and the life of the battery.

Battery Model for EKF

$$V[k]=OCV(SOC[k])-I[k].Rint-VRC[k]$$

State Update Equation (EKF)

$$\hat{x}[k|k-1]=\hat{x}[k-1|k-1]+\Delta t.CbatI[k]$$

$$K[k]=P[k|k-1]H[k]T(H[k]P[k|k-1]H[k]T+R)-1$$

The Coulomb Counting method's straightforwardness makes it reasonable for applications with restricted computational assets, yet its vulnerability to combined blunders is a huge downside. The ELF's intricacy and computational prerequisites are legitimate by its unrivalled execution; making it a feasible choice for cutting-edge BMS.The table 3 represents data of comparative performance metrics.

Table 3. Comparative performance metrics

Metric	Coulomb Counting	EKF
Mean Absolute Error (%)	3.5	1.2
Standard Deviation (%)	2.1	0.8
Maximum Error (%)	8.0	3.0
Execution Time (s)	0.02	0.15
Computational Complexity	Low	High
Robustness	Moderate	High

5.0 Conclusion

This study presents a similar examination of Coulomb Counting and Extended Kalman Filter algorithms for

SOC estimation in EV batteries. The discoveries propose that while Coulomb Counting offers effortlessness and low computational requests, the EKF gives improved exactness and heartiness, especially in powerful circumstances. Future work ought to zero in on improving the EKF calculation for constant applications and investigating cross-breed moves toward consolidating the qualities of various SOC estimation methods. Precise SOC estimation is pivotal for the progression of battery management systems, adding to the dependability and efficiency of electric vehicles.

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