

# Performance Evaluation of Kalman-based Algorithms for SoC Estimation in Electric Vehicle Batteries

P. R. Dhabe<sup>1</sup>, Dr. S. R. Paraskar<sup>2</sup> and Dr. S. S. Jadhao<sup>3</sup>

<sup>1-3</sup>Department of Electrical Engineering, Shri Sant Gajanan Maharaj College of Engineering, Shegaon (M.S.), India  
Email: pratikdhabe5052@gmail.com, srparaskar@gmail.com, ssjadhao@gmail.com

**Abstract**— Accurate estimation of the State of Charge (SoC) is vital for the reliable and safe operation of lithium-ion batteries used in Electric Vehicles (EVs). The Battery Management System (BMS) relies on precise prediction of SoC to ensure optimal battery usage, prevent overcharging or deep discharging, and extend battery life in long term. This paper attempts to sincerely investigate and compare the performance of two widely used filtering techniques—Standard Kalman Filter (KF) and Extended Kalman Filter (EKF)—for SoC estimation using battery data from the real-world. The KF is often implemented under the assumption of linear battery dynamics. On the other hand, the EKF incorporates the nonlinear relationship between Open Circuit Voltage (OCV) and SoC through a fitted curve extracted from experimental data. A publicly available open source dataset from high-rate discharge tests of a lithium-cobalt-oxide pouch cell is used for validation purpose. Based on cumulative discharge capacity, the true SoC is computed and is then compared against SoC estimates from both filters. The results are indicative of the fact that the EKF, with its nonlinear measurement model, more closely follows the true SoC trajectory, especially under dynamic current conditions. The improved accuracy of EKF over the standard KF is confirmed by evaluation metrics such as RMSE and MAE. These findings emphasize the importance of model selection and also highlight the advantages of nonlinear filtering for SoC estimation in practical battery systems. The findings also contribute to the ongoing efforts in enhancing the accuracy of battery state estimation which in turn supports safer, reliable, and more efficient operation of electric vehicles.

**Index Terms**— Electric Vehicles; State of Charge; Standard Kalman Filter; Extended Kalman Filter; Open Circuit Voltage; Battery Management System.

## I. INTRODUCTION

The rising global demand for sustainable and eco-friendly solutions for transportation has catalyzed the rapid development and adoption of EVs more than ever before. As nations across the globe commit to cut down carbon emissions and fossil fuel dependency, EVs have cropped up as a viable alternative to conventional internal combustion engine (ICE) vehicles. The EVs are becoming increasingly viable in terms of performance, and affordability due to the recent advancements in battery technology, vehicular electronics, and the battery charging network. A report from the Global EV Outlook published in 2018 predicts that by 2030, there will be about 117.6 million EVs, which shall eventually cut down CO<sub>2</sub> emissions by 262 Mt [1]. A lithium-ion battery — a complex electrochemical system that serves as the primary energy source for vehicle propulsion, happens to be the heart and soul of the EVs.

Apart from the applications in EVs, batteries have seen a growth in its usage for storing electrical energy for other reasons as well such as improving grid stability and overcoming energy crisis [2]. Due to the rising demand of batteries for various applications, they are produced in different types. However, the lithium ion batteries clearly seem to have an upper hand owing to their superiority over the other types in terms of energy density, comparatively lower deviation in operating voltage levels, longer life cycle, and lighter weight [3]. The potential benefits of the lithium ion batteries serve as the motivation for EV manufacturers to get them on-board as the principal source of energy storage systems [4].

However, the efficiency, reliability, and safety of an EV are primarily dependent on the management of its battery system. This critical role is achieved by the BMS, which is an embedded control unit responsible for real-time monitoring, control, and protection of the vehicle battery pack. It is a crucial requirement to have an effective BMS to operate the battery in a safe operating range, which is achieved through the uninterrupted monitoring of different battery parameters such as internal impedance, OCV, charge-transfer constant, diffusion-and-polarization constants [5]. One of the most crucial functions of the BMS is the accurate estimation of the battery's SoC — a parameter that is analogous to the fuel gauge in conventional vehicles, clearly indicating the remaining usable capacity of the battery. More often than not, incorrect SoC estimation leads to the unexpected vehicle shut-down, reduced driving range, battery overcharge or deep discharge, and potential safety hazards.

Despite the importance of SoC estimation, it still remains a non-trivial challenge owing to the complex, nonlinear, and time-varying nature of battery behavior. Lithium-ion batteries are dependent on various factors such as SoC, current, temperature, aging, and internal resistance which eventually lead them to exhibit significant variation in voltage characteristics [6]. All the more, the SoC cannot be measured directly and has to be deduced from measurable parameters such as terminal voltage and current, which calls for the employability of robust estimation algorithms. Table 1 depicts some popular chemistries of lithium-ion battery available in the market that are commonly used for EV applications [7].

TABLE I. OUTLINE OF PREVALENT BATTERY CHEMISTRIES USED IN EVs

| Battery Chemistry             | Nominal Voltage (V) | Energy Density | Life Cycle   | Safety                   | Cost      |
|-------------------------------|---------------------|----------------|--------------|--------------------------|-----------|
| Lithium-iron-phosphate (LFP)  | 3.2                 | Low            | Long life    | Safest to use            | Expensive |
| Nickel-manganese-cobalt (NMC) | 3.6                 | High           | Average life | Safe to use              | Expensive |
| Lithium-cobalt-oxide (LCO)    | 3.6                 | High           | Average life | Requires safety measures | Cheaper   |
| Lithium-manganese-oxide (LMO) | 3.7                 | Low            | Short life   | Safe to use              | Expensive |
| Nickel-cobalt-aluminium (NCA) | 3.6                 | High           | Average life | Requires safety measures | Expensive |

Several techniques for SoC estimation have been reported in the literature, which can be broadly categorized into direct and methods, model-based approaches [8], [9]. Direct methods, such as Coulomb Counting (CC) and Open Circuit Voltage (OCV) lookup, are simple but are prone to suffer from cumulative errors and the need for long rest periods, respectively [10], [11]. Indirect methods, comprising sophisticated data-driven Machine Learning (ML) techniques [12] and model-based filters [13], offer comparatively more robust solutions. Among these, the Kalman Filter family has gained significant prominence for BMS applications owing to its recursive nature, computational efficiency, and ability to handle sensor noise suitable for real-time application. Non-linear techniques are often applied to the model based estimation for online applications. These non-linear techniques can further be categorized into adaptive filtering based and non-linear observer based methods as shown in Figure 1. This work focuses specifically on a comparative analysis of two fundamental members of this family: the KF and the EKF.

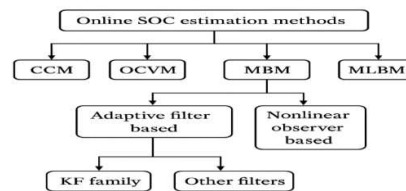


Figure 1. Categorization of online SoC estimation methods

This paper emphasizes on evaluating and comparing two Kalman-based estimation techniques — the standard KF and the EKF — for SoC estimation in lithium-ion batteries used in EVs. The KF is effective under simplified, ideal conditions such as a linear OCV–SoC relationship as it assumes linear system dynamics. However, real battery exhibits inherently nonlinear behavior. The EKF addresses these limitations by linearizing the nonlinear system around the current estimate by making use of a Jacobian-based approach.

Although the theoretical superiority of the EKF for nonlinear systems is highly established, there is a scarcity of a clear and empirical demonstration of its performance gain over the standard KF using a high-fidelity, real-world dataset. Many studies in the literature rely on simulated data or simplified battery models. The original contribution of this work happens to be a direct, quantitative performance evaluation of the KF and EKF techniques for SoC estimation that is implemented and validated on a publicly available experimental dataset. A prominent feature of our EKF implementation is the usage of an empirically derived 5th degree polynomial for accurately capturing the nonlinear OCV–SoC relationship, thereby moving beyond the linear assumption that seriously limits the standard KF. This approach promises to provide a more practical benchmark for the expected improvement in estimation accuracy when adopting a more complex and nonlinear filter in a real-time BMS context.

By implementing both filters, the study presented in this paper aims to test the impact of linear vs. nonlinear modeling on SoC estimation accuracy and helps quantify the performance of KF and EKF in terms of robustness to noise and steady-state error. It also targets to demonstrate the significance of adaptive filtering in development of a reliable BMS for EVs. The definitive purpose of the study lies in making a contribution to the ongoing development of smart and reliable BMS which can enhance the battery life, and aid in the transition from conventional vehicles to cleaner EVs.

## II. BATTERY MODELLING AND MEASUREMENT MODEL

A single-state battery model is used in this research work. The terminal voltage of battery is expressed as a function of SoC through an OCV–SoC relationship. The effects such as temperature variation, hysteresis, and dynamic resistance are neglected in order to keep the model computationally tractable.

The state evolution is governed by the CC method, which estimates SoC based on the current integration over time:

$$SoC_K = SoC_{k-1} - \frac{I_K \Delta t}{C} \quad (1)$$

Where,  $SoC_K$  is the estimated state of charge at  $k$  time step,

$I_K$  is the current drawn from the battery at  $k$  time step (in amperes),

$\Delta t$  is the sampling interval (in seconds),

$C$  is the nominal battery capacity (in ampere-seconds or coulombs).

The measurement model uses the terminal voltage  $V_K$ , which is expressed to be a function of SoC and additive measurement noise:

$$V_K = h(SoC_K) + v_K \quad (2)$$

Where,

$h(\cdot)$  is the OCV–SoC function,

$v_K \sim N(0, R)$  represents measurement noise, assumed to be zero-mean Gaussian with variance  $R$ .

Simply put, the system model in (1) serves as prediction, informing as to how the SoC should change depending on the current. The measurement model in (2) is the reality check, telling as to what the battery voltage should be for a given SoC, based on a pre-defined OCV–SoC curve. The Kalman filters work by consistently balancing these pieces of information, the prediction and the measurement, in order to provide a better estimate of the true SoC.

## III. STANDARD KALMAN FILTER (KF) TECHNIQUE

The Standard KF works on the assumption that both the system dynamics and the measurement model are linear in nature. The state-space model used for KF is represented as:

$$x_K = Ax_{K-1} + Bu_K + w_K \quad (3)$$

$$z_K = Hx_K + v_K \quad (4)$$

Where,

$x_K$  is the SoC,  $u_K = I_K$ , and the matrices are defined to be:

$$A = 1, \quad B = -\frac{\Delta t}{C}, \quad H = 1$$

$w_K \sim N(0, Q_K)$ , and  $v_K \sim N(0, R_K)$  are the noise terms in the equation.

Equations (3) and (4) are the state and measurement equations respectively.

The KF technique effectively works in two steps – namely, the Prediction, and the Correction step. The state prediction and error covariance prediction is shown by (5) and (6) respectively.

$$\hat{x}_{K|k-1} = A\hat{x}_{K-1|k-1} + Bu_K \quad (5)$$

$$P_{K|k-1} = AP_{K-1|k-1}A^T + Q \quad (6)$$

Where,

$\hat{x}_{K|k-1}$  is the prior state predicted,

$P_{K|k-1}$  is the estimate covariance predicted

$Q$  is the process-noise covariance

The correction step is represented by (7) – (9), which involves computation of Kalman gain, state updation, and error covariance updation.

$$K_K = P_{K|k-1}H^T(HP_{K|k-1}H^T + R)^{-1} \quad (7)$$

$$\hat{x}_{K|k} = \hat{x}_{K|k-1} + K_K(z_K - H\hat{x}_{K|k-1}) \quad (8)$$

$$P_{K|k} = (I - K_KH)P_{K|k-1} \quad (9)$$

Where,

$K_K$  is the Kalman gain which is an indication as to how much the measurement can be trusted vs. prediction,  $z_K - H\hat{x}_{K|k-1}$  is the measurement residual.

The KF is a simple and commonly used algorithm for estimating battery SoC in EVs due to its certain advantages. It is found to robustly handle the measurement noise if any and provide real-time estimation. In addition to this, it is capable to fuse multiple sensor inputs. It is highly versatile in being applicable across almost all battery chemistries. However, the KF is derived under the assumption that the system dynamics and the measurement model are linear. But in real-world battery systems, the OCV-SoC relationship is non-linear assuming natures like exponential, logarithmic, sigmoid etc.

#### IV. EXTENDED KALMAN FILTER (EKF) TECHNIQUE

In order to counter the shortcomings of the standard KF technique, a variant of the Kalman Family - Extended Kalman Filter (EKF) - is proposed and discussed in this paper. The EKF is an adaptation of the KF which is used to address the issue of SoC estimation in case of non-linear systems. The EKF handles the non-linear systems by using the non-linear functions and linearizing them using the Taylor series – by virtue of computing Jacobian, and then running the KF steps on the linearized system at each time step. This makes the EKF more suitable for real-world battery systems with non-linear OCV behaviour. A breakdown of the EKF technique and its equations involves the prediction and correction steps as under.

The state prediction step is represented by (10) as shown below.

$$\hat{x}_{K|k-1} = \hat{x}_{K-1|k-1} - \frac{I_K \Delta t}{C} \quad (10)$$

The covariance prediction is governed by (11).

$$P_{K|k-1} = AP_{K-1|k-1}A^T + Q_K \quad (11)$$

Equation (12) is the innovation step, also called the residual or prediction error. It represents the difference between the measured and the predicted voltage. In EKF, it is computed using non-linear function (h.), unlike KF where a linear function computes it.

$$y_K = z_k - h(\hat{x}_{K|k-1}) \quad (12)$$

Where,  $h(\hat{x}_{K|k-1})$  denotes the predicted voltage from the non-linear model based on the predicted SoC.

$$S_K = H_k P_{K|k-1} H_k^T + R \quad (13)$$

The above equation represents the Innovation covariance ( $S_K$ ), where,

$H_k = \frac{\delta h}{\delta x}|_{x=x_{K|k-1}}$  is the Jacobian of the measurement function at  $\hat{x}_{K|k-1}$  and  $R$  is the measurement noise.

The Kalman gain which is indicative of how much the prediction should be corrected using the innovation is given by (14) below.

$$K_K = P_{K|k-1} H_k^T S_K^{-1} \quad (14)$$

The state update and the error covariance update is represented by (15) and (16) respectively.

$$\hat{x}_{K|k} = \hat{x}_{K|k-1} + K_K y_K \quad (15)$$

Where,

$\hat{x}_{K|k}$  is the updated SoC estimate,

$K_K y_K$  represents the correction based on new measurement.

$$P_{K|K} = (I - K_K H_k) P_{K|k-1} \quad (16)$$

Where,

$P_{K|K}$  is the updated covariance.

The EKF, by virtue of its ability to deal with non-linear systems effectively, turns out to be a viable technique for SoC estimation in EVs. Figure 2 illustrates the basic operational flow diagram for SoC estimation using Kalman Filtering method. Figure 3 depicts the basic steps involved in Kalman Filtering technique.

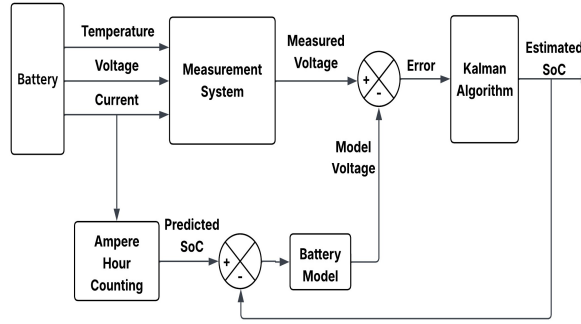


Figure 2. Systematic Operational Flow Diagram of the Kalman Filtering Method for SoC Estimation

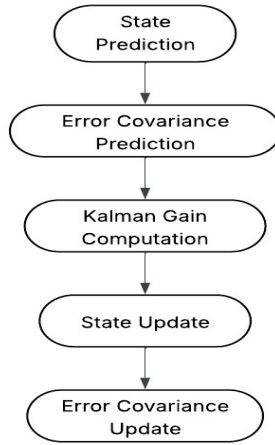


Figure 3. Kalman Filtering Steps for SoC Estimation

## V. RESULTS AND DISCUSSION

The Oxford Battery Degradation Dataset used in this paper for SoC estimation using KF and EKF technique was obtained from [14], as it is otherwise improbable and highly cumbersome to obtain it from experimentation. The datasets contains 460,381 entries in total, making it an extensive and rich. It consists of time, actual current profile, voltage, charge & discharge capacity, and cell temperature. Making use of the charge/discharge capacity, we computed the true SoC. Later, KF and EKF algorithms were employed to estimate SoC that was compared to the true SoC computed earlier. So as to aptly utilize the rich dataset, it was suitably filtered to use only the first discharge cycle and the idle segments, where the current was zero, were removed. The true SoC was computed using (17). The nominal capacity of the battery was considered to be 2.3Ah, as it is typical of the LCO battery cells.

$$SoC_{true} = 1 - \frac{\text{Discharge Capacity}}{\text{Nominal Capacity}} \quad (17)$$

As discussed in the previous sections, the KF technique is simple and works best for only the linear systems. However, the real-time systems are dynamic in nature and hence the KF may tend to imprecisely give the SoC estimates. Additionally, the KF estimates are heavily dependent on the initial conditions. For incorrect capacity estimates, wrong OCV values, and too high or low initial SoC value, the KF estimates for SoC will always give wrong readings. The Figure. 4 illustrates the SoC estimates using the standard KF algorithm.

As it can be seen from Figure. 4, the SoC estimates using KF technique start pretty much in proximity to the true SoC values. However, as the actual system is dynamic in nature, and we are using KF that typically works on linear systems, or to be more precise - ignores the non-linearity, the KF estimates are gradually diverging from the true SoC values.

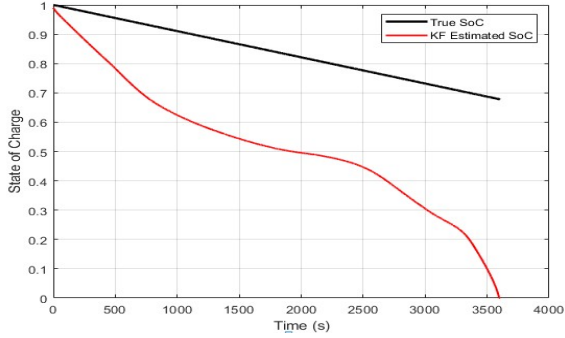


Figure. 4 SoC Estimation using standard KF Technique

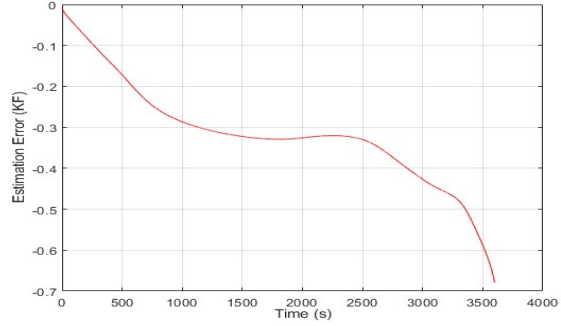


Figure. 5 SoC Estimation Error using standard KF Technique

This unusual drift from the true readings can be attributed to the inherent shortcomings of the applicability of standard KF technique. This is often the outcome of – assuming the OCV-SoC relationship to be linear, slightly off current integration that eventually accumulates the small integration errors, large sensor noise that makes Kalman gain to look tiny and give inaccurate estimates, and mismatched initial SoC value (too high or too low). Figure. 5 demonstrates the estimation errors when calculated using standard KF technique. Conclusively, KF technique gives correct estimates only when the measurement model is reliable, system and measurement noise levels are well modelled, the system is linear, and the sensor data is clean.

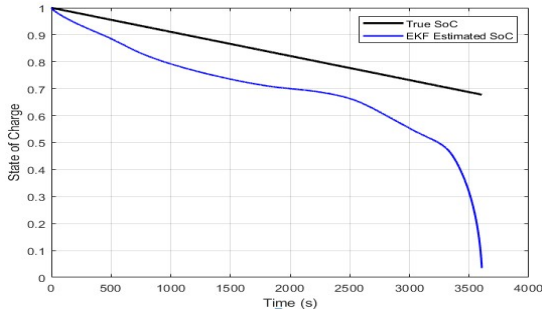


Figure. 6 SoC Estimation using EKF Technique

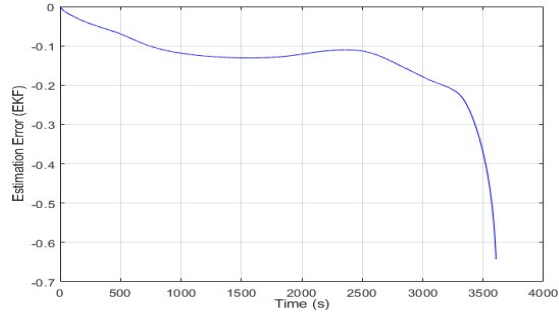


Figure. 7 SoC Estimation Error using EKF Technique

To overcome the pitfalls and shortcomings of the KF, this paper proposes the EKF technique – which is more suitable to deal with non-linear and dynamic systems for SoC calculation. As stated earlier, the dataset used was obtained from an open-source battery testing repository and contains measurements from a commercial LCO pouch cell. The selected discharge cycle for analysis purpose is the first complete discharge cycle, where the cell was discharged under controlled constant-current conditions. This data was further processed to ensure - data points from only the first discharge cycle were chosen, and it is inspected for any NaNs, zero-voltage segments, or idle periods. In order to incorporate a nonlinear measurement model in the EKF, an empirical OCV-SoC relationship was derived by fitting a 5th-degree polynomial to the Voltage vs. SoC data. Finally, the EKF was simulated across the entire first discharge cycle, for approximately 3600 seconds. The Figure. 6 illustrates the SoC estimates using the EKF algorithm. It is evident that the EKF estimation closely tracks the true SoC throughout the simulated discharge cycle. Figure. 7 indicates the estimation errors when calculated using EKF technique.

The Table 2 provides the statistical analysis of the various errors in SoC estimation by the standard KF and EKF techniques.

TABLE II. STATISTICAL ERROR ANALYSIS OF STANDARD KF AND EKF

| Metric                         | Standard KF | Proposed EKF |
|--------------------------------|-------------|--------------|
| Root Mean Square Error (RMSE)  | 0.3406      | 0.1595       |
| Mean Absolute Error (MAE)      | 0.3166      | 0.1363       |
| Maximum Absolute Error (MaxAE) | 0.6784      | 0.6429       |

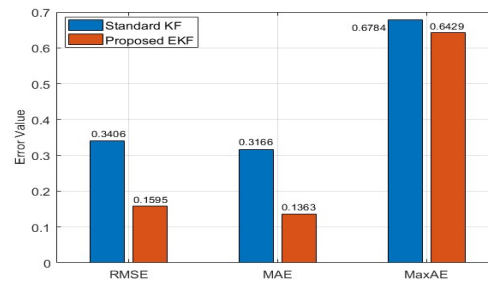


Figure. 8 Error Metric Comparison: standard KF vs. EKF

The graph plotted in Figure. 8 compares the error metrics—Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Maximum Absolute Error (MaxAE)—between the Standard KF and the proposed EKF.

The results clearly indicate that the EKF maintains close tracking of the true SoC throughout the discharge cycle and gives better convergence compared to that of standard KF. Despite the existence of measurement noise and nonlinear voltage response, the EKF adapts effectively, owing to the Jacobian-based correction step that captures the local curvature of the measurement function. The KF displays quick divergence when the model assumptions are violated, especially near the higher SoC range where the nonlinear OCV curve flattens and the KF fails to correct adequately. Contrastingly, the EKF shows more stability and converges to the true SoC value quickly towards the end. Also, the Kalman gain in the EKF decreases over time which indicated increased confidence in the estimate. It can be noted that the standard KF, assuming a linear OCV-SoC relationship, struggled to provide accurate SoC tracking owing to the inherent non-linearity of the battery behaviour. This is starkly clear from the higher RMSE and the weak convergence that is observed. On the contrary, the EKF algorithm, which implemented a realistic non-linear OCV-SoC polynomial model, has shown to significantly outperform the standard KF algorithm as shown in all error metrics.

## VI. CONCLUSION

The precise and reliably accurate estimation of the SoC of lithium-ion batteries is inevitable for the reliable and safe functioning of EVs. In this study, a comprehensive comparison between the Standard KF and the EKF is

presented for SoC estimation using real-world LCO pouch cell data. The results have depicted that the Standard KF exhibited considerable errors since it relied on the assumption of a linear relationship between voltage and SoC, especially as the battery discharged towards lower SoC ranges. The MSE reported for the standard KF was comparatively higher, and the estimated SoC has seen to be diverged substantially from the true SoC during the later stages of the discharge cycle.

On the other hand, the EKF, equipped with a non-linear polynomial model of the OCV-SoC relationship, has recorded a more accurate SoC estimation of the battery. The EKF method seems to have closely followed suit the true SoC trajectory, almost throughout the discharge cycle, resulting in a lower MSE and depicting better robustness.

With the growing focus on upgrading the reliability, efficacy and safety of EVs, it is inevitable to build and develop more robust SoC estimation algorithms. The proposed EKF technique in this paper, thus, makes a sincere attempt to provide an effective solution toward achieving a smart and reliable BMS.

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