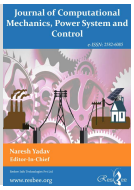
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Ensemble-Based State Estimator of Battery Management System in Electric Vehicles using the Adaptive Singular Evolutive Interpolated Kalman Filter (ASEIKF)

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Abstract: By advancing EV technology, a lot of studies have been conducted concerning Battery Management Systems (BMSs) to track thecondition of the battery. This rapid growth in electric mobility has intensified the need for accurate and reliable battery monitoring strategies to ensure safety and longevity. Similarly, a new vehicle technology has led to extensive study on BMSs that track the state of the battery. The reliability of the battery condition evaluation is greatly impacted by the accuracy of the battery model parameters used in this process. However, it also has several difficulties which are related to accuracy and resilience due to the dynamic and complicated environments. The estimator is used to efficiently handle the computational load related to high-dimensional, nonlinear battery models according to an ensemble-based approach. Comparably, the Singular Evolutive Interpolated Kalman Filter (SEIKF) can produce accurate results with a lower ensemble size, and it is computationally efficient when compared to other ensemble approaches. Therefore, without imposing a significant computing burden, the suggested Adaptive SEIKF (ASEIKF) technique performs well with complicated, high-dimensional battery structures, including electrochemical-thermal models. The effectiveness of the suggested adaptive ensemble-based battery state estimator in EVs is evaluated by comparing it with a number of popular nonlinear estimating methods that have been used in EV battery state estimation models. The proposed framework is validated in MATLAB, and the proposed ASEIKF-based model generated a voltage value of 3.7448V; however, the measured voltage rate is 3.7455V, and the voltage rates of existing methods, such as UKF, EnKF, and SEIKF for BMS of EVs, attained the values of 3.7455V, 3.7364V, 3.7311V, and 3.7408V, respectively. These results demonstrate that the proposed approach achieves superior estimation accuracy compared to conventional methods. The outcomes of the proposed model validate the outstanding performance which offered in terms of various metrics.

Keywords: Electric Vehicle; State of Charge; Adaptive Singular Evolutive Interpolated Kalman Filter; Battery Management Systems; State Estimator

Nomenclator

Abbreviation	Description
EV	Electric Vehicle
SEIKF	Singular Evolutive Interpolated Kalman Filter
Li-ion	Lithium-ion
ABMSs	Advanced Battery Management Systems
BMSs	Battery Management Systems
ASEIKF	Adaptive Singular Evolutive Interpolated Kalman Filter
SOC	State of Charge
MMSE	Minimum Mean Squared Error
SOH	State of Health
QG	Quasi-Geostrophic
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
AEKF	Adaptive Extended Kalman Filter
RLS	Recursive Least Squares
SVD	Singular value decomposition
KF	Kalman Filter
UKF	Unscented Kalman Filter
DST	Dynamometer Schedule for Town driving
UDDS	Urban Dynamometer Driving Schedule
EnKF	Ensemble Kalman Filter

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1. Introduction

Generally, Li-ion batteries have the significant benefits of high power and high energy densities, low self-discharge rate, attractive flexibility, and also the recent rapid cost drop has made them the most popular electrochemical energy storage technology [1]. These characteristics make Li-ion batteries particularly suitable for applications requiring both high performance and compact energy storage. Modern industrial applications, such as smart grids with a sizable number of EVs and renewable energy sources, have made extensive use of it. However, there is extensive research has been conducted to produce ABMSs, which is driven by the growing requirement of Li-ion batteries [2]. Thus, it attained improved safety and longer service lifespan that are compatible with a larger operating range. Lithium-ion batteries are gradually replacing other rechargeable secondary batteries, which act as the primary power source for portable electronics, grid energy storage systems, and EVs due to their numerous advantages, including high specific energy density, no memory effect, and long lifetime [3]. Despite these advantages, accurate monitoring of battery internal states remains a challenging task. As active materials and cyclable lithium are lost, the lithium-ion battery's capacity of storing energy and power will decrease from the standpoint of cycle operation, which is intuitively represented by a rise in impedance and a decrease in maximum possible capacity. Even worse, safety problems could result from lithium-ion battery degradation [4].

Evensen [1992, 1993] previously addressed the application of the extended KF for data simulation in a multilayer QG model. This work laid the foundation for the development of ensemble-based filtering techniques. The discovery of an apparent closure issue with the error covariance evolution formula [5] is the primary outcome of EVENSEN'S study [1992]. In most applications, the system dynamics and observation equations are nonlinear, requiring proper expansions to the KF [6]. This limitation motivates the use of advanced nonlinear filtering methods in practical applications. It is well known that maintaining an exhaustive overview of the conditional probability density is necessary for the optimal solution of the nonlinear filtering challenge [7]. However, EVs are estimated to have a significant impact on sustainable mobility because of their effective energy use and zero emissions when in use [8]. The battery essentially determines the driving range and has a significant impact on how well EVs operate. Typically, a battery string with the necessary voltage (up to 400 V) is constructed by connecting a significant number of cells in series, depending on the application [9].

Extending battery life by addressing the charge imbalance problem that might occur in series-connected cells is another crucial role of a BMS. Cell-to-cell imbalance can significantly reduce the overall usable capacity of the battery pack. This minimizes the battery's useful capacity because, even while energy is still stored in the battery's other cells, the least charged cell is controlled when the discharge occurs [10]. Li-ion batteries are governed by strong voltage limitations, which prevent charge imbalance from self-correcting and cause it to deteriorate over time. Therefore, precise estimation of internal battery states is required to support effective balancing strategies. In fact, the charging process must be stopped when a cell exceeds the upper voltage limit, which prevents some batteries from being fully recharged [11]. In this paper, the model proposed a novel ensemble-based state estimator of BMS in EV is proposed by using the ASEIKF to provide extremely exact and dependable assessment of crucial battery states like SOC and SOH. The proposed method leverages adaptive mechanisms to enhance robustness under uncertain operating conditions. This model provided an ensemble-based approach that enables the estimator to efficiently handle the computational load related to high-dimensional, nonlinear EV battery models. The ASEIKF is used to handle noise and system parameter uncertainty because they are often unknown or changing in real-world applications. By adaptively tuning the error covariance matrices, estimation accuracy can be significantly improved. The error covariance matrices can be modified in this case by the adaptive component.

The study is organized as follows: Section 1 introduces the proposed ensemble-based state estimator of BMS in EV. The relevant survey and problems with the current work based on the state estimator of BMS in EV are displayed in Section 2. The suggested approach for the ensemble-based state estimator of BMS in EV using ASEIKF is shown in Section 3. Section 4 presents the outcome and a discussion of the suggested model. Finally, the suggested work's conclusion is provided in Section 5.

2. Literature Survey

2.1. Related Work

In 2024, Jiang et al. [11] developed a thorough analysis of the battery's fundamental deterioration mechanism, including an algorithm for distinguishing and determining battery states in BMS. This study provides a comprehensive foundation for understanding degradation-aware battery state estimation. They then thoroughly examined and discussed the most popular methods and cutting-edge algorithms for

battery status estimation in BMS from the viewpoints of three distinct BMS configurations: functional integrated BMS, cloud BMS, and onboard BMS. It was anticipated that the evaluation could encourage more research and attempts to create sophisticated BMS for creative and intelligent battery control.
In 2021, Li et al. [12] suggested a computationally effective Li-ion battery condition evaluation method based on a high-fidelity electrochemical thermal framework for advanced BMSs that takes depletion into consideration. Their work emphasized the importance of combining physics-based models with advanced estimation algorithms. Using the SEIKF and an ensemble-based state estimator, the computational load resulting from the battery model's high-dimensional nonlinearity was effectively reduced. The model was adaptively changing the error covariance matrices of the SEIKF to address the model uncertainty caused by battery degradation and measurement errors. This adaptive feature significantly enhanced robustness under uncertain operating conditions. The model's effectiveness was assessed by contrasting it with some well-known nonlinear estimation methods that were previously employed for battery electrochemical state estimation. The findings demonstrated that excellent performance in terms of accuracy, computational speed, and robustness could be offered.

In 2021, Yang et al. [13] proposed an enhanced technique for lithium-ion battery parameter identification and SOC estimation. The method focused on separating battery dynamics to improve estimation accuracy. The battery model was split into two components based on fast and slow dynamics using a two-order equivalent circuit model. The extended Kalman filter predicted the model's open-circuit voltage and SOC when the battery's parameters were ascertained using the recursive least squares method. Existing comprehension of the open circuit voltage and the state of SOC is not necessary for the suggested method, which was utilized to calculate the parameters and the SOC in real time. This characteristic makes the approach suitable for real-time applications. Data from dynamic stress testing were used to test the method; the average SOC estimation error was 0.0139, and the RMSE of the prediction model's accuracy was roughly 0.01 V. The method outperformed conventional recursive least squares techniques in both online state estimation and offline parameter identification, according to the results.

In 2021, Zhang et al. [14] suggested a multi-time-scale framework to co-estimate SOC and capacity for the purpose of lowering the computation costs and increasing the accuracy of SOC estimation over the battery's lifetime. This framework addressed the trade-off between computational efficiency and estimation precision. Model parameters were originally calculated online using forgetting factor recursive least squares in order to forecast SOC in real-time. An adaptive extended Kalman filter was then fed these parameters. In order to determine the optimal operating temperatures for batteries, Federal urban driving schedule tests were carried out at 20°C, 30°C, and 40°C. Temperature-dependent performance analysis further strengthened the practical relevance of the study. There were most of the MAE and RMSE of capacity prediction results are below 1% and 2%, respectively, and the validation results demonstrated that the MAE and RMSE of SOC estimation outcomes in three different macro time-scales over the optimal operating temperature range were typically contained within 1%.

In 2020, He et al. [15] suggested an innovative approach to online SOC estimation that blends an adaptive RLS-based parameter identification algorithm with a novel AEKFA. The integration of adaptive identification and filtering improved tracking performance. In particular, the battery model parameters were computed online in accordance with the first-order R-C network equivalent circuit model, utilizing the RLS with multiple forgetting factors. Based on the determined parameters, the battery SOC was accurately calculated using the novel AEKF. The real-time parameter identification tracked the evolving model. According to the simulation test findings, the maximum absolute errors occurred under DST and UDDS. Furthermore, in both the DST model with current offset sensor error as well as the DST simulation including current and voltage measurement noise, the greatest absolute error was less than 0.02. The testing showed that the suggested approach had excellent durability and accurately estimated battery SOC.

2.2. Problem Statement

The benefits and drawbacks of several current filtration techniques utilized for the ensemble-based state estimator of BMS in EVs are compared and discussed in this section. This comparison helps identify existing research gaps and performance limitations. Similarly, Paper [11] had high accuracy, computational efficiency, and robustness against noise using SEIKF. However, it had issues with the complicated nature of the underlying high-fidelity electrochemical-thermal structure and the requirement for efficient adaptation mechanisms to deal with changing conditions. These limitations motivate the development of more adaptive and scalable estimation frameworks. However, Paper [12] had the better range prediction, energy management, and a longer battery lifespan, which were the advantages of the advancements in battery state estimation of BMS in EVs. However, issues still exist, including difficulties in maintaining high precision under dynamic conditions and the difficulty of immediate implementation

and long-term validation. Paper [13] proposed that the EKF had the benefit of increased robustness and accuracy due to the decoupling of variables that change at different rates. However, the primary issues were the model's complexity and the EKF's tendency for errors because of its linear approximation, which can cause errors in real-world situations and necessitate the use of robust techniques like adaptive approaches for improvement. This highlights the need for nonlinear and ensemble-based filtering techniques. The AEKF in Paper [14] had the advantages of lower processing costs and increased accuracy because it can handle varying time scales for various activities. However, some of its challenges include implementation complexity and finding a balance between the accuracy provided by smaller time scales and the lower processing cost of larger time scales. Finally, Paper [15] was an accurate battery model, and the possibility of algorithm complexity in certain variations was a drawback, while the benefits include high accuracy and robustness against noise. Overall, existing studies indicate the necessity for an adaptive, computationally efficient, and robust ensemble-based estimator suitable for real-world EV applications.

3. Proposed Methodology

An EV is a vehicle that drives with the use of electricity for the battery, fuel cell, or other electric power source instead of an internal combustion engine. This shift toward electrification aims to reduce greenhouse gas emissions and dependence on fossil fuels. In addition to their high initial cost, EVs have a limited infrastructure for charging and also it had the challenges of battery depletion. As a result, the BMS is crucial for EVs since it guarantees safety, improves battery life, and enhances performance by monitoring and regulating the current, temperature, and voltage of the battery pack. It also gives accurate data about the battery's health and state of charge. Accurate estimation of these parameters directly influences driving range and operational reliability. This work provides a more robust and probabilistic measurement of uncertainty of BMS in EVs by estimating the internal states of a system from data, utilising the ensemble-based battery state estimator of BMS in EVs. This approach creates a single, more accurate, flexible, and consistent prediction of a battery's condition by combining many separate estimation models. Similarly, the main objective of the work is to eliminate the drawbacks of a single estimation model, including overfitting, model uncertainty, and noise susceptibility. Ensemble learning strategies are particularly effective in mitigating these limitations. Moreover, this model suggested an ASEIKF to increase the precision and dependability of state estimations, especially for nonlinear systems, by addressing the issues of estimating critical battery states, including SoC, SoH, and internal temperatures. Fig.1 implements the procedure of the proposed complex state estimator for an EV battery using ASEIKFP. The overall workflow illustrates the interaction between data acquisition, estimation, and aggregation stages. The steps of the model are mentioned below,

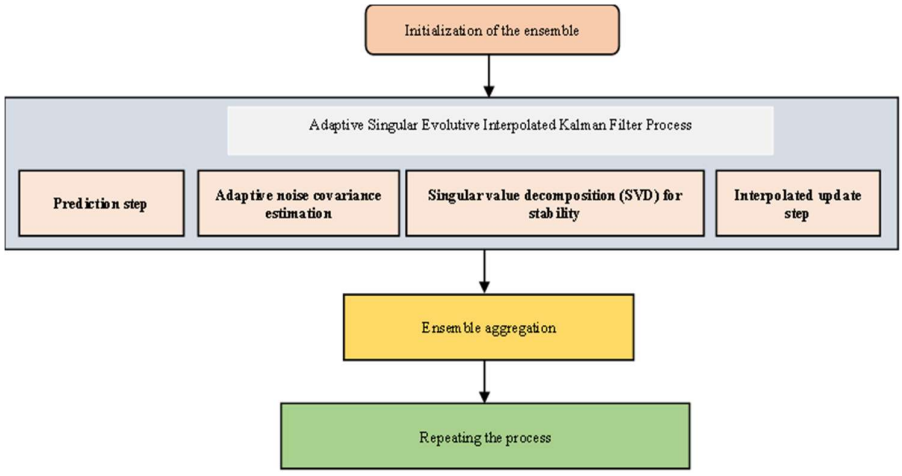


Fig. 1. *Implementation procedure of the proposed complex state estimator for an EV battery*

In this model, initially, the data is obtained from the BMS of the EV and ensembled. Data ensemble generation helps capture the variability present in real battery measurements. In the initialisation process, the model initialises state estimate (y_0), covariance matrices (G_0), and noise covariances (H_0), which are ensembled in the process. This approach initialises multiple filters, each with a slight variation. Such diversity among filters improves estimation robustness. Then, the ensembled data is given in the

filtration process using ASEIKF. In the ASEIKF process, the prediction step, adaptive noise covariance estimation, SVD for stability, and the interpolated update step are conducted. Subsequently, the filtered data is sent into the ensemble aggregation to aggregate these individual results to form the final, more robust estimate. Finally, this complete process is carried out again for each new measurement that the BMS sensors produce. This recursive structure supports real-time implementation in EVs. The ensemble is an effective approach for the high-variability situations observed by EV batteries because it offers an extent of certainty and durability that a single filter cannot.

The battery state of the proposed BMS of EV for SOC and SOH is given below,

$$\text{For SOC, } y = y_0 + \frac{\int_0^t Idt}{H_t} \tag{1}$$

$$\text{For SOH, } z = \frac{H_t}{H_0} \tag{2}$$

The battery state of the proposed BMS of EV is given below,

$$H_t = H_0 - \Delta H \tag{3}$$

$$\Delta H = H_{SEI}^{\text{cov}}(t) + nH_{SEI}^{fr} + H_{Li,Fe}(t) + H_{SEI,Fe}(t) \tag{4}$$

$$H_{SEI}^{\text{cov}}(t) = \frac{\sigma^{in} r_{Li}^{in} A^{\text{cov}} gK}{2\lambda N_{Li}\sqrt{2n\Delta E}} \ln\left(1 + \frac{(6+0.5)\sigma c_6 v_e \lambda N_{Li} G_0 \sqrt{2n\Delta E}}{2Nc_6 \sigma^{in} r_{Li}^{in} g} t \exp\left(-\frac{2l_0^{in}\sqrt{2n\Delta E}}{g}\right)\right) \tag{5}$$

$$H_{SEI}^{fr} = \chi \tag{6}$$

$$H_{Li,Fe}(t) = 3Kl_e d_H^2 + t \tag{7}$$

$$\frac{dH_{SEI,Fe}(t)}{dt} = \frac{2\pi K \sigma_{Fe} u_e M}{N_{Fe}} \left(\frac{3l_e d_H^2 + N_{Fe}}{2\pi N \sigma_{Fe}}\right)^{\frac{2}{3}} G_0 \exp\left(-2\left(k_{Fe}^0 + \frac{N_{Li}\rho H_{SEI,Fe}(t)}{2\pi N \sigma^{in} r_{Li}^{in} K\left(\frac{3l_e d_H^2 + N_{Fe} t}{2\pi M \sigma_{Fe}}\right)}\right)^{\frac{\sqrt{2m\Delta E}}{\hbar}}\right) \tag{8}$$

These equations collectively describe the dynamic behavior of the battery states under varying operating conditions.

The entire charge or ampere-hours of the battery can be determined by integrating the current over time. Additionally, it has frequently been used in conjunction with other methods as a complement for onboard state estimates. Coulomb counting serves as a foundational technique for SOC estimation. The time integration of charge and discharge current is computed in the following equation, which can be used to predict the instantaneous SoC value at a given time:

$$SoC_t = SoC_o - \frac{\int_{t0}^{t} \eta I_t \bullet dt}{H} \tag{9}$$

where I_t symbolises the load current of the battery system, H indicates the notional capacity (the overall battery capacity is sometimes regarded as the nominal capacity), SoC_o signifies the initial SOC value, and η represents the coulombic efficiency.

3.1. Adaptive Singular Evolutive Interpolated Kalman Filter

In this model, the ensemble-based state estimator of BMS in EVs uses the ASEIKF [12] to estimate the battery's SOC online with high accuracy, stability, and robustness. This filter combines adaptive mechanisms with ensemble-based estimation principles. On the other hand, the ASEIKF is a more sophisticated kind of the KF that performs well in nonlinear, high-dimensional systems, such as battery models.

An ensemble-based approach approximates the n-by-n covariance matrix using an n-by-m state ensemble matrix, which is defined in Eq. (10).

$$\hat{Y}_l := \left[\hat{y}_l^{(1)}, \hat{y}_l^{(2)}, ..., \hat{y}_l^{(m)}\right] \in P^{n\times m} \tag{10}$$

A sample estimate of the state vector in n dimensions is represented by each ensemble member, or column, in the state ensemble matrix. The $\bar{x}k$ ensemble mean and ensemble perturbation matrix $\hat{X}_k$ are as follows.

$$\hat{y}_k \coloneqq \frac{1}{n}\sum_{p=1}^{m}\hat{y}_l^{(p)} \tag{11}$$

$$\tilde{Y}_k \coloneqq \hat{Y}_k - \overbrace{\left[\bar{y}_k, \bar{y}_k, ..., \bar{y}_k\right]}^{n} \tag{12}$$

In this filtering process, the proposed model initialises the battery state estimator by selecting the efficient initial state ensemble $\hat{Y}_0^+ \coloneqq \left[\hat{y}_0^{+(1)}, \hat{y}_0^{+(2)}, ..., \hat{y}_0^{+(n)}\right]$.Proper initialization plays a critical role in convergence speed and estimation accuracy. The equation of $\hat{Y}_0^+$ is obtained from the p^{th} column and q^{th} row is denoted in Eq. (13),

$$\hat{Y}_0^{+(q,p)} = \begin{cases} d_{s0}^{pos(p)} & \forall_q \in S_s^{pos} \\ d_{s0}^{neg(p)} & \forall_q \in S_s^{neg} \\ d_{e0} & \forall_q \in S_e \\ R_0 & q = n-1 \\ s_{\deg 0} & q = n \\ 0 & otherwise \end{cases} \tag{13}$$

where the index groups for the elements in d_s^{pos}, d_s^{neg}, and d_e, respectively, are $S_e \coloneqq \{M^{pos} + M^{neg} + 1, ..., M^{pos} + M^{neg} + M^{tot}\}$, $S_s^{neg} \coloneqq \{M^{pos} + 1, ..., M^{pos} + M^{neg}\}$, and $S_s^{pos} = \left\{1, 2, ..., M^{pos}\right\}$. An estimated range of SOC from $SOC_0^{m\text{in}}$ to $SOC_0^{\max}$ is assumed to be entirely occupied by the solid-phase concentration state in $\hat{Y}_0^+$.

In order to attain the posterior state ensemble $\hat{Y}_l^+ \coloneqq \left[\hat{y}_l^{+(1)}, \hat{y}_l^{+(2)}, ..., \hat{y}_l^{+(m)}\right]$, the update phase of an ensemble-based filter aims to incorporate the most relevant measurements x_l. Measurement incorporation improves consistency between predicted and observed states. A measuring ensemble $\hat{X}_l^+ \coloneqq \left[\hat{x}_l^{+(1)}, \hat{x}_l^{+(2)}, ..., \hat{x}_l^{+(n)}\right]$ for the EnKF and the SEIKF is produced. Every element of $\hat{Z}_k^+$ is derived from [2] Eq. (7b) of Ref [1], that is given in Eq.(14),

$$\hat{x}_l^{(p)} = \mathrm{H}\left(\hat{y}_l^{-(p)}, g_l\right) \ \forall_p \in \{1, 2, ..., n\} \tag{14}$$

The ensemble mean and ensemble perturbation matrix of $\hat{X}_l$ can be defined similarly to Ref [1] of Eq. (8).

$$\bar{x}_l = \frac{1}{n}\sum_{p=1}^{n}\hat{x}_l^{(p)} \tag{15}$$

$$\tilde{X}_l = \hat{X}_l - \overbrace{\left[\bar{x}_l, \bar{x}_l, ..., \bar{x}_l\right]}^{m} \tag{16}$$

The covariance matrices are completely known in the adaptive adjustment of covariance matrices, and they are impacted by battery deterioration and measurement errors. Adaptive covariance tuning is essential for long-term operation under aging effects. The paper presents an online technique for modifying the covariance matrices in the SEIKF-based battery state estimate. First, the measurement residual can be used to estimate the measurement error covariance matrix J_l. Here, an extensive term is employed, i.e.,

$$J_l = \mathrm{E}[m_l m_l^T] = \mathrm{E}[\varnothing_l \varnothing_l^{\mathrm{T}}] + P_{xx,l}^+ \tag{17}$$

where $\varnothing_l$ is the residual, $\mathrm{E}[\cdot]$ is the anticipated value, and $P_{xx,n}^+$ is the residual covariance. In order to avoid short-term fluctuation in the estimated findings, a minor forgetting factor $0 < \zeta_J << 1$ is employed here to approximate the expected value.

where $\varnothing_l$ represents the residual covariance, $\varnothing_l$ denotes the expected value and $P_{xx,n}^+$ is the residual. Here, an insignificant forgetting factor $0 < \zeta_J << 1$ is used to approximate the expected value to prevent short-term fluctuation in the predicted findings, i.e.,

$$\hat{J}_{l+1} = (1 - \zeta_J)\hat{J}_l + \zeta_J\left(\varnothing_l \varnothing_l^{\mathrm{T}} + P_{xx,n}^+\right) \tag{18}$$

The residual and residual covariance in the SEIKF can be easily estimated using an ensemble $\hat{X}_l^+ \coloneqq \left[\hat{x}_l^{+(1)}, \hat{x}_l^{+(2)}, ..., \hat{x}_l^{+(m)}\right]$,

$$\hat{x}_l^{+(p)} = R(\hat{y}_l^{+(p)}, g_l) \quad \forall_p \in \{1, 2, ..., n\} \tag{19}$$

$$\varnothing_l = x_l - \bar{x}_l^+ \tag{20}$$

$$G_{xx,l}^{+}=\frac{1}{n-1}\left(\tilde{X}_{l}^{+}\right)^{\mathrm{T}}\tilde{X}_{l}^{+} \tag{21}$$

where $\tilde{X}_{l}^{+}$ and $\bar{x}_{l}^{+}$ denote the perturbation matrix and mean vector of $\tilde{X}_{l}^{+}$, correspondingly. Conversely, the model error covariance matrix H_l is defined by

$$H_{l}=\mathrm{E}[v_{l}v_{l}^{\mathrm{T}}] \tag{22}$$

From the Ref [1], the noise method may be calculated as given in Eq. (23)

$$\hat{v}_{l}=\bar{y}_{l}^{+}-F(\bar{y}_{l-1}^{+},g_{l},\Delta t)=\bar{y}_{l}^{+}-\bar{y}_{l}^{-}=\tilde{Y}_{l}^{-}\overline{w_{l}} \tag{23}$$

Using a forgetting factor, a similar process can be used to smooth $\hat{H}_l$ the predicted value in Eq. (18). However, processing $\hat{H}_l$ with dimensions n-by-n requires more computer resources, which are then used in the subsequent time step. The SEIKF's short-term performance is unaffected by the variation of $\hat{H}_l$, as will be demonstrated in the next sections. The approximation can thereby avoid the necessity for smoothing $\hat{H}_l$.

$$\hat{H}_{l+1}=\left(\tilde{Y}_{l}^{-}\overline{w}_{l}\right)\left(\tilde{Y}_{l}^{-}\overline{w}_{l}\right)^{\mathrm{T}} \tag{24}$$

Therefore, the ASEIKF that has been implemented in the EV's BMS can enhance performance in several crucial areas, which is prominent with them being the provision of more reliable and accurate battery state evaluations. Such improvements directly contribute to safer and more efficient EV operation. Consequently, the battery pack might be better controlled, enhancing the overall performance of the vehicle.

4. Result and Discussion

In this section, the data from the Simulink model was used for the evaluation, which was carried out in MATLAB 2021b, to evaluate the performance of the ASEIKF-based BMS technique in the EVs. The simulation environment was selected to ensure repeatability and controlled testing conditions. Numerical research and real-world outcomes will validate the suggested ensemble-based state estimator for Li-ion batteries based on the adaptive SEIKF. By contrasting different approaches, such as the actual technique, SEIKF, EnKF, and UKF, the efficacy of the results attained has been evaluated. The model's performance was extensively calculated utilising several metrics, including predicted SOC, curved SOC and voltage. These performance indicators provide a comprehensive assessment of estimation accuracy and stability. The efficacy of the model was confirmed by these analyses. All of the simulated results were obtained using a 64-bit Windows 10 machine with an Intel Core 2 Q9400 @ 2.67GHz processor, 8GB RAM, and a sample time of t = 1 second.

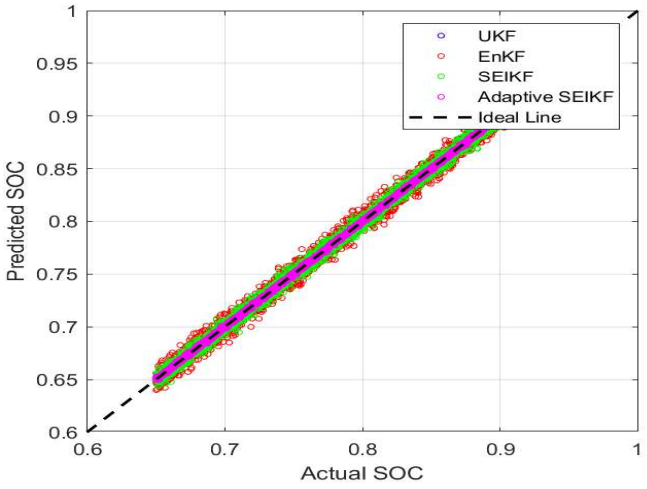


Fig. 2. *Estimation of the suggested model's predicted and actual SOCs*

The estimation of the proposed model's predicted and actual SOCs is demonstrated in Fig.2. The close alignment between predicted and actual SOC curves indicates strong tracking capability.This indicates the model's capacity to predict SoC accurately in an expanded range of scenarios than those utilised for interpolation training. In this analysis, the proposed ASEIKF-based model produced the predicted SOC

value of 0.9489, which is smaller than the other existing filters of BMS in EV's model, such as UKF of 0.9490, EnKF of 0.9622, and SEIKF of 0.9509, respectively, at the actual SOC of 0.9492. The reduced deviation demonstrates improved estimation precision under dynamic conditions.

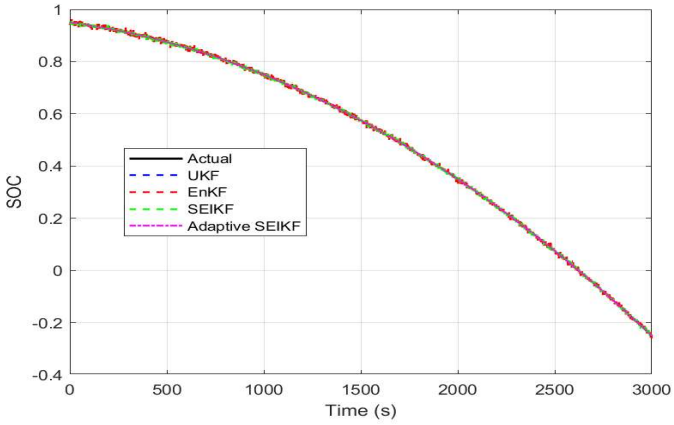


Fig. 3. *Comparison of the SOC of the proposed adaptive SEIKF-based state estimation in comparison to current models*

The comparison of the SOC of the proposed adaptive SEIKF-based state estimation in comparison to current models is given in Fig.3. This figure highlights the consistency of the proposed estimator over time. In this analysis, the proposed ASEIKF-based model produced the SOC value of 0.9490, while the other existing models, such as actual SOC, UKF, EnKF, and SEIKF, achieved the values 0.95, 0.9504, 0.9521, and 0.9450, respectively, at time t=0.

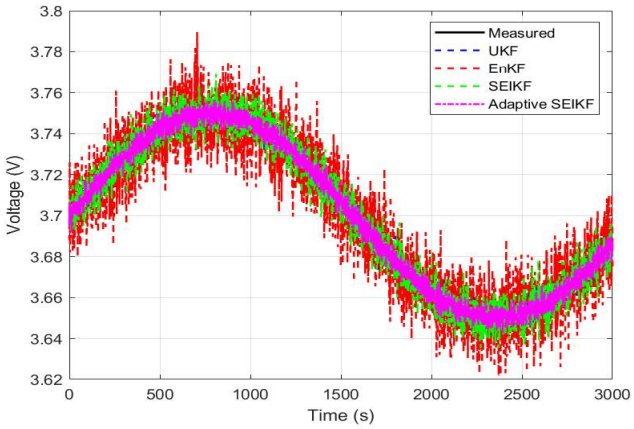


Fig. 4. *Evaluation of the voltage rate of the proposed adaptive SEIKF-based state estimation in comparison to current models*

The evaluation of the voltage rate of proposed adaptive SEIKF-based state estimation vs current models is given in Fig.4. In this voltage analysis, the proposed ASEIKF-based model produced the value of 3.7448V, and it attained the measured voltage rate of 3.7455, while the other existing models, such as UKF, EnKF, and SEIKF for BMS of EVs, achieved the values of 3.7455V, 3.7364V, 3.7311V, and 3.7408V, respectively. These results confirm the superior voltage tracking performance of the proposed approach.

Table 1. *Comparison analysis of estimation error for MSE_SOC and MAE_SOC*

Method	MSE_SOC	MAE_SOC
UKF [1]	0.0000010412	0.00081049
EnKF [2]	0.000034988	0.0047121
SEIKF [11]	0.000016261	0.0032132
Adaptive SEIKF	0.0000010242	0.00080752

Table 1 shows the comparison analysis of estimation error for MSE_SOC and MAE_SOC over various existing techniques and the proposed model. Lower error values indicate enhanced estimation accuracy. In this table, the MSE_SOC rate for the proposed ASEIKF obtained the value of 0.0000010242, however, other existing methods, such as UKF, EnKF, and SEIKF, attained the values of 0.0000010412, 0.000034988, and 0.000016261, respectively. Similarly, the proposed ASEIKF for the BMS of EV achieved

the value of 0.00080752, however, other existing methods, such as UKF, EnKF, and SEIKF, attained the values of 0.00081049, 0.0047121, and 0.0032132, correspondingly. Overall, the results demonstrate that the proposed ASEIKF-based estimator outperforms existing methods in terms of accuracy and robustness.

5. Conclusion

This work proposed a unique adaptive SEIKF-based BMS for EVs, and it also provided ensemble-based battery state estimates to evaluate the SoC and SoH of the battery, more resilient, accurate, and dependable than single-model estimators. The proposed framework effectively combines adaptability and ensemble learning principles. However, the ensemble of potential states could be used to represent the system's probability distribution, and the ensemble-based state estimator to estimate the system's state. To address the intricate and nonlinear behaviour of lithium-ion batteries, an ASEIKF was incorporated into the estimate algorithm for the purpose of monitoring the system, correcting the observation noise covariances, and adjusting the filter gain. Such adaptive mechanisms are essential for real-world battery applications subject to aging and environmental variations. In this proposed model, the suggested ASEIKF-based BMS state estimation model of EV obtained a value of 0.9490 in the SOC study, whereas other models, including the real, UKF, EnKF, and SEIKF, obtained values of 0.95, 0.9504, 0.9521, and 0.9450, respectively, at time t=0. As a result, the ensemble-based state estimator of BMS in EVs with ASEIKF obtained great accuracy in estimating the battery's SOC, respectively. Even in a variety of dynamic operating situations, the proposed model increases the flexibility and effectiveness of the battery state in EVs. The robustness of the estimator ensures consistent performance under varying load and temperature conditions. Regarding the suggested strategy, the future scope will concentrate on improving the functionality and performance of the system using cutting-edge modelling and integration methodologies.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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