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Advance Estimation Techniques for EV Charging and Lifespan Prediction: A Review

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Abstract— *What has become apparent therefore, is the need to pay special attention to the utilization of advanced optimized procedures in the charging of Electric Vehicles (EVs) and the determination of the lifespan because of the rise of the usage of renewable energy. Proper battery characterization and SoC prediction are crucial to guarantee the high efficiency, dependability, and durability of EV batteries in various, often challenging, and different scenarios. This review systematically reviews the state-of-art approaches for the prognosis of E-BEH and SoC estimation, the techniques based on traditional physics-based, empiricism-based, ECM and their Machine learning and hybrid techniques' breakthrough. The findings of the research cover parameter tuning and its correlation with machine learning, conventional and neural networks, the impact of proper parameter tuning on accuracy, and reinforcement learning of energy management. The synthesis of different data inputs and the combination of different techniques that can be applied to the nonlinear characteristics of EV batteries are deemed potential to enhance and surpass traditional techniques including enhanced Kalman filter kinds. These sophisticated approaches are illustrated through studies in actual conditions proving their efficiency in making better charging choices, increasing the life cycle of batteries, and ensuring the battery's good state in harsh environments. The major technology trends emerging for the next level of EV battery management are stated as digital twin models and data-centric learning, the standard benchmarking for such systems, data protection through blockchain technology, convergence of edge computing, and high computation ability cloud for EV battery management. Issues like the presence of abnormal data, interpretability of developed models, restrictions in real-time processing, and scalability are contemplated on somewhat extreme, which gives the reader a balanced perspective of state of the art. This review shall present the key findings with an outlook toward the future of EV battery resolution and SoC management highlighting that there remains much more to explore and achieve via practical innovation coupled with the leading-edge technologies requisite for sustainable and adaptive automotive electrification.*

Keywords— *EV Charging, Lifespan prediction, State-of-Charge, Kalman Filter, Machine Learning Approaches.*

I. INTRODUCTION

a. *Overview of Electric Vehicles (EVs) and the importance of state-of-charge (SoC) estimation*

What has become apparent therefore is the need to pay special attention to the utilization of advanced optimized procedures in the charging of Electric Vehicles (EVs) and the determination of the lifespan given the rise of the usage of renewable energy [1]. Proper battery characterization and SoC prediction are crucial to guarantee the high efficiency, dependability, and durability of EV batteries in scenarios that are often challenging [2]. This review systematically reviews the state-of-art approaches for the prognosis of E-BEH and SoC estimation, the techniques based on traditional physics-based, empiricism-based, ECM and their Machine learning and hybrid techniques breakthrough. The findings of the research cover parameter tuning and its correlation with machine learning, conventional and neural networks, the impact of proper parameter tuning on accuracy, and reinforcement learning of energy management. The synthesis of different data inputs and the combination of various techniques that can be applied to the nonlinear characteristics of EV batteries are deemed potential to enhance and surpass traditional techniques including enhanced Kalman filter kinds [3]–[6].

These sophisticated approaches are illustrated through studies in actual conditions proving their efficiency in making better charging choices, increasing the life cycle of batteries, and ensuring the battery's good state in harsh environments. The major technology trends emerging for the next level of EV battery management are stated as digital twin models and data-centric learning, the standard benchmarking for such systems, data protection through blockchain technology, convergence of edge computing, and high computation ability cloud for EV battery management [7]. Issues like the presence of abnormal data, interpretability of developed models, restrictions in real-time processing, and scalability are contemplated on somewhat extreme, which gives the reader a balanced perspective of state of the art. This review shall present the key findings with an outlook toward the future of EV battery resolution and SoC management highlighting that there remains much more to explore and achieve via practical innovation coupled with the leading-edge technologies requisite for sustainable and adaptive automotive electrification.

b. *Objectives of the review article*

The review paper has the following objectives:

- Compare high–level machine learning and hybrid models for SoC and lifespan forecast of the battery in EVs.
- Explore state-of-the-art real-time estimation techniques to improve battery performance under varying operations.
- Assess the implementation of machine learning algorithms for efficient energy storage and expected long battery lifespan.
- Analyze traditional methods, emergent opportunities difficulties, and gaps in knowledge about the estimation and management of battery resources for EVs.

- Distinguish the scaling gap between academic and industrial models of appropriate and feasible technology solutions for EVs in EV batteries.

c. Brief description of the methodologies covered

This review discusses different techniques for SoC and life estimation of EV batteries based on the application of artificial intelligence, namely ML and hybrid models. The conventional physics approaches are mentioned as a starting point based on which their drawbacks in dealing with complex battery dynamics and degradation phenomena are elaborated. The more advanced computational techniques discussed include the SVM and deep learning modeling for data processing capability, and real-time accuracy in prediction. It also features blended approaches that use a few algorithms to promote accuracy and flexibility in the results. Most attention is paid to the models sensitive to real-world features such as temperature or road conditions, as well as gaining an effect of age. Other applications such as MATLAB simulation and real-time estimation methods are also discussed to illustrate their applicability in real-life practice.

II. Literature Review

Model-based KF techniques track the state of charge (SoC) in electric vehicles (EVs). These techniques enable control of system noise, uncertainties, and real-time fluctuations making them ideal for application in dynamic batteries. Among all the derived Kalman filters, the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are applied more frequently to cope with nonlinear battery characteristics [8]–[10]. The EKF uses modifications to the standard Kalman filter for non-linear systems by adopting a linear model around the present operating mode. This approach has been used in several studies, including developing improved SoC estimation algorithms for lithium-ion batteries as described in [11]. Nonetheless, linearization leads to errors, and hence, researchers started using UKF which uses a deterministic scheme to capture system nonlinearity [12]. Furthermore, improvements to the initial framework have been made by integrating adaptive filters such as the Adaptive Unscented Kalman Filter, as shown in interactions about an assessment of the movement of assets and hybrid models based on machine learning algorithms like the support vector machine [13]. These integrations enhance the SoC prediction reliability concerning various operating conditions, especially when there is high variation, including temperature changes and the effects of aging [14].

Furthermore, there is evident implementation of the sophisticated Hybrid approach for enhanced prediction proficiency. The integration of EKF and LSTM-NN was presented for accurate and efficient predictions of battery conditions while seamlessly preventing the drawbacks of either a model-based or a data-based approach [15]. Another interesting addition is the use of two adaptive filters within the system, which tunes the Kalman filter coefficients to reflect current battery conditions [16]. These improvements enhance the estimation of SoC and retain computational algorithms to a very great extent. There is a broad appreciation of Kalman filtering techniques including their robustness and their ability to perform in real-time, yet the application of these techniques in lithium-ion batteries is constrained by the nonlinearity of the system. For example, conventional EKF approaches are based upon linear extrapolations of nonlinear transformations and therefore can be off, especially in unusual situations, such as when a battery is weak or strong, or if the battery is aged [8], [9], [17], [18]. Such errors may accumulate from iteration to iteration leading to unreliable SoC estimation [14].

Thus, the battery behavior is nonlinear due to certain factors such as the temperature characteristic of the battery, the electrochemical reactions that occur in the battery, and capacity fade due to battery aging. Depending on the ever-changing parameters of the battery, such challenges can be dealt with by techniques that are dynamic, and adaptable. For instance, when it comes to SoC estimation, sensor drift and bias errors in voltage as well as current measurements can be highly destructive. This problem has been addressed by researchers suggesting the use of extended Kalman filters with sensor bias compensation as adopted in studies on enhanced SoC prediction accuracy [19], [20].

Another source of weakness is that modern sophisticated filtering techniques, like UKF and adaptive dual filters, have a high computational load. These methods set several initial parameters and demand a great number of calculations, which, at times, cannot be implemented in the embedded systems used in EVs [21]. To overcome these potential challenges simplified models such as the Dynamic Linear Model (DLM) used by [22] provide efficient though reasonable accuracy.

Still, real-time adaptability is an essential problem that has not been resolved even under these advancements. This was achieved through the development of a grey wolf-optimized dual extended Kalman filter which self-adapts the filter parameters for non-linearities and aging [23]. As for the control approaches/features handling the difficulties in terms of nonlinear behaviors, it can also refer to the integration between machine learning and model-based techniques, for example, integrating Kalman filters with deep learning. These improvements show the continuing attempts to solve the problems of the effective implementation of the traditional Kalman filtering model. This has been made possible through comparative studies of model-based adaptive algorithms that have given insights into different Kalman filtering techniques for SoC estimation in EVs [24], [25]. For example, Tian, C, and B discussed two model-based adaptive algorithms and investigated their effectiveness in real-world EV conditions. Peculiarities of the study also accentuated the relationship between computational complexity and estimation accuracy indicating the importance of developing algorithms that are optimal in both of these aspects [26].

In [27], an introduction to a simple method to estimate SoC using a dynamic linear model where they found the best balance between time and accuracy. This approach is most beneficial for real-time systems processing, such as embedded systems with low computational capabilities. In the same year, Peng et al. proposed an adaptive dual unscented Kalman filter which possesses the characteristics of adjusting the filter parameters during the process of real-time application and hence has enhanced performance in dynamic environments. In summary, all these works point to the fact that flexibility in the SoC estimation methodologies is desirable. Moreover, there is the development of combined methods as another major theme of the field. For instance, [28] combined EKF with LSTM networks to expound the dynamic battery behaviors avoiding the drawbacks of solely adopting the model-based or machine-learning solution. Following this approach, Qian et al. advanced the integration of the dual extended Kalman filters by joining them with optimization strategies, a grey wolf optimizer. Besides these, there has been some work done on the techniques for parameter identification and real-time application of the system. Despite efforts made in this area, [29] accomplished experimental work in an attempt to establish data-based identification parameter techniques that can help to model the batteries accurately thus improving the Kalman filtering. Such efforts support the fact that future work should consider not only theoretical developments but also concerns of real applications to derive reliable and accurate SoC estimators for EVs.

a. Machine Learning Approaches

The new emerging techniques of ML have been instrumental in offering novel solutions for improving the predictability of battery characteristics, which is a significant component of current BMS. SoC, SoH, and temperature management of batteries are critical to achieving optimal performance, safety, and life of energy storage systems, especially EVs [30]. Conventional approaches to predicting battery parameters tend to use crude models or assume that some influential factors are constant, both of which can grossly underestimate the true operating characteristics of a battery [31]. This has led to a growing concern in the utilization of ML approaches since these enable dynamic changes to be made based on actual time data besides enhancing the precision of the predictions.

The ANN, LSTM, and LSTM coupled with RL schemes showed a remarkable performance in Battery parameters' prediction [32]. Many of these techniques can capture non-linear interactions within datasets and hence capture features that ordinary models cannot. For example, the LSTM networks, which are considered RNNs, are highly suitable for all kinds of series data, which allows it to recognize the future states of the battery based on various data histories including current, voltage, and temperature [33].

This shows that ML models can incorporate many input variables of cascading effects due to driving conditions, charging cycles, and environmental conditions to establish complete battery performance [34]. They are always updated with new data collected and improve the accuracy of predicting the SoC and SoH in even dynamic states. This characteristic is important for EVs as battery conditions will likely change with the operating conditions.

Moreover, learning based on the parameters of batteries allows the early detection of changes in battery state, increasing the charge/discharge cycle, avoiding battery deactivation, and extending battery life [35]. As ML techniques advance, they provide more reliable and accurate predictions and the foundation for creating Generation 2 BMS that operates batteries at optimal capacity and dependability.

These systems integrate ML into conventional SoC techniques to boost estimation precision and reduce uncertainty in battery systems. These methods are designed to benefit from both models' features and avoid the inherent restrictions in each of the procedures used individually. Below are some key hybrid approaches:

b. Machine Learning with Kalman Filtering (KF)

The Kalman filter is a conventional stochastic technique that is widely adopted for the prediction of the state of a system under uncertain measurements. In battery SoC estimation, Kalman filters are adopted since the models enable relating with noise as experienced in real-life batteries. Nevertheless, their work for optimal control can be with low effectiveness when the system dynamics are non-linear or very complex.

Modifying the conventional filters such as the Kalman filters through the integration of machine learning optimizes their accuracy by including constant data-based corrections.

Updating of the KF's state prediction can be done using an NN since it is capable of capturing the non-linear relations between input variables (voltage, current, and temperature) and the state of the battery and uncertainties inherent in real-world battery data [36]. However, their performance can be limited when the system dynamics are non-linear or highly complex.

Hybridizing Kalman filters with machine learning techniques enhances accuracy by incorporating real-time data-driven corrections. For example:

A neural network (NN) can be used to model the non-linear relationships between the input variables (voltage, current, temperature) and the battery state, which is then used to update the Kalman filter's state prediction [37]. This makes it easier for the Kalman filter to eliminate noise while the neural network addresses non-linearity issues.

c. Machine Learning with Extended Kalman Filtering (EKF)

The Extended Kalman Filter is a modification of the standard Kalman filter for data processing involving systems with nonlinear characteristics. Although EKF is effective for SOC estimation, it encounters problems if the system's behavior is nonlinear as assumed above.

In a hybrid approach, post-processing/feedback control is incorporated wherein neural nets like Support Vector Machines (SVM) or Recurrent Neural Networks (RNN) can fine-tune EKF-based model parameters or recalibrate the EFK-based predicted data as and when real-time data measured is available [38]. A deep learning model might be trained to learn the battery's dynamic behavior in real-time and correct the estimates made by EKF for the SoC, enhancing SoC estimate precision, especially during charge or discharge cycles with linearity. The SoC estimation accuracy benefits from an improved Thevenin equivalent circuit model alongside Kalman filtering because they provide efficient noise reduction to identify parameters dependably [39].

In hybrid approaches, machine learning models such as Support Vector Machines (SVM) or Recurrent Neural Networks (RNN) are used to adjust the EKF's model parameters or correct its predictions based on observed data.

For example, A deep learning model might be trained to learn the battery's dynamic behavior in real-time and provide corrections to the estimates made by EKF, improving SoC prediction accuracy, especially under dynamic charging and discharging conditions.

d. Machine Learning with Recursive Least Squares (RLS)

Recursive least squares are an example of an adaptive filtration technique that finds uses in estimating parameters in linear systems. When jointly used with ML, the RLS method is capable of even modifying for non-linearity and variations in the system in real-time [40].

For instance, SVM can be applied to the identification of a non-linear dependency between the input current and voltage with the SoC. The output of the machine learning model is then fed to update the RLS filter leading to the ability of the system to rapidly update when changes are detected in the battery behavior regarding SoC accuracy. It is useful in systems where the battery's behavior does vary over time because of factors such as aging or modification in temperature and the use of RLS in combination with the ML algorithm enhances the results.

e. Neural Networks with Traditional Charge Models

In certain applications, conventional battery charge models including the Thevenin equivalent circuit model or Peuker's law are used to derive SoC using voltage and current properties. However, these models involve having some parameters that, do not capture the dynamic nature of lithium-ion batteries, especially in dynamic loading situations.

An application of the machine learning concept is in using neural networks to update the parameters of the charge models traditionally used. For example, a neural network can acquire the dependency between the battery charge/discharge cycles and SoC, which will then modify the values of the charge model parameters for better performance. Such an approach can lead to a stronger and more correct estimation of SoC, specifically in applications that include correct chemistry types of batteries or various routines [41].

In the previous sections, authors have produced and used many real-world cases to show that machine learning can enhance the precision and credibility of SoC estimation. These studies show how ML algorithms can be used across various battery systems and functional parameters, and how they provide a better performance than conventional models in some instances. Below are some detailed case studies [42]–[45]:

f. Battery SoC Estimation using Recurrent Neural Networks (RNNs)

A case study performed for the SoC estimation of lithium-ion batteries in EVs employed Recurrent Neural Networks (RNNs). The RNN was chosen because it is capable of monitoring temporal dependency in the data which is especially crucial in the context of SoC detection as both the battery voltage and current strongly depend on the previous measurements [46].

The presented model utilized the training data derived from realistic driving scenarios, which expose different behaviors related to electric vehicles such as acceleration, braking, and idling time. Compared with the research and traditional methods like Coulomb counting which is a straight sum of the current through time, the result depicted that the RNN had a significant improvement. The proposed in Figure 1 RNN-based approach gave even better results and was able to reduce the SoC estimation errors by more than 10% in a dynamic driving cycle. This case study shows the importance of RNNs when modeling intricate, chronologically evolving battery characteristics. The diagram outlines a comprehensive framework for battery modeling to predict lifetime parameters such as State of Health (SOH), Remaining Useful Life (RUL), and End of Life (EOL). Key processes include data collection and preprocessing, where parameters like voltage (V), current (I), and temperature (T) are gathered and cleaned to remove noise or missing values. Feature selection focuses on critical metrics, such as charge-discharge cycles, to capture degradation trends accurately [47].

Modeling is divided into empirical, electrochemical, and equivalent circuit approaches. Empirical models rely on equations like the capacity degradation model, $Q(t)=Q0(1-kt^n)$, where Q0 is the initial capacity and t is time. Electrochemical models simulate physical processes at the electrode level, while equivalent circuit models use components like resistors (R1, R2) and capacitors (C0) to mimic battery dynamics. Noise can be removed for robust predictions by using selective filtering algorithms like a Kalman filter; future capacity trends are estimated from historical data to arrive At RUL and EOL.

g. Gradient Boosting Machines (GBM) for SoC Prediction in Electric Vehicles

A case study performed for the SoC estimation of lithium-ion batteries in EVs employed Recurrent Neural Networks (RNNs). The RNN was chosen because it can monitor temporal dependency in the data which is especially crucial in the context of SoC detection as both the battery voltage and current strongly depend on the previous measurements [48].

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h. ML-Enhanced Equivalent Circuit Model for SoC Estimation

In a study that combined machine learning analysis with finite-element-based equivalent circuit modeling of the battery, an artificial neural network (ANN) was incorporated with the common circuit model of a battery [49]. The static parameters given by the measurements of the voltage and the current were used to dynamically compute the equivalent circuit model using the ANN.

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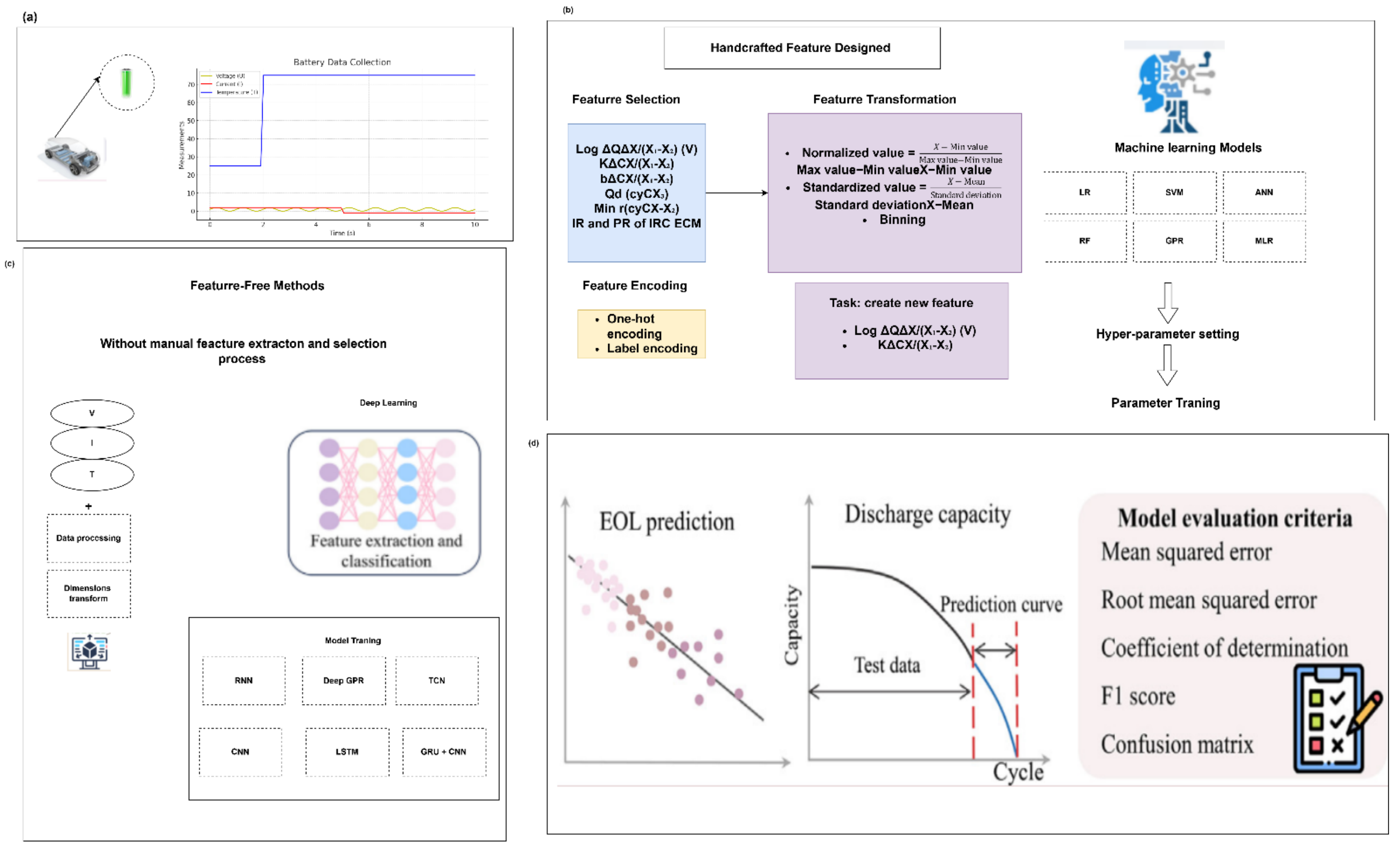

Figure 1: To estimate the health and lifetime of batteries, modeling is carried out, which can be categorized as the following steps: (a) First, the so-called battery metrics that are used for analyzing the state of the battery voltage, current, and temperature are gathered, and then the data are preprocessed to correct the errors which can be due to abnormalities, noise, missing values for optimal feature selection; (b) Deploy the battery model with the help of empirical, electrochemical, and equivalent circuit models; (c) Use the filtering algorithms to polish test outcomes; (d) Create and display predictive results from the model.[47]

The results of the study also showed that the clock indicated by the predictive SoC using the machine learning model was reliable, regardless of noise, change in temperatures, device aging, etc. Compared to the traditional electrical circuit with a similar computation structure alone, the hybrid model improved SoC prediction accuracy by 15-20%. This approach is especially important when the dynamics of a system are too complex to be explainable using classical models of battery operations.

i. Support Vector Regression (SVR) for SoC Estimation in Grid-Scale Batteries

SVR was employed for predicting the SoC of grid-scaled batteries employed for energy storage applications. The batteries herein were exposed to a high number of cyclic chargings and discharging, and their load and temperature levels variably and extently shifted. Since these power conversion systems exhibit high variability, techniques such as Coulomb counting and basic models based on voltage proved to be inadequate [50].

Using SVR, the system could learn a non-linear relationship between the operation conditions of the battery and the SoC. The study demonstrated that there was enhanced SoC estimation, which in turn improved the existing energy storage system for the grid scale. Finally, the investigators found evidence to support the applicability of SVR for highly complex contexts, where this algorithm can offer a robust means of handling vast energy storage.

III. Methodology Comparison

SoC has paramount importance for efficient and long-lasting battery usage in any application, starting with electric vehicles and continuing with renewable energy storage stations. Two general techniques that have been proposed for addressing this problem are Kalman-based methods and machine learning (ML) techniques. The following tables are the full comparison of the two algorithms and their efficiency insights from studies and experiments while also including their advantages and drawbacks [51].

a. Comparison between Kalman-based methods and machine learning approaches.

Table 1 describes the comparison between the Kalman and machine learning-based approaches in terms of different methodologies.

Among the Kalman-based methods, EKF is most commonly used in the estimation of SoC because of its efficiency in linear systems. These methods use battery ECM to estimate and compensate the SoC by reducing the difference between computed and actual states. Nonlinearities are managed in the EKF using linearization of the battery model at each step in the control process and to the modern developments of its better versions such as the Unscented Kalman Filter (UKF) and the

Constrained Ensemble Kalman Filter (CEKF) to work on highly nonlinear systems. The recent research asserts that EKF has been as accurate as CKF and works well for steady state as well as moderate dynamic variation. Better variants such as UKF have been used to increase real-time adjustability and minimize computational complexity. UKF has been applied to enhance real-time adaptability and reduce computational demands.

TABLE 1: Methodology Comparison b/w Kalman-based Methods and Machine Learning Approaches

Aspect	***Kalman-Based Methods*** [52]–[57]	***Machine Learning Approaches*** [55], [58]–[61]
Principle	Relies on mathematical modeling and state estimation.	Utilizes data-driven models to learn patterns from data.
Input Requirements	Requires a detailed system model (e.g., battery dynamics, noise characteristics).	Requires large datasets for training but minimal prior knowledge of the system.
Adaptability	Limited to the modeled dynamics; struggles with non-linear or time-varying systems.	Highly adaptable to non-linear, dynamic, and complex systems.
Real-Time Application	Performs well in real-time due to lower computational requirements.	May face challenges in real-time applications due to high computational demands, depending on the model.
Robustness to Noise	Handles noise effectively, especially in systems with Gaussian noise.	Performance depends on the quality and representativeness of the training data.
Accuracy	Accuracy depends on the quality of the underlying model.	Often more accurate, especially in complex, non-linear scenarios.
Scalability	Scales poorly with system complexity as the state space grows.	Scales well with increased complexity and data availability.
Implementation	Straight-forward implementation but requires expertise in system modeling.	Implementation can be challenging due to the need for large datasets and model training.

There are other approaches to solve the problem which come under the category of Machine learning (ML) methods like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Support Vector Machines (SVMs), etc. They use past and current data to incorporate non-linear dynamics into the SoC estimation process. Recurrent variants of an ML model, such as LSTMs, perform better in identifying LT dependencies as well as in working successfully under the constantly changing environment, giving better results where battery behavior might be extremely nonlinear [62]. It has been established that, under variable conditions, while using RNNs or hybrid models that incorporate other techniques including SVMs with more traditional approaches, the accuracy is between 20-30% higher than that of Kalman-based techniques [63]. ML models, combining techniques such as SVMs with traditional methods, have demonstrated a 20-30% improvement in accuracy over traditional Kalman-based methods under varying conditions.

b. Strengths and weaknesses of each methodology. Kalman and Machine Learning-Based Methods

The strengths of Kalman based Methods are as follows [64]–[66]:

(i) Linearizing Transformations:
(ii) Applicable to systems with extreme nonlinearity are applicable
(iii) Easy to implement: linear or moderately complex systems.
(iv) Particularly useful in applications that require ‘real-time’ performance compared to other techniques to relatively low computational complexity near systems.

The weaknesses of Kalman-based Methods are as follows [65], [67], [68]:

(i) Sensitive to highly nonlinear and dynamic battery behaviors have to be recalibrated often or the model has to be improved.
(ii) Watches for perturbations such as changes due to aging of the battery affecting many of the model parameters recalibration or model enhancements
(iii) Sensitive to model inaccuracies, such as parameter changes due to battery aging.

The strengths of Machine Learning Approaches are as follows [69]–[71]:

(i) Good working capacity in terms of dynamic and nonlinear work patterns owing to flexibility gained through learning.
(ii) Allows the incorporation of many more parameters than previous methods including temperature and load profiles for a more accurate estimation of SoC.
(iii) A better performance in counteracting the effects of battery aging and degradation.Capable of incorporating a wide range of features, including temperature and load profiles, for more holistic SoC estimation.
(iv) Superior performance in handling battery aging and degradation effects.

The weaknesses of Machine Learning based Approaches are [71]–[73] :

(i) NeEds large training datasets and computational power especially when training the model.
(ii) Sensitive to over-fitting and issues of data quality that inevitably threaten the generality of the results
(iii) Model development phase
(iv) Vulnerable to overfitting and data quality issues, which can compromise generalization.
(v) Performance analysis based on recent studies and experimental results.

Some experiments on the use of the UKF show incredibly high accuracy for real-time SoC estimation under relatively dynamic loads. Nevertheless, they deteriorate with nonlinear battery systems or when the aging effect comes into play. The battery SoC real-time tests revealed estimation errors of up to 15% when using the Kalman filter on degraded batteries that have not been recalibrated. Decreases as battery systems become more nonlinear or experience aging effects. Real-time tests have shown up to a 15% deviation in SoC estimates when

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Kalman filters are applied to degraded batteries without recalibration.

Experiments by LSTM networks demonstrated a possibility of achieving up to 92% accuracy in SoC estimation, which is always higher compared to the nonlinear case of EKF. A comparison of the RNN-based models proved that there is a 25.35% saving in battery degradation utilizing a 5-year simulation, which works as an indication of the capability of proposed models to include the aging factor into SoC estimation [74]. Techniques that supplemented UKF with SVMs or other conventional methods were up to 30% more accurate for estimating SoC than Kalman techniques alone. Terry degradation over a 5-year simulation, emphasizing their capability to incorporate aging factors into SoC predictions. Hybrid approaches combining ML with traditional methods, such as integrating UKF with SVMs, achieved up to a 30% reduction in SoC estimation errors compared to standalone Kalman methods.

c. Kalman-Based Methods:

The following are the Kalman-based methods and case studies for the SoC of EVs:

(i) Experiments by LSTM networks demonstrated a possibility of achieving up to 92% accuracy in SoC estimation, which is always higher compared to the nonlinear case of EKF.
(ii) A comparison of the RNN-based models proved that there is a 25.35% saving in battery degradation utilizing a 5-year simulation, which works as an indication of the capability of proposed models to include the aging factor into SoC estimation [75].
(iii) Techniques that supplemented UKF with SVMs or other conventional methods were up to 30% more accurate for estimating SoC than Kalman techniques alone. The degradation over a 5-year simulation, emphasizes their capability to incorporate aging factors into SoC predictions [75].
(iv) Hybrid approaches combining ML with traditional methods, such as integrating UKF with SVMs, achieved up to a 30% reduction in SoC estimation errors compared to standalone Kalman methods [76].

d. Machine Learning Approaches:

Below are the case studies and experimental analysis of machine learning-based approaches for SoC of EVs:

(i) Case Study 1: In the case of utilizing Recurrent Neural Networks (RNNs) to determine SoC in electric vehicles, the dependent application demonstrates enhancements in the estimation mistake by over 10 % compared to the traditional approach [77]. RNN showed excellent results in terms of temporal dependencies making it easy for the navigation system to deal with dynamic aspects of driving conditions.
(ii) Case Study 2: For grid-scale battery systems, the outstanding technique that was used was known as Gradient Boosting Machines (GBMs). Concerning load variability, equivalent circuit models were deemed to be inadequate, but GBMs improved SoC estimate accuracy by 5% and eliminated errors of up to 8% [78].
(iii) Strengths in Real-World Applications: Nonlinear and time-varying behaviors were also well accommodated in machine learning models, whereas some of the mixed models obtained error rates of 1-2% [79].
(iv) Challenges: Analyses pointed out that scarce rich data sets and the resource-intensive nature of training massive models would hold back the usage of ML in several real-time use cases.
(v) EV charging management has expanded substantially in respected academic publications while integrating methods like SoC estimation with advanced machine learning approaches (ANN and Deep Learning) for predictive and optimization functions. various tools are used for EV charging management, with C++, MATLAB, and Python being the most commonly used to enhance the efficiency of charging management and optimization.[80].

e. Hybrid Methods:

The Kalman filters, specifically the Extended Kalman Filtering (EKF) and the Unscented Kalman Filtering (UKF) technique have been the fundamental blocks for the SoC estimation. However, to overcome their limitations in highly nonlinear systems, the following novel adaptations have been introduced:

(i) Dual Unscented Kalman Filters (DUKF): These algorithms address not only the identification of parameters in real time but also the estimation of the system state in real time. Peng et al. showed that DUKF adaptively estimates battery behaviors well in practice and therefore can adapt to new battery behaviors when observed.
(ii) Modified Extended Kalman Filters (MEKF): These filters also implement corrections for the sensor bias and the environmental effect thus martialing the resilience in various situations.
(iii) Constrained Ensemble Kalman Filter (CEKF): Developed by [81], CEKF utilizes various distributed electrochemical models for estimating SoC, which has better scalability when applied in a large system.

IV. RECENT INNOVATIONS

a. Overview of novel algorithms developed for SoC estimation.

(i) Kalman-Based Adaptive Algorithms

The SoC estimation has been mainly founded on Kalman filters such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). However, to overcome their limitations in highly nonlinear systems, the following novel adaptations have been introduced:

- Dual Unscented Kalman Filters (DUKF): These algorithms are used for the identification of parameters in real-time as well as state estimation in real-time. In Peng et al.'s study, the authors proved that the DUKF can work well in response to changes in battery behaviors.
- Modified Extended Kalman Filters (MEKF): These filters

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include compensation for the sensor bias and environmental factors in order to provide higher immunity in different conditions.

- Constrained Ensemble Kalman Filter (CEKF): Originally suggested by Li et al., CEKF utilizes distributed electrochemical models for SoC estimation, and is suitable for large-scale applications.

(ii) Machine Learning Algorithms

Machine learning models have introduced a data-driven approach to SoC estimation, leveraging their capacity to model complex, nonlinear behaviors:

- Support Vector Machines (SVM): As used for regression problems, SVMs have been found to yield better results in situations where other approaches fail, for instance when the input data has large dimensionality.
- Recurrent Neural Networks (RNN): These models are particularly good at modeling temporal dependencies and thus are able to provide dynamic SoC estimations that are sensitive to the operating conditions. Huang et al. claimed that RNN-based models helped to reduce the errors in SoC prediction by 12.58% [82].
- Long Short-Term Memory (LSTM): LSTMs expand RNN capabilities by solving the vanishing gradient issue, which is crucial for monitoring battery degradation and minor performance changes over time.

(iii) Hybrid Deep Learning Algorithms

- A multiple-algorithm deep learning prediction model with improved performance achieved a high convergence rate and fewer error numbers in SoC estimation.
- [83] Proposed the use of a less complex dynamic linear model along with corrections through machine learning while lessening the computational loaded learning prediction model integrating multiple algorithms provided a fast convergence rate and reduced error numbers in SoC estimation.
- [83] Also introduced a simplified dynamic linear model paired with machine learning corrections, streamlining computational requirements without compromising accuracy.

b. Hybrid methods combining adaptive filtering and machine learning techniques for enhanced accuracy

Adaptive filtering and machine learning are combined in hybrid methods to eliminate their weaknesses while keeping the benefits of both. These techniques are used extensively for handling nonlinearities as well as noise that is inherent to battery systems and their dynamic behavior.

(i)- Adaptive Filtering Techniques

Filters such as EKF, UKF, and their modifications are more suitable for real-time applications, but accurate models are required and can perform poorly when confronted with highly nonlinear systems. To overcome these limitations, they have integrated them with machine learning solutions.

(ii)- Integration with Machine Learning

- EKF with Support Vector Machines (SVM): When extending the EKF with SVMs, the parameters of the filter can be adjusted in real-time, thereby enhancing the performance of the filter for non-linear dynamics.
- UKF with Neural Networks (NN): However, in situations where standard filters do not work well UKF's state predictions are corrected by neural networks.
- Dual Adaptive Filters and ML Models: [84] developed a grey wolf optimization fused with two simplified EKFs for the parameters' dynamic selection, making the method more adaptive and efficient.
- Enhanced Kalman Filters with LSTM: The Combination of LSTMs with EKF, which enabled the model to use both the historic data and the correct real-time data for SoC estimation, and this gave a high level of accuracy for Li–$NiCoMnO_2$/graphite batteries.

(iii)- Benefits of Hybrid Methods

- Increased ability to resist sensor noise and changes in environment.
- Improved capability to deal with calendar and cycle aging of batteries and other operating conditions.
- Enhanced adaptability in nonlinear and dynamic settings that can be illustrated by up to 30% error decrease in contrast to standalone approaches at operating conditions.
- Increased accuracy in nonlinear and dynamic scenarios, with error reductions of up to 30% compared to standalone methods.

c. Insights into real-time prediction models and their implications in practical applications.

Real-time SoC prediction models are crucial for accurate battery performance, safety, and durability to meet demanding requirements of use cases such as EVs where conditions vary frequently. The embedded system uses Kalman-based real-time models to predict SoC requirements. Their speed-led calculations work efficiently enough for electric vehicle systems. The evidence shows both UKF and CEKF generate reliable predictions during rapid speed changes and dynamic vehicle load demands allowing for quick updates, making them suitable for EV applications. For example, UKF and CEKF have demonstrated the ability to maintain accurate predictions even under high-speed variations and dynamic loads.

The use of machine learning models RNNs and LSTMs improves real-time SoC predictions by learning from actual data operations. Key applications include: Dynamic Adaptation ML models continuously revise their prediction results as new datasets arrive which proves valuable in many live driving environments. RNNs reach 92% effective performance when used in real-time systems [85]. Battery Aging Mitigation LSTM-based models use aging information to provide reliable battery state of charge estimates from start to end of battery life.

The use of LSTM and EKF by Xu et al.in Step-of-charge prediction delivered real-time results 15- 20% more precise than earlier approaches. Engineers use adaptive filters together with machine learning enhancements to produce precise and dependable predictions in different operating environments with real-time SoC prediction with a 15-20% improvement in accuracy over traditional models [86]. Dual adaptive filtering with machine learning corrections has been employed to optimize predictions in varying conditions, ensuring robustness and reliability. Research assesses the application of Tensor Flow NN models for real-time Remaining Useful Life (RUL) prediction that reaches 93% accuracy as well as their operational efficiency within restricted resource settings through features optimization combined with performance evaluations [87].

d. Practical Implications

Real-time prediction models have critical implications for battery management systems:

- Improved Energy Efficiency: Battery efficiency increases when we use real-time calculations to manage energy usage and extend driving distances.
- Enhanced Safety: Real-time SoC measurement stops battery issues before they create safety hazards.
- Prolonged Battery Lifespan: Accurate SoC and aging measurements help users maintain perfect battery upkeep for better battery life.

Scientists make important progress in SoC estimation by developing innovative prediction tools that use multiple techniques in real time. Researchers enhance SoC estimation by combining machine learning and adaptive filtering techniques to solve battery nonlinearity issues while predicting dynamic changes and monitoring aging patterns. Better battery control systems are helping electricity storage become standard for electric vehicle adoption.

IV. Potential Challenges and Constraints

a. Current limitations in SoC estimation methodologies

SoC estimation methodologies face several challenges that impact their accuracy, adaptability, and scalability:

1. Dynamic Non-linear Behavior: Traditional battery monitoring approaches are unable to handle the system's rapid shifting behavior that results from temperature changes, loading variations, and the natural degradation process. The methods produce poor estimates when batteries experience fast changes in speeds or when electric vehicles brake to charge the battery.
2. Computational Complexity: The systems yield very precise outcomes yet need substantial computing systems to work. The complexity of these processes reduces reactiveness when used on embedded systems that have restricted computational power.
3. Data and Model Uncertainties: Most techniques learn from old data sets that might have measurement errors or miss important environmental changes. Such inconsistencies in training data lower the confidence level of our prediction systems.
4. Calibration Challenges: The task of getting exact battery charging status measurements presents challenges because of calibration requirements when facing different usage scenarios. The need for regular battery calibration grows because battery materials, temperature, and daily usage patterns keep changing.
5. Real-Time Implementation: The slow processing speed of complex models makes it hard to perform accurate power state estimation in real-time. The processing delay makes it hard to respond quickly when making energy decisions. Electric vehicle SoC estimation benefits from machine learning since it improves accuracy rates and operational speed along with battery life duration and handles issues regarding available data and real-time processing requirements [3].

b. Future research areas and potential advancements in the field.

Future advancements in SoC estimation are geared toward addressing these limitations through innovative techniques:

1. Hybrid Models: Conducting joint operations between machine learning techniques and physics-based models shows real potential. By uniting knowledge from data analysis with basic physical laws we get high-accuracy results at a reasonable processing speed.
2. AI Hardware Acceleration: Real-time SoC estimation becomes possible through GPU and TPU hardware systems that speed up complex models.
3. Transfer Learning: Applying learnings from similar subject areas makes models adaptable to many conditions and speeds up their modification process.
4. Data Augmentation and Quality Improvement: Synthetic data creation plus enhanced preprocessing techniques help train models well when real training data is limited.
5. Integration with Edge Computing: By using edge computing platforms for real-time SoC estimation we decrease our reliance on cloud infrastructure and make processing faster.

c. Emphasis on the need for robust uncertainty handling and real-time applications.

1. Quantification of Uncertainties: Machine learning systems give battery status forecasts with reliable probability scores to express prediction confidence levels. The approach supports clear decisions under conditions where the outcome is not clear.
2. Dynamic Adaptation: The models automatically track shifting battery conditions and user activity patterns through self-learning algorithms to preserve their accuracy levels.
3. Scalable Real-Time Solutions: The EKF and adaptive neural networks help produce reliable SoC predictions at fast speeds through efficient calculation methods.
4. Integration with IoT and Big Data: The pairing of IoT sensors and big data tools lets us track and refine battery models to work better in any situation.
5. Resilience to Noise and Anomalies: Leading-edge data cleaning methods combined with effective error handling systems protect battery state of charge estimations from unpredictable input data problems.

V. Conclusion

The study reveals important progress in electric vehicle SoC estimation as new technologies advance including machine learning and combined methods. Research shows that both the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are effective tools for State-of-Charge (SoC) estimation because they excel at dealing with noise and uncertainty. Battery models need precise accuracy while the non-linear nature of systems poses challenges to their expanded use. At their core Equivalent Circuit Models and electrochemical models excel in SoC estimation yet these solutions prove less effective in scaling and handling dynamic battery behavior in real time. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models detect patterns in time sequences and understand non-linear connections to create better estimates for dynamic circumstances. Support Vector Machines (SVMs) prove useful because they work well with high-dimensional and noisy data across different operating conditions. Hybrid machine learning models enhance prediction results by improving accuracy and quick performance when dealing with batteries and changing environments. Machine learning approaches that merge AI methods with conventional techniques deliver superior SoC estimation results compared to single-system solutions relying on machine learning (ML) techniques and hybrid approaches. Kalman filters, particularly the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been extensively used for SoC estimation due to their robustness in handling noise and uncertainties. However, their dependence on accurate battery models and limitations in non-linear systems restrict their adaptability. Equivalent Circuit Models (ECMs) and electrochemical models provide a strong foundation for SoC estimation but struggle with scalability and real-time implementation under dynamic conditions. RNNs and LSTM models excel in capturing sequential dependencies and non-linear relationships, significantly improving SoC estimation accuracy in dynamic and complex scenarios. SVMs have demonstrated robustness in handling high-dimensional and noisy data, making them effective in diverse operating conditions. The performance of SVM surpasses Decision Tree when used to forecast SoC and Battery Voltage and Cabin Temperature during summer travel because it generates lower Mean Squared Error ratings [88]. By combining multiple machine learning techniques, hybrid models improve generalizability, convergence speed, and accuracy, especially in cases involving battery aging and environmental variability. Hybrid methods that combine machine learning with traditional techniques, such as EKF-SVM or RNN-UKF, have proven to address the limitations of standalone models. The methods use Kalman filters' signal processing strength alongside ML's adaptability and precision features. Machine learning algorithms now keep real-time SOC estimates up to date by learning how drivers use their batteries and how these batteries perform. The connection to IoT/edge technology improves immediate system functionality. Adding battery aging models to state-of-charge systems helps predict battery life more precisely to extend battery life and decrease wear. Predicting the battery state of charge remains difficult due to demanding processing needs and strict requirements for accurate high-quality data inputs that affect all ML methods and battery behaviors. Integration with IoT and edge computing further enhances real-time capabilities. Incorporating aging models into SoC estimation frameworks allows for accurate predictions over the battery's lifecycle, reducing degradation and prolonging lifespan. SoC estimation methodologies face challenges such as high computational complexity, dependency on large datasets for ML models, and sensitivity to data quality and noise. Real-time application on embedded devices continues to limit system performance. This study looks at the development of EV State-of-Charge estimation through Machine Learning applications while identifying the main obstacles in this field. The EKF and UKF-based Kalman filters have become essential tools for SoC estimation due to their superior ability to handle uncertain data. Their accuracy and non-linear capabilities limit their ability to work with imperfect battery models. The foundation of state-of-charge estimation by Equivalent Circuit Models and electrochemical models proves useful but both systems have limitations in quick response and adapting to changing battery behavior. When battery aging models are included in SoC estimation tools they track battery health accurately across all usage stages to improve lifespan. SoC prediction algorithms confront problems related to time-consuming processing and require large amounts of clean data to work properly stations for standalone models. These methods leverage the noise-handling capabilities of Kalman filters while incorporating ML's adaptability and precision. Advances in real-time SoC estimation have been driven by ML algorithms capable of instantaneous adaptation to changing driving patterns and battery behaviors. Integration with IoT and edge computing further enhances real-time capabilities. Incorporating aging models into SoC estimation frameworks allows for accurate predictions over the battery's lifecycle, reducing degradation and prolonging lifespan. SoC estimation methodologies face challenges such as high computational complexity, dependency on large datasets for ML models, and sensitivity to data quality and noise. The integration of real-time sensors within embedded systems faces performance limits. Final thoughts on the evolution of SoC estimation methods and their impact on the EV industry. SoC estimation technology has progressed from basic physical modeling to data-based and blended estimation methods. The rise in EV system complexity requires precise real-time energy management tools to fulfill current requirements. Enhanced Performance and Efficiency: EVs achieve better efficiency and extended range by using accurate estimates of their battery power level. Improved Battery Longevity: Battery lifetime increases and replacement costs decrease when we use aging-aware prediction models. Accurate battery status monitoring reduces range fears which creates a better EV adoption rate. The EV sector can meet its sustainability targets more effectively when new battery monitoring methods deliver enhanced efficiency and waste reduction. Hybrid methods fix SoC estimation problems by joining proven techniques with machine learning technology. The pairing enables systems to handle challenging processes that change rapidly in batteries across multiple chemistry types. SoC estimation systems become more flexible and work in real-time through cloud-edge platforms that combine big data analysis and Internet of Things technology. Emerging models need to perform efficiently while maintaining quick response times for integration into embedded systems. The combination of AI analysis with blockchain protection will boost SoC estimation system trustworthiness and visibility. The industry can better adopt new methods when we create universal testing requirements and measuring standards for fair comparison. The battery industry builds progressive methods by combining Kalman filters with hybrid machine learning to enhance battery performance standards as new techniques emerge. These improvements boost EV performance while helping them become more popular and supporting worldwide efforts to make the world more sustainable. Technology progress will bring improved energy storage solutions through advanced methods that will make SoC estimation essential for future electric vehicle development.

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