Chapter 2

Literature Review

2.1 Role of Energy Storage Systems in Smart Grids

Energy storage systems (ESS) play a key role in transforming traditional electrical grids into intelligent, robust, and sustainable smart grids. A smart grid optimizes electricity generation, distribution, and consumption by combining digital communication, sophisticated monitoring, and control technology [45]. In order to improve grid efficiency and reliability, ESS facilitates load balancing, peak shaving, voltage/frequency regulation, and integrates renewable energy sources into the smart grid [46].

2.1.1 ESS Technologies: Batteries and Supercapacitors

The widely preferred ESS technologies in smart grids include SCs and rechargeable batteries such as LIB, lead-acid batteries, and sodium-sulphur batteries. Among these batteries, LIBs are widely used due to their ease of use, high energy density, long lifetime, and low self-discharge property [47]. SC, on the other hand, are perfect for short-term, high-power applications because of their high power density, long life cycle, and rapid charge-discharge capability [48]. A comparative overview of the two widely used ESS technologies, that is, the LIB and the SC, is presented in Table 2.1.

Hybridization of battery ESS with supercapacitor storage systems combines the comple-

Table 2.1: Comparison Between Lithium-ion Batteries and Supercapacitors

Feature	**Lithium-ion Batteries**	**Supercapacitors**
Energy Density	High; suitable for energy storage	Low to moderate; not ideal for long-term storage
Power Density	Moderate; limited peak power	Very high; excellent for burst power needs
Charge/Discharge Speed	Seconds to hours depending on use	Milliseconds to seconds
Cycle Life	Around 1000–3000 cycles	Extremely high (up to 100,000 or more cycles)
Degradation Sensitivity	Prone to chemical degradation and aging	Mostly physical aging; stable over long periods
Key Advantages	High energy capacity, compact size, rechargeable	Rapid charging/discharging, high power output
Ideal Applications	Electric vehicles, portable electronics, grid storage	Regenerative braking, backup systems, hybrid power systems
Usage Duration	Suitable for long-duration applications	Best for short-duration, high-power delivery

mentary strengths of both technologies—achieving high energy density from LIBs and high power density from SCs [49]. This integration enhances the operational flexibility of the overall ESS and helps decouple system requirements, allowing each component to function optimally. As a result, it leads to reduced system sizing, lower investment costs, and improved efficiency [50]. Hybrid ESS has shown significant promise across multiple applications, including power smoothing and dispatchability for intermittent renewable energy sources, power quality improvement in microgrids, voltage and frequency regulation, regenerative braking in EVs, and wireless power transfer in medical instrumentation systems [51].

2.1.2 Need for Health prognostics in ESS

The ESS plays a key role in safety-critical applications such as aerospace, medical, and military applications, where a failure of an ESD can lead to catastrophic consequences [52]. Inaccurate life estimation in large-scale grid applications can result in sudden power loss affecting millions of people and causing billions in economic damage, while also leading to equipment destruction and environmental contamination [53]. Accurate SOC estimation is essential in ESS, as inaccurate SOC readings can result in overcharging or deep discharge circumstances that cause thermal runaway events that cause fires, explosions, and sometimes fatalities [54].

The degradation in LIBs is sophisticated and occurs due to repeated charge-discharge cycles, varying environmental conditions, and operating irregularities. The prognostic parameters, such as SOC and SOH estimation, are vital for:

- Ensuring efficient and reliable operation of ESS.
- Optimizing system operation and reducing costs in smart grid environments.
- Extending the service life of ESS through predictive maintenance and timely interventions.
- Enhancing safety, especially in safety-critical applications such as aerospace, medical, and military systems.

These prognostic parameters are fed into BMS for real-time control and long-term planning.

2.2 State of Charge and State of Health estimation in LIB

With the rise of smart grid technology and the usage of EVs [55], the battery acts as a critical ESD in the modern world. The primary advantage of using battery EVs [56] is the ability of an EV to operate with zero emissions, generating a higher torque, smoother acceleration, and lower noise pollution. The battery cells in LIB have a limited capacity and voltage. Many cells are integrated to form a module to increase the capacity and voltage. A BMS [57] is required to coordinate and control thousands of battery cells. A typical BMS consists of controllers, sensors, and actuators with wiring and algorithms. The essential role of BMS is the protection of battery cells, the maintenance of a battery with correct voltage and current values, and a stable state of operation. The inputs to the battery are the current, voltage, and temperature [58]. These characteristics aid in determining the condition of the battery and in safeguarding it.

The most significant function of a BMS is determining the SOC and SOH of a battery. Typically, the SOC of a battery varies from 0 to 100, representing the available capacity at a given moment. Cell characteristics such as age, current, voltage, and temperature affect the determination of SOC. The SOC of a battery is the ratio of the battery's present capacity to its maximum capacity. SOC is a nonlinear function that is dependent on numerous variable parameters, and the estimation of SOC is a difficult operation due to the battery's erratic dynamics.

The SOH can be used to compare the energy storage and delivery of a healthy battery to that of a fresh battery. The SOH can be determined by measuring the internal resistance of the battery. The internal resistance of a battery is dependent on its age and state of deterioration. Internal Resistance is defined as the drop in voltage when the current flows through a battery [59].

$$IR(t) = (OCV(SOC, t) - V_b(SOC, t))/I_b \tag{2.1}$$

Where IR is the internal resistance, OCV is the open current voltage, V_b is the voltage battery, and I_b is the current applied to the battery.

Cell balancing is one of the BMS's fundamental functions and is used to increase the life of a battery by increasing the capacity of a battery pack through the efficient series connection of battery cells. Variations in cell resistance, self-discharge, and temperature within the cell affects cell balancing. There are two categories of cell balancing: active

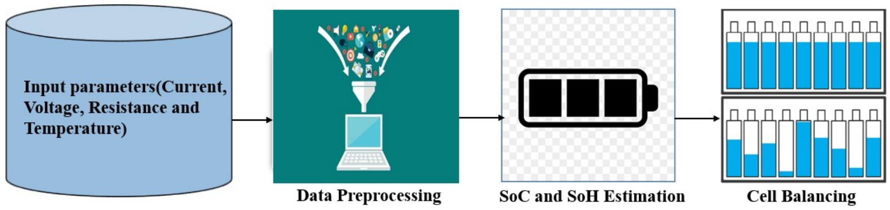

Figure 2.1: Cell Balancing

cell balancing and passive cell balancing. To conserve battery energy, the active system transfers excess charge from highly-charged cells to low-charged cells, whereas the passive system employs balancing resistors to remove the excess charge from overloaded cells. SOC estimation is a vital part of a BMS that affects various other functions. Other computations, including cell balance, use the SOC and SOH values as input, as shown in figure 2.1. In work, [60], cell balancing is carried out by ML algorithms by evaluating the resistor values considering various factors such as an increase in temperature, loss of power, balancing time, and other constraints related to the operation. This passive cell-balancing technique using various resistors works well on real-time data with better efficiency. Performance can be evaluated using various neural networks, among which the LSTM performs well in non-linear data.

2.2.1 Look-up table

The SOC of a battery can be estimated via different techniques [61], as shown in figure 2.2. One of the widely used traditional approaches is using the look-up table. In this method, the SOC of a battery is directly related to input parameters such as current, voltage, resistance, and temperature. SOC can be mapped to more than one parameter for better results. Efficiency is high in these methods, but collecting these parameters in real time is a considerable challenge.

In traditional methods, SOC is measured using a look-up table-based method called

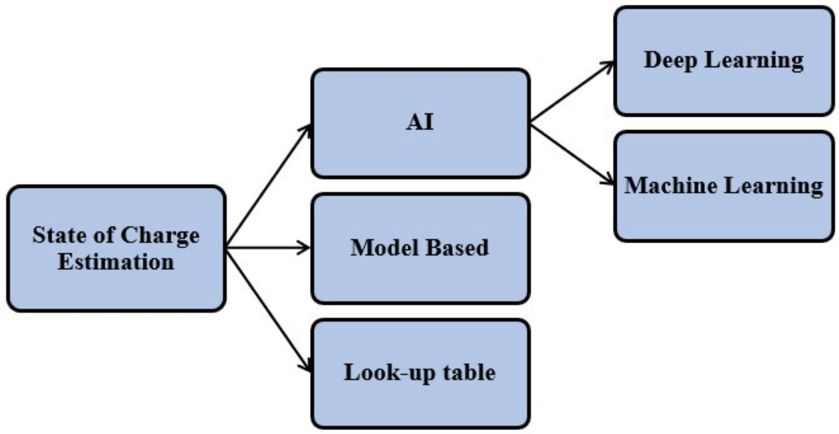

Figure 2.2: State of Charge Estimation methods

open circuit voltage (OCV) when the battery is in its resting condition. A direct relation exists between the OCV and the battery SOC, and a lookup table is created from the lab data. This OCV varies significantly with temperature, affecting the direct relationship between SOC and OCV. To enhance the accuracy in this case, authors in [62] proposed an OCV-SOC-temperature lookup table, that maps the relationship across varying temperatures. The proposed model is tested under dynamic load conditions and performs better with the attribute temperature. A major drawback with this method is that it needs a lot of offline testing to make the OCV–SOC–temperature lookup table. This process is time-consuming and may need to be initialised for different battery types, chemistries, or aging levels.

Like OCV, a look-up table can be used for mapping internal resistance and battery capacity for various SOC levels. The measured internal resistance is compared to or interpolated with the stored data to figure out the SOC during the operation of the device [63]. This method provides a quick and easy way to estimate SOC without requiring dynamic modeling or complicated real-time computing. Despite being a simple method, a static look-up table can't capture the real-time battery conditions, as the internal resistance changes with variations in temperature, current, load, and battery ageing. So, a dynamic table with frequent updates is required to estimate SOC at varying operating conditions. Furthermore, it might be challenging to discern precise states when resistance values overlap at several SOC levels, particularly during high current or transient events.

2.2.2 Model-based approach

A model-based approach for SOC estimation [64] learns about the battery's electrical, chemical, or both properties and models it accordingly. Models are represented in the form of state equations. An internal study of the battery state is carried out with the help of filters and nonlinear state estimation algorithms. The major drawback of this approach is the requirement for domain knowledge and the time required to develop these models.

The Kalman filter (KF) is a widely used recursive algorithm that works well in noisy environments by estimating the states of a dynamic system internally. LIBs have a non-linear and sophisticated degradation pattern due to the electrochemical complex characteristics of the battery. Two variants of KF, such as extended Kalman filter (EKF) and unscented Kalman filter (UKF), are employed for these issues, and they are nonlinear extensions of the standard KF [65]. The EKF uses a first-order Taylor expansion to linearize the nonlinear battery model around the current estimate. This technique is simple and computationally efficient. Accuracy diminishes when nonlinearities are severe or when the system deviates markedly from the linearization point, resulting in instability. The UKF addresses the limitations of the EKF by using a smarter approach called the unscented transform. Instead of approximating the system through linearization, it selects a set of sample points that better represent the system's actual behavior, allowing for a more accurate estimation of the mean and variability. The major issue with the UKF is the requirement for higher computational resources, and it is not suited for real-time systems with constrained processing capabilities.

The authors developed a dual forgetting factor-based adaptive EKF for SOC estimation in EVs [66]. The proposed novel KF methodology uses a dual forgetting factor technique to incorporate adaptive parameter tuning, in contrast to conventional dual EKF, which suffers from parameter divergence under dynamic settings. This improves convergence and robustness by allowing real-time correction of battery model parameters in conjunction with SOC estimation. One potential disadvantage of the technique is its reliance on empirically derived SOC-state of energy relationships, which may limit its applicability to different battery types or untested operating situations.

Because of their ease of use and efficiency, equivalent circuit model (ECM) based methods are among the most widely used techniques for battery modeling [67]. These techniques use simple electrical components like resistors and capacitors to simulate the internal activity of a battery. In order to estimate states like SOC and SOH, ECMs are frequently combined with estimation methods like the KF, EKF, UKF, and Particle Filter. The primary benefit of ECM is its cheap computational cost, which makes it perfect for real-time applications. Their accuracy is mostly dependent on accurate parameter identification, which might change with age and environmental factors, which is a major disadvantage.

Electrochemical Model-Based Methods are a physics-based approach to battery modeling that captures the underlying chemical reactions and ion diffusion mechanisms within the cell [68]. Unlike ECMs, these models correctly describe the intrinsic electrochemical behavior. These models are frequently used in conjunction with observer techniques, advanced filtering, and optimization algorithms to estimate SOC and SOH. Their primary advantage is their great accuracy and physical interpretability, particularly under changing and demanding operating conditions. However, the main disadvantage is their high processing cost and implementation complexity, which can limit their real-time use in BMS.

2.2.3 AI-Based Approaches

AI-based methods are entirely data-driven, and the primary advantage of AI-based methods is using deep learning systems, which can work on large volumes of data and complex features. These methods avoid the plant models altogether. In a model-based system, uncertainty is high, and developing a model for such a system is complex. AI-based models can work well on unpredictable data using various deep learning and machine learning algorithms, and there is no requirement for domain knowledge.

In the work [69], a typical LIB, the SOC is calculated using an RNN and LSTM. LSTM-RNN can swiftly compute SOC, understand time-dependent data, and map battery management parameters like V, I, and T to battery SOC. This helps users avoid expensive filters that require considerable processing. The capability of an RNN to self-learn weights using the gradient descent algorithm makes it a preferred alternative to conventional mathematical models. Additionally, the LSTM-RNN aids in the network's accurate measurement of the SOC at various ambient temperatures.

The SOC of a battery is estimated using a deep neural network (DNN) with transfer learning in the work [70]. RNN and transfer learning methods can be combined to enhance performance. Transfer learning saves time and resources from training multiple machine learning models from scratch to complete a similar task. Transfer learning is transductive transfer learning, which is applied to many data sources but produces the same output task—namely, the ability to forecast a battery's SOC. Overall, the advantages of transfer learning include shorter training times, precise SOC estimations, and fewer training data requirements. Using a layered, bidirectional LSTM model, the SOC of a lithium battery is computed [71] in this work. This model has an advantage over traditional RNNs in that it can capture sequential data from sensors in both forward and backward directions for a LIB. These measured variables, such as V, I, and T summarize the temporal dependencies in both the past and the future. The proposed model includes a multilayered structure that is stacked in both forward and reverse directions. Adding the multilayer, stacked, bidirectional recurrent structure enhances accuracy even more. Results from evaluations of the validity and application of Stacked Bidirectional LSTM (SBLSTM) using publicly available datasets reveal a more accurate SOC estimation method under diverse ambient temperature settings.

For the safe and reliable usage of batteries, deep learning networks that understand the relationship of lithium-ion signals during the charging cycle estimate battery capacity, which plays a crucial role in monitoring battery age. Feed-forward neural networks (FNN) and LSTM [72] can interpret battery characteristics, whereas a convolutional neural network (CNN) learns the sophisticated patterns in the battery data since it learns layer by layer. Sparse battery signals can represent battery information without any loss, enhancing performance and decreasing cost. A better SOH estimation can be achieved using battery signals instead of a single battery signal. It is possible to estimate the battery capacity using voltage, current, and battery capacity. Unlike other neural network models, LSTM understands variable-sized time series data more effectively; hence, FNN performs better when learning complex battery phenomena. CNN is helpful since it can scale well with sparse battery data. So the battery's remaining life can be effectively determined by all these deep-learning models.

Another study [73] focuses on a prediction model that uses LSTM networks and multiple linear regression (LR) on actual EVs. A novel LSTM model with solid learning and memorizing capabilities is used, and it performs better than other algorithms and models when applied to historical data. The suggested weather vehicle driver assessment strategy takes into account how a driver's behaviours and the weather can affect a battery system. We can adaptably modify the prediction steps of LSTM using the linear regression LSTM (LRLSTM) based technique, utilizing the one-forward-step prediction accuracy of LR as the accuracy benchmark, within an acceptable prediction accuracy. Fuzzy adaptive federated filtering (FAFF) can be used to estimate SOC for a group of connected battery packs; Federated filter and mean difference models are used to

Table 2.2: SOC/SOH estimation using AI-based methods

Methodology	Input	Purpose	Limitations
RNN, LSTM [69]	V, I, T	Estimate SOC at different ambient temperatures without the usage of expensive filters.	RNN and LSTM models can suffer from vanishing gradient problems in extended temporal sequences.
DNN with transfer learning [70]	V, I, T	Transfer learning provides the advantage of shorter training time, precise SOC estimation and works with fewer data.	Negative transfer is one of the key issues within transfer learning. Initial and target problems must be similar to efficiently use transfer learning.
SBLSTM Model [71]	V, I, T	Capture sequential data from sensors from either direction and accurately predict SOC at different ambient temperatures	SBLSTM model is resource-intensive and often struggles with performance at edge-case temperature extremes.
FNN, CNN, LSTM [72]	V, I, Charge Capacity, T	Interpret battery data using LSTM and FNN; CNN learns sophisticated patterns, estimates SOH accurately using many battery	When FNN, CNN, and LSTM are combined, the model becomes more complex and is unable to generalize effectively in the absence of significant amounts of training data for all input types.
LSTM and Multiple LR [73]	V, T, charging/discharging current, and other-weather vehicle data such as humidity, precipitation, barometric pressure, visibility, wind speed, mileage, vehicle, and motor speed.	Novel LSTM with stronger learning and memorization capability. Fast and accurate multi-forward step prediction for battery SOC.	The batch size count is small in the work. All the data can't be uploaded simultaneously, because of memory constraints.
FAFF [74]	V, I, T	Helps to calculate battery SOC with high reliability using information coefficient distribution of cell SOC.	FAFF operates at a modular scale and lacks scalability for large-scale pack integration or vehicle-level estimation.
DNN [75]	V, I, T	Better SOC estimation at different environment temperatures and no need for a look-up table.	Standard DNN models lack temporal awareness and are unsuitable for sequential battery behaviour prediction without time-series embedding.
LSSVM [76]	V, I, Degeneration degree, T	Accurate model for Li-Ion battery SOH estimation under multi-working condition	LSSVM has high sensitivity to noise and is computationally inefficient for large or high-dimensional battery datasets.
GRU-CNN [77]	V, I, T	Combined structure takes advantage of CNN and GRU-RNN network with shared, spatial and temporal features of charging data for SOH estimation	Training time of the proposed GR-CNN method is high.
GRU-RNN [78]	V, I	Better SOC convergence speed due to gradient-descent with momentum, better generalization ability of GRU-RNN model for SOC estimation	The hybrid GRU-CNN model requires significant training time and may struggle to balance spatial-temporal dependencies efficiently.
DBN-KF [79]	V, I, T	The DBN model can extract the relationship between measurable parameters and battery SOC, meanwhile KF increases accuracy and eliminates the noise effects in measurements	DBN requires deep architecture tuning, and Kalman Filter may degrade under non-Gaussian noise or sudden battery behavior changes.
LSTM, UKF [80]	V, I, T	Learns to estimate SOC in varying temperatures with less mean square error and mean average error.	LSTM-UKF integration is less accurate during load profile transitions (peaks/plateaus), due to lag in state updates and filter adaptation.
TCN, LSTM [81]	C, V, I, T	Combines TCN temporal feature extraction with LSTM sequential modeling for accurate SOH and RUL estimation	Fails to capture multi-scale dependencies and no interpretability.
NARX Transformer [82]	V,I,T, cycles	The integration of nonlinear autoregressive dynamics with transformer attention mechanisms enables highly accurate long-term battery health predictions by temporal dependency modeling	High computational complexity in transformers and need of large datasets

calculate SOC for the pack as a whole and SOC for the individual cells [74]. The local filter is used to estimate the SOC of the cell, while the master filter uses the SOCs of the individual cells to calculate the SOC of the battery pack. Varying the information distribution coefficient of the cell SOC can boost reliability. The estimated SOC of the cell mean model and the standard deviation of the cell SOCs are used to create fuzzy rules. An adaptive method is used to calculate the SOC fusion weights with improved accuracy. When calculating the SOC, DNN [75] maps different observable signals like the V, I, and T to the SOC instead of using different inference techniques and filters. By employing gradient descent algorithms, these DNNs may learn to determine the SOC at various environmental temperatures.

The SOH is estimated using a least square support vector machine (LSSVM) based approach [76] in many operating conditions. Input features are theoretically retrieved from the charging curves and then mathematically filtered to address the problems associated with battery discharging. These features also more thoroughly reflect the phenomenon of battery degeneration from capacity, internal resistance, and charging performance.

Due to the intricacy of the degeneration mechanism, data-driven methods are preferable in SOH estimation over model-based methods. The constant current and voltage charging mode's charging curve represents the capacity-dependent SOH magnitude. The proposed solution employs a GRU-CNN with the ability to learn and transfer information about the charging curve's time dependencies[77]. V, I, and T are eventually employed to estimate SOH inside the charging curve. The technique is successful with lower estimation error when applied to the Oxford Degradation battery set and the NASA randomized battery dataset. For SOC estimation, a momentum gradient-based GRU-RNN is proposed in the work [78], where the current weight changes direction based on both the historical time and the present time to prevent the weight change oscillation and to speed up SOC computation. GRU-RNN uses several metrics, including observed voltage and current, to estimate SOC. To increase the generalizability of the model and prevent overfitting, noises are added to the sample data to increase the accuracy of the SOC estimate. Because the momentum term is included when computing the gradient descent, the SOC convergence speed is also high.

The work [79] proposes a hybrid model based on deep belief networks-KF (DBN-KF)for SOC estimation under dynamic operating conditions. The model aims to eliminate uncertainty by giving a starting point. V, I, and T are input parameters, while battery SOC is the output. The DBN aids in fitting non-linear data, has effective feature extraction capabilities, and aids in modeling the assumed link between the SOC and the measurably constant parameters. By lowering the overall system noise, the KF is utilized to strengthen the robustness of the model.

A hybrid SOC estimator that combines the benefits of machine learning and model-based filtering is proposed in the work [80]. Using the LSTM-RNN, the SOC of a battery is inferred from factors including V, I, and T. The LSTM-RNN model is paired with a UKF to remove outliers. The proposed network learns the battery dynamics well and is resilient in unidentified beginning states because it is trained to operate on highly complex battery dynamics under various temperature conditions. The method outperforms alternative feed-forward machine learning algorithms in terms of root mean square error and mean absolute error.

The work [81] proposes a hybrid model combining the TCN and LSTM for accurate and reliable SOH estimation in LIBs. The TCN effectively captures the temporal degradation trends in the battery data, and the dilation rates in the TCN help to learn varying dependencies in deterioration patterns. LSTM helps to understand the sequential trends in this battery data. The parameters of the model are tuned by Bayesian optimization. The TCN-LSTM model performs better than the state-of-the-art hybrid algorithms with better life estimation results. This novel hybrid algorithm generalizes well in the NASA as well as the Oxford dataset with its excellent nonlinear mapping performance, and adaptive learning of evolving degradation patterns.

Transformer-based designs have great potential for processing sequential battery data because of their ability to record long-range relationships and dynamic behaviors across numerous cycles. This work [82] incorporates the nonlinear autoregressive exogenous (NARX) inputs into a transformer encoder-decoder model, which is specifically built for long-term SOH and end-of-life (EoL) prediction. This hybrid NARX-transformer strategy uses 2-D convolution filters to extract both temporal and localized cycle-level characteristics, and a feedback mechanism allows for the use of previous predictions to improve model understanding of SOH evolution. When evaluated utilizing a half-half experimental setup—where the model is trained on the first half of battery cycles and tested on the second, this method produced a mean absolute percentage error lower than other existing models, exhibiting resistance to measurement noise. The summary of various AI-based techniques used in SOC/SOH estimation is shown in Table 2.2.

2.3 RUL estimation in supercapacitors

Supercapacitors (SCs) have become a key technology for storing energy in the search for sustainable and efficient power systems today. They have many benefits, such as the ability to charge and discharge quickly, a high power density, a wide range of operating temperatures, a long cycle life, and reliability [83]. These attributes have established SC as an essential element in various applications, including backup and emergency power supplies, peak power support alongside batteries, control mechanisms, telecommunications infrastructure, hybrid electric transportation, and smart grid technologies. SCs are used in conjunction with LIBs in hybrid ESS, enhancing power management in various applications by leveraging the complementary advantages of these ESS. Despite their advantages, implementing SC-based ESS in real-world scenarios poses significant difficulties due to their inherently nonlinear and complex characteristics. The malfunction or degradation of even a single ultracapacitor can critically impact the performance and stability of the entire system. As a result, accurately estimating the RUL of SC is crucial for improving system dependability and preventing unexpected, potentially disastrous failures [84].

Two energy storage mechanisms widely used in SC are double-layer capacitors and Faraday capacitors [85]. Double-layer capacitors use carbon-based electrodes and work through electrostatic storage of energy through reversible material interactions. Such units store energy by establishing a potential difference when the positive and negative ions get adsorbed on opposite respective electrode surfaces at the solid electrode-electrolyte interface. Charging can be thought of as the movement of the electrolyte ions to the electrode surfaces under the influence of electrical attraction, whereas discharge is the reverse, wherein the stored energy is released through some external circuitry. Faraday capacitors are electrochemical capacitors, with electrolyte ions moving to the electrode-solution interfaces under imposed electric fields to take part in surface oxidation-reduction reactions with active oxide materials. The thin oxide electrodes with high specific surface area allow a large number of electrochemical processes to occur at the same time, and hence, charge separation occurs to a large extent within the electrode. During the discharge process, the ingested ions move back into the electrolyte, simultaneously liberating electrical energy by running it through an external load circuit. When it comes to electrochemical properties, the performance and aging of both types of SCs are very much dependent on the electrochemical properties of the materials that make the electrodes in each type. This is also true of the electrolyte system present.

2.3.1 Degradation mechanism in supercapacitors

The knowledge of the degradation of SCs is core to the formulation of proper RUL prediction mechanisms. The electrodes, electrolyte, separator, and current collector structural components of SCs are prone to numerous aging phenomena that appear in the form of housing, electrolyte decomposition, and electrode material losses [86]. Highstress levels on operational processes greatly accelerate these aging processes, with V, I, and T being the most important accelerants of degradation. High temperatures increase the chemical activity of activated carbon electrodes and accelerate aging kinetics, and electrolyte decomposition creates pressure on the inside, which may disrupt the structure during long operation cycles. The explicit relationship between SC capacitances and the electrode specific surface area implies that the degradation of materials would inevitably result in a decrease of the capacities, which is caused by structural changes underlying the loss of the available electrochemically active surface area [87].

The performance-degrading effects caused by the aging process build up over operational time in a cascading manner. The byproducts of polymer degradation, as well as the products that lead to electrode ageing, progressively decrease the pore sizes on the electrodes. This causes electrolyte decomposition to introduce impurities, hindering ionic transport and increasing the equivalent series resistance. Consequently, the RUL of SCs decreases. Trace impurities and oxygen-containing functional groups left deposited on the electrode surfaces are manufacturing residues causing a faster capacitance loss in early stages of aging [88]. The synergetic effects of these degradation processes lead to SC RUL decaying according to typical non-linear dynamic patterns until reaching critical operational thresholds [89]. Accurate RUL prediction capability is, therefore, a prerequisite to safe and reliable SC operation in the real world.

2.4 Techniques for RUL estimation

The accurate prediction of the RUL of the SCs is key to reliable, efficient, and resilient operation of the smart grids and other applications using these ESSs. RUL prediction is also relevant when it comes to facilitating proactive maintenance practices, as it provides necessary information regarding possible failures of the system [90]. Technically speaking, RUL is defined as the point to which the SC functions in a normal manner, that is, usually up to a threshold value known as its EOL (usually taken as 70 to 80 percent of its initial capacity). So, it is proposed to replace the SC before reaching this threshold [91].

An appropriate estimation of the RUL of SCs is extremely crucial because it provides imperative information to forecast the occurrence of failures and avoid service interruptions. The RUL concept is the most important determinant of the SC condition and the reason why it has attracted considerable research interest owing to the broad adoption of this concept in various ESSs [92]. The calculation of supercapacitor RUL is usually achieved in two main process streams of the methodological framework, namely: model-based estimation methodologies and data-based analytical methodologies.

2.4.1 Model-based estimation

Model-based techniques use predefined models, like an electrochemical model or an ECM, to understand the degradation pattern in the SCs. This method uses prior information about the electrochemical behaviour to predict the aging of the SC. These models are commonly embedded with filter algorithms such as KF and particle filter (PF) to provide more precise estimates of the internal variables over time and track degradation parameters.

The authors in this work [93] proposed a PF-based prediction model for RUL prediction in SC. This work considers the aging factors, such as temperature and voltage, for prediction. The model is successful in estimating the posterior capacitance and resistance values, predicting important variables of aging, that is, capacitance and resistance, under different operational stresses. Aging factors become part of the degradation law in this model, compared to the conventional prognosis methods, where the aging effects were described as a separate model, thus allowing one to predict the RUL in different initial conditions accurately. The model tested has been proven to be robust and accurate through experimentation under various calendar aging conditions. It is characterized by its simplicity, accuracy, and versatility in terms of the heterogeneous aging conditions that it can handle.

A KF-based technique is proposed in the work [94] to predict the buffered energy in SCs, so as to overcome the disadvantage of using terminal voltage solely in dynamic situations. The method uses a physically motivated three-branch combination of equivalent circuits to follow internal state voltages that are unobservable, and each voltage represents short, medium, and long-term charging dynamics. Through the use of an EKF, internal states receive continuous updating with observable inputs to achieve a much higher energy estimation accuracy in comparison to ideal capacitor models or recursive algorithms.

2.4.2 Data-based analytical methodologies

Although these model-based techniques are effective in the life estimation of SC compared to direct measurement techniques, they fail to learn the sophisticated and nonlinear degradation trends in the SC. These predefined models can't adapt to sudden changes in the behaviour of the SC due to variations in operational conditions. In order to tackle these changes in the operating environment of SC, non-linearity as well as sophisticated degradation patterns, data-driven techniques are employed. These data-driven methods use AI-based techniques, using machine learning and deep learning algorithms to accurately estimate the RUL of the SC in varying prediction scenarios.

Machine learning algorithms are a popular choice in life estimation in SCs, due to their ability to understand the degradation patterns without knowing the inner workings within the system. The ML models using support vector regression, random forest regression and gradient boosting algorithms effectively predict the usable life left over in the capacitor. Gaussian Process Regression (GPR), as a probabilistic model, and its capability to learn about nonlinear degradation behavior have led to its increased use in making health predictions of SCs. Nonetheless, the traditional GPR methods have been characterized by intense use of manually-adjusted optimal explicit mean and covariance functions, which hinder the scalability and necessitate multiple screenings.

To address this, a GPR-implicit function learning framework has been proposed [16], where the implicit mean and covariance functions are derived from preliminary cyclic test data of SC. This technique avoids explicit screening of the functions by calculating the statistical relationships without making additional assumptions, i.e., computing the statistical relationships, mean values and inter-cycle covariances, directly on the data and modeling the statistical relationships efficiently in a generalized manner with a minimum data dependence.

Although these techniques work well in the life estimation, they cannot handle complex, diverse, and large sequential datasets. In addition, these techniques require handcrafted features for life prediction. Deep learning techniques involving RNNs resolve these issues, as they are effective in handling the diverse, complex, and sequential degradation patterns. These networks use the past information to predict future data, and are good at handling temporal dependencies. The major drawback of these RNNs is the vanishing gradient issue. These issues can be overcome by the gated architecture of LSTM and GRU.

The paper [95] presents a composite denoising and prediction system that can improve the integrity of the RUL and the performance degradation law prediction of a SC backup power supply, especially due to noise caused by operating conditions. This strategy is designed in three major steps of smoothing, noise reduction, and prediction. The first step is to apply the Savitzky-Golay smoothing filter to eliminate high-frequency and small local variations on the capacitance signal, usually brought about by irregularities in charging and discharging. The next step is the processing of nonstationary, nonlinear, large-scale noises due to temperature changes inside, as well as electrochemical reactions, using variational mode decomposition with the optimisation of its parameters. Then the denoised capacity sequence is reconstructed and provided as an input to an LSTM model for prediction. These RNN variants, such as LSTM and GRU, are limited by their inability to extract features at a multi-scale network to predict the RUL of the SC.

Table 2.3: Summary of Existing RUL techniques in LIB.

Technique	**Model**	**Core Mechanism**	**Pros**	**Cons**
Experimental Analysis Technique	Coulomb counting, Ohmic internal resistance	Lab-based measurement	Simple, high accuracy	Not applicable in real-world data
Model-Based Method	Equivalent circuit model, Electrochemical model	Predefined mathematical or physical model for understanding degradation mechanism	Theoretically interpretable	Not adaptive to variable degradation patterns
Classical ML Techniques	Support Vector Regression, Gradient Boosting	Learns mapping from engineered features	Excels in small, nonlinear datasets	Not suited for time series, manual feature extraction
RNN Models	LSTM, GRU	Sequence-based learning	Handles time series data, good at handling long-term sequences	Struggles with multiscale degradation, vanishing gradient in long-term temporal dependencies
Convolutional Models	CNN and variants	Convolutional-based local pattern learning and spatial feature extraction	Good in local dependencies and spatial feature extraction	Not good at handling global dependencies and long-term temporal dependencies
Transformer	Transformer, Informer, Transformer-XL	Attention-based models	Strong global context modeling	High computational cost and fails to handle local patterns in small data
Hybrid Models	CNN-LSTM, TCN-GRU	Combine the strength of individual models	Capture spatio-temporal features	Lack seamless fusion of temporal attention and multiscale feature extraction

CNN and their variants are a popular choice in RUL estimation, as they are good at local feature extraction and handle spatial features well. The time-varying input features, such as voltage and current, are temporal in nature. These CNN models are not good at handling temporal data and fail to capture the long-term global dependencies in the SC data. The paper uses a hybrid CNN-Bidirectional Gated Recurrent Unit (CNN-BiGRU) model [96] to predict RUL of SC. This provides a solid method to extract the spatial and temporal dependencies in the degradation data. Under this approach, CNNs are used to detect local results and tendencies in the raw input sequence, which is remarkably noisy data, and to eliminate noise and highlight meaningful degradation patterns. These features are subsequently endowed into a BiGRU network where time is taken in both forward and backwards directions, allowing the model to master longer-term dependencies and contextual relationships as compared to unidirectional networks. The CNN-BiGRU model improves the prediction accuracy because it leverages the spatial perception of CNN and the temporal context of BiGRU to have a more detailed knowledge of the health state of the SC.

For global feature extraction, attention-based models involving transformers are a popular choice. These transformer models provide a strong global context modelling for life prediction within an SC. This article proposes a new method for RUL prediction using a BiLSTM with a denoising autoencoder (BiLSTM-DAE) [97]. The BiLSTM-DAE is able to learn stable features on the multivariate sensor data of the time-series that are then fed to the transformer to acquire the long-term temporal dependencies. This framework trained the combination of the autoencoder and the Transformer together, unlike in the traditional sequential models, and this enhances feature representation and accuracy of predictions. Self-supervised structure creates strong noise robustness in the model, which is effective in a real-time environment.

Although these transformer-based models excel at global dependencies, they are not good at local feature extraction and are computationally expensive. Hybrid models that combine the benefits of individual models are robust and can leverage spatio-temporal patterns in SC data. These models are also not effective in capturing dependencies at varying scales, such as short-term, mid-term and long-term dependencies in the degradation of the SC. The summary of RUL estimation techniques used in LIBs are shown in Table 2.3.

2.5 Research Gaps

Prognostics and health management frameworks in ESS have advanced significantly with the data-driven techniques; however, there are still several significant drawbacks with the existing techniques. These limitations undermine the effectiveness of current approaches in accurately predicting the life of ESS and adjusting to intricate, real-world degradation patterns. The major research gaps identified from the existing literature are as follows:

- **Inadequate Temporal Pattern Representation:** Existing state-of-the-art approaches fail to capture both the short-term fluctuations and long-term degradation trends in the LIB/SC data. This issue originates from restricted temporal modeling capabilities, which impede the precise representation of real-world aging phenomena in intricate systems.
- **Static Treatment of Input Features:** Existing methods assign fixed importance to all input features, overlooking how their relevance evolves over time. This limits the model's ability to focus on the most informative signals during different stages of system degradation
- **Limited Interpretability and Transparency:** The black-box aspect of AI-based models in ESS reduces their trustworthiness and prevents their widespread use in safety-critical applications. There is an increasing demand for interpretable technologies that offer clear insights into decision-making processes.
- **Lack of Model Adaptability:** The static structures used in the existing frameworks are unable to dynamically adjust to shifting deterioration patterns or operational environment. As a result, these models struggle to generalize well when applied to different usage scenarios or varying system conditions.
- **Inadequate Handling of Real-World Data Imperfections:** Most current life estimation models in ESS are trained and tested on pre-processed datasets, which do not consider operational challenges in the real world. Sensor data encountered in practice may be noisy, incomplete or have calibration drift. The scalability and dependability of these models in industrial settings are limited by the absence of robust procedures to handle such imperfections.