A comparative review of neural network approaches for advancements in state of charge estimation for electric vehicles

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Abstract

An electric vehicle (EV) operates using batteries and electric motors, serving as an eco-friendly alternative to traditional vehicles by cutting emissions and decreasing reliance on fossil fuels. EVs are pivotal in advancing environmental sustainability and aiding global efforts toward carbon neutrality. As the push for carbon neutrality and emission reduction intensifies, advancements in the electric vehicle sector become imperative, with lithium-ion batteries serving as key power sources. Accurate estimation of the state of charge (SOC) of these batteries is crucial for optimizing the performance and management of electric vehicles. This article delves into SOC estimation using neural network approaches, which utilize their advanced feature extraction and modelling capabilities to achieve high precision without requiring detailed knowledge of the battery's internal electrochemical processes. The concept of SOC is defined, and its relationship with battery aging is explored to establish a basis for further analysis. Recent studies are reviewed, categorizing neural network-based SOC estimation methods into three main types: recurrent neural networks, convolutional neural networks, and hybrid models. Additionally, it offers recommendations for the future development of intelligent battery management systems and SOC estimation methods. The insights from this review are intended to inspire researchers in the battery technology field and support the evolution of next-generation electric vehicles.

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Introduction

Electric vehicles (EVs) have been a significant part of automotive history, dating back over a century. Around 1900, when they were viewed as a competitive alternative to automobiles with internal combustion (IC) engines, the idea of EVs reached its zenith. The smooth running, quiet engines, and user-friendliness of the early electric automobiles won them accolades. But even with a bright beginning, EV technology encountered several obstacles that prevented widespread acceptance. The prevailing use of internal combustion engines and fossil fuels was the biggest obstacle for electric vehicles. Because fossil fuels were widely available and reasonably priced in the early 20th century, gasoline and diesel engines were more alluring. Further supporting the usage of fossil fuels is the fact that advances in IC engine technology have improved performance, efficiency, and cost. Electric cars were overshadowed by internal combustion engines (IC) because to their simplicity and dependability as well as the massive infrastructure that supported the transport of fossil fuels. Consequently, EVs were mostly limited to niche uses like golf carts and delivery trucks. Internal combustion engines were the focus of the automobile market because, at the time, they were thought to be more useful and advantageous economically. Early electric cars' short range and dearth of a comprehensive charging infrastructure also led to their restricted deployment.

However, interest in electric cars has recently increased due to the increased emphasis on environmental sustainability and the pressing need to address climate change on a worldwide scale. The need for greener transportation alternatives has been highlighted by problems including global warming, the depletion of fossil fuel supplies, and growing greenhouse gas (GHG) emissions. The transportation industry, which is one of the main sources of hazardous emissions, is now at the center of both technical innovation and environmental legislation. Transportation electrification is now regarded as a viable way to lower greenhouse gas emissions and fight climate change. The market for electric vehicles has seen a resurgence thanks to developments in battery technology, increased EV efficiency, and the creation of extensive charging infrastructure. Due to its ability to reduce environmental impact and provide a competitive alternative to conventional fossil fuel-powered cars, electric vehicles (EVs) are becoming more and more recognized as essential to a sustainable future.

The EVs' progression history is depicted in Fig 1. Transportation electrification increases energy security by reducing reliance on petroleum imports for transportation needs. However, the adoption rate of EVs is still limited due to a variety of problems, such as high initial prices, battery degeneration, a poor infrastructure for charging, range anxiety, etc. [1]. Around the world, governments offer a range of incentives and rules to promote the use of electric vehicles (EVs) and to eliminate barriers that would otherwise prevent a complete switch to electrified transportation. The International Energy Agency's "Global EV outlook" research projects that by 2030, there will be 130 million EVs worldwide [2].

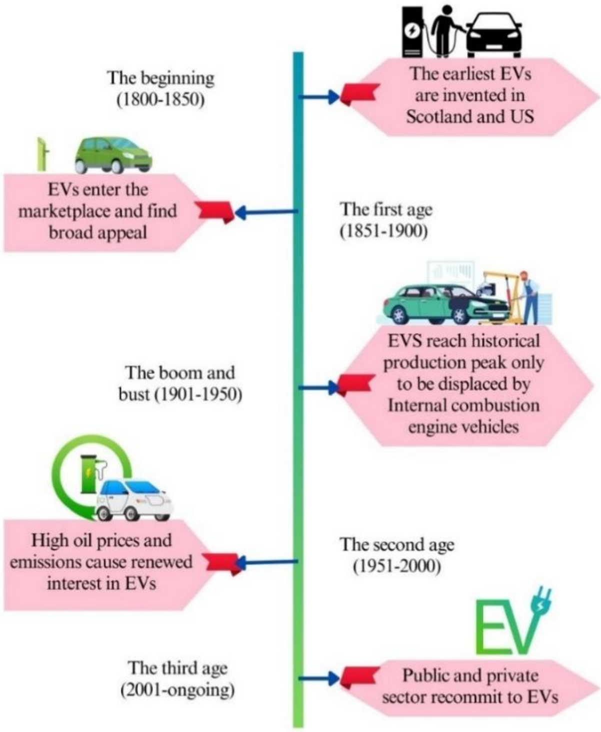

Fig 1. Electric vehicles (EVs) evolution.

Moreover, the distribution network's quality is put under strain by the extensive use of EVs, mainly in relation to problems with off-nominal frequency, three-phase voltage imbalance, and network congestion. Since electric vehicles are single-phase loads that are transportable, they may be linked at random to any of the 3 stages in distribution networks. Thus, it is possible that under certain situations, one phase of an electrical system—such as transformers, overhead wires, power supply cables, and other components—will experience overloading while the other two phases remain idle. Relays malfunctioning, equipment failure, and transformer failures are just a few of the issues that can arise from imbalanced three-phase loads and have a detrimental impact on power quality. Furthermore, it is challenging to handle EVs as extra loads while preserving the security and dependability of the grid due to their high degree of geographical and temporal uncertainty. Additional system peaks result from the temporal coincidence of residential load peaks and EV home charging. Furthermore, a neighborhood's power quality might be negatively impacted by numerous EV charges since they can create large harmonics [3].

Consequently, a major focus of research and engineering is the integration of considerable EV penetration in distribution networks, which necessitates a rise in ESS size or capacity [4]. As a result, there is a large capital requirement, particularly because ESS is expensive per unit. Since EVs primarily operate on batteries and we are currently shifting to electric cars to reduce greenhouse gas emissions, they may also function as a dynamic type of energy storage system (ESS) to the V2G feature, which allows EVs to return energy stored in their batteries to the grid [5-6].

Due to their involvement in V2G, EVs may also take part in energy trading, which provides an additional revenue stream for the aggregator and consumers to offset battery deterioration. Nevertheless, in order to compete in the majority of global energy markets, an aggregator of a sizable fleet of EVs would be necessary [7]. To counter this, more research is being done on peer-to-peer (P2P) or transactive commerce systems [8]. Furthermore, the advantages of electric mobility in terms of lower emissions cannot be fully realized if non-renewable energy sources are used for EV charging. According to research, nations where fossil fuels are the main source of electricity generation tend to have greater emissions from well to wheel, or source to exhaust, when it comes to EVs [9]. RES-powered EV charging, however, has the potential to lower greenhouse gas emissions. This is demonstrated in [10], where 400 Metric Tons fewer emissions were produced annually by 50,000 EVs powered by a combination of solar and wind energy sources.

Research Status of State of Charge (Soc) In Ev

The State of Charge (SOC) is a fundamental metric in the operation and management of battery systems within Electric Vehicles (EVs). The state of charge (SOC), which expresses the amount of energy left in a battery as a percentage of its entire capacity, is essential in estimating the driving range of a vehicle as well as its charging needs and overall energy management tactics. The significance of SOC extends to optimizing the performance, safety, and lifespan of the battery, which is one of the most costly and vital components in an EV. Ensuring accurate SOC estimation is crucial for preventing overcharging or deep discharging, both of which can severely reduce battery longevity and efficiency. Furthermore, SOC information is essential for predictive maintenance, allowing vehicle systems to preemptively address potential battery issues, thus enhancing the reliability and safety of the vehicle. However, accurately estimating SOC is not a straightforward task. The process is complicated by the inherently non-linear behavior of batteries, which is influenced by a variety of factors including temperature fluctuations, load variations, and the aging process of the battery cells. These factors contribute to the dynamic and complex nature of battery behaviour, making SOC estimation a challenging endeavour.

In response to these challenges, several methodologies have been developed for SOC estimation, each with its own set of benefits. These methods can be broadly classified into four categories: direct measurement, model-based, data-driven, and hybrid approaches. Direct measurement techniques, though straightforward, are often limited by their inability to capture the full complexity of battery behavior under varying conditions. Model-based techniques, which use mathematical models to mimic battery dynamics, are more accurate but need in-depth understanding of the internal workings of the battery, which can be hard to come across and may not take into consideration all external factors. Because they can handle big datasets and adapt to new patterns, data-driven methods—which make use of statistical methods and machine learning—have gained popularity. However, they frequently need for substantial training data and processing resources. Hybrid methods combine the strengths of the aforementioned approaches, seeking to balance accuracy with practical applicability across a range of scenarios. This review explores these SOC estimation methods in depth, providing a comprehensive analysis of their suitability for different EV applications, and offering insights into the future direction of SOC estimation technologies as the industry moves toward more advanced and reliable battery management systems.

Direct Measurement Methods

Direct methods estimate the SOC by directly measuring battery parameters like current, temperature, and voltage. The Coulomb Counting approach is the most often employed of these techniques. Using this method, SOC is calculated through incorporating the current flows out and into of the battery. The SOC at any given time ttt can be represented as in equation (1):

$$\mathrm{SOC}(t) = \mathrm{SOC}(t_0) + \frac{1}{Cn}\int_{t_0}^{t} I(t)dt \quad (1)$$

Where (C_n) is the nominal capacity of the battery, and (I_t) is the current at time (t). While Coulomb Counting is straightforward, it suffers from cumulative errors due to current sensor inaccuracies and drift over time, making it unreliable for long-term SOC estimation [11]. Another direct method involves using pen Circuit Voltage (OCV), which has a direct correlation with SOC under equilibrium conditions. However, the OCV-SOC relationship is non-linear and depends heavily on temperature and battery chemistry [12]. Furthermore, achieving equilibrium for accurate OCV measurement requires the battery to rest for a significant period, which is impractical in real-time EV applications.

Model-Based Methods

Model-based approaches model the electrical behavior of the battery by mathematical representations. ECM, which reduces the battery to a mixture of resistors and capacitors, is the most often used model. By fitting the model parameters to the real-time battery data, the SOC is computed. The precision of the model parameters, which can change with temperature, age, and operating circumstances, determines how accurate ECM-based SOC estimate is [13][14].

Another advanced model-based method is the Electrochemical Model, which provides a more detailed representation of the battery's internal processes, such as ion diffusion and charge transfer. While the accuracy of electrochemical models is better, their computational complexity and need for in-depth understanding of battery chemistry make them less useful for onboard SOC estimates in electric vehicles. [15]. Kalman Filters are commonly employed in conjunction with model-based methods to enhance SOC estimation accuracy. The UKF and EKF are particularly popular for handling the non-linearities and uncertainties in the battery models. These filters dynamically adjust the model parameters based on real-time measurements, thus improving SOC estimation under varying operating conditions [16][17].

Data-Driven Methods

Data-driven methods rely on machine learning algorithms to estimate SOC based on historical and real-time data. These methods include techniques such as SVMs, Deep Learning models, and ANNs. Data-driven approaches can capture complex, non-linear relationships in battery behavior without requiring detailed physical models [18]. However, they require large datasets for training and may struggle with generalization to unseen conditions. The main benefit of data-driven approaches is their capacity to adapt from the data, which enables them to adjust to various battery chemistries and circumstances. However, the number and quality of training data greatly influence these techniques' accuracy, and a significant amount of computing power may be required for both deployment and training [19].

Hybrid Methods

To improve SOC estimate accuracy and resilience, hybrid techniques combine the best features of data-driven and model-based methodologies. For example, a hybrid approach might use a Kalman Filter to provide initial SOC estimates, which are then refined using a machine learning model [20]. This combination allows for more accurate SOC estimation across a wide range of operating conditions, while also mitigating the limitations of individual methods. Another example of hybridization is the integration of Coulomb Counting with data-driven corrections, where the cumulative errors of Coulomb Counting are corrected using a ML model trained on historical SOC data [21]. Such hybrid methods are increasingly popular as they offer a balance between computational efficiency and estimation accuracy [22].

Despite the progress in SOC estimation techniques, several challenges remain. The non-linearity of battery behavior, especially under extreme temperatures and aging, continues to pose difficulties for accurate SOC estimation [23]. Additionally, the diversity of battery chemistries used in EVs requires SOC estimation methods to be adaptable and generalizable across different types of batteries [24]. The creation of more complex ML models that can function in real-time with less processing power is one of the emerging themes in SOC estimate research [25]. The use of cloud computing and the Internet of Things (IoT) to enable centralized SOC estimate, where data from several cars are combined and processed to increase accuracy and reliability, is also gaining popularity. [26]. The application of big data analytics to improve SOC estimates is another exciting avenue. Through the examination of extensive information gathered from electric vehicle fleets, scholars may discern trends and associations that enhance the precision of supply chain models. [27]. Additionally, the integration of SOC estimation with battery management systems (BMS) that monitor other parameters such as State of Health (SOH) and temperature can lead to more comprehensive and reliable battery management solutions [28].

To sum up, SOC estimate plays a critical role in EV battery management and has a direct effect on the safety and performance of the vehicle. There isn't a single approach that works for everyone, despite the fact that several have been devised, each having advantages and disadvantages. The application in question, the available computing power, and the level of precision required all influence the choice of SOC estimating technique. The difficulties associated with SOC estimate are being greatly addressed by hybrid techniques that integrate model-based and data-driven methodologies. Future research will likely focus on further improving the adaptability, accuracy, and computational efficiency of SOC estimation techniques, ensuring that EVs can operate safely and efficiently under all conditions.

Neural Network Applications in Electric Vehicles: A Review of CNN And RNN Techniques

The environmental advantages and promise to lessen dependency on fossil fuels have made electric vehicles (EVs) a major emphasis in the goal of sustainable mobility. But creating and maintaining EV systems is extremely difficult, especially when it comes to autonomous driving, battery management, and energy efficiency. Neural networks, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have emerged as powerful tools for addressing these challenges. This review discusses the applications of CNNs and RNNs in EVs, highlighting their roles in areas such as battery management, energy prediction, and autonomous driving.

Deep learning models

Much effort has been devoted to extracting representative features straight from the original signal, in contrast to typical machine learning techniques that depend on human feature identification. However, duplicate or insensitive information may frequently be included in this derived data. Dimensionality reduction techniques are used to discover sensitive traits in order to remedy this, however they can have an impact on computational performance as well as diagnostic results.

Despite much study in the field of intelligent issue identification, two main challenges need to be addressed. Initially, the process of manually extracting characteristics necessitates a great deal of previous information, which might be inconsistent and need a great deal of practical work to discover. Second, the shallow structure of artificial neural networks hinders their ability to capture the complicated nonlinear correlations inherent in measurement data, and typical machine learning approaches are ill-equipped to extract complex information from raw data. One potential option is the use of DNNs, which enable the capture of nonlinear representations of data due to their huge number of hidden neurons. DNNs have proven to perform better in the diagnosis and identification of motor faults.

The adoption of electric vehicles (EVs) is steadily rising, necessitating robust management of charging infrastructure to ensure grid stability and customer satisfaction. DL models can accurately predict charging times, durations, and frequency based on historical usage patterns, enabling better load forecasting and management of charging stations. Deep learning models like CNNs were used to forecast the load on the grid due to EV charging. By analysing spatial and temporal data, these models help in predicting peak demand periods and potential overload scenarios. This information is crucial for grid operators to manage energy distribution efficiently and to implement demand response strategies.

Convolutional Neural Networks (CNNs) in EVs:

CNNs are a subset of DL models that are particularly good at handling spatial data, which makes them ideal for tasks involving images. In the context of EVs, CNNs have been widely applied in autonomous driving systems, where they are used for image recognition and object detection which is displayed in Fig 2.

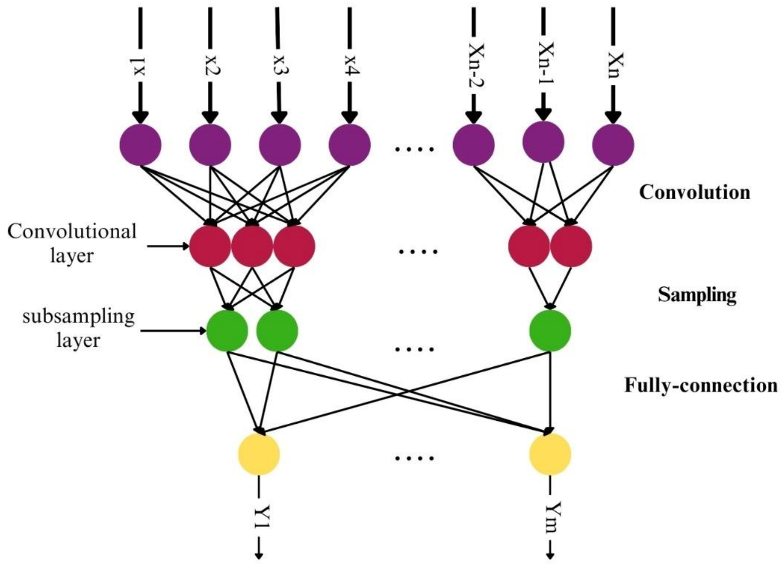

Fig 2. CNN structure

Autonomous Driving and Object Detection

In autonomous driving, one of the main uses of convolutional neural networks (CNNs) in electric vehicles (EVs) is the processing of visual input from cameras installed on the vehicles. CNNs are used to identify and categorize things, including cars, people, and traffic signs. For example, CNN-based models have shown a high degree of accuracy in identifying and recognizing traffic signs in a range of environmental scenarios, which is essential for the safe operation of autonomous electric cars [29][30]. These models typically consist of many convolution and pooling layers, which are followed by fully connected layers that generate output for classification. Because CNNs can automatically extract hierarchical characteristics from raw images, they excel at challenging tasks like object detection. This is where their power resides in this domain. Moreover, advancements in CNN architectures, such as Faster R-CNN and YOLO, have significantly improved real-time processing capabilities, which is essential for the high-speed decision-making required in autonomous driving [31].

Battery Management and Energy Efficiency

CNNs have also been applied in the domain of battery management systems (BMS) for EVs. While CNNs are primarily known for their application in image processing, they have been adapted for analyzing spatial correlations in battery data. For example, a CNN can be trained to forecast the SOH and SOC of batteries by analyzing thermal images or other spatial representations of battery parameters [32]. This approach allows for the detection of hotspots and other anomalies that might indicate battery degradation or failure. The application of CNNs in battery management is still a developing field, but early research has shown that these networks can outperform traditional methods by providing more accurate and timely predictions, thereby enhancing the overall safety and efficiency of EVs [33].

Recurrent Neural Networks (RNNs) in EVs

An especially useful type of neural networks for situations where the sequence and context of data points matter is the RNN. RNNs are specifically built to process sequential input. Since RNNs include an internal memory system, they may retain knowledge from past inputs even when processing fresh data, which sets them apart from standard neural networks. In applications like language processing, time-series forecasting, and speech recognition, where the temporal dynamics of the data are important, this skill is very helpful. Understanding context and forecasting future trends based on historical data is made possible by recognizing the relationships between successive data points, a job at which RNNs excel.

In the context of electric vehicles (EVs), RNNs find substantial application due to the prevalence of time-series data, which is integral to various aspects of vehicle operation and management. For instance, EVs generate a continuous stream of data related to battery performance, energy consumption, and driving patterns, all of which are sequential in nature. RNNs, particularly their advanced variants like LSTM networks, are adept at processing this type of data. LSTM networks, in particular, address the limitations of traditional RNNs by effectively managing long-term dependencies in the data. They prevent issues like vanishing and exploding gradients, which can hinder the learning process in standard RNNs when dealing with long sequences. This makes LSTM networks especially useful for predicting battery state of charge (SOC) over time, forecasting vehicle range, and analyzing driving behavior patterns, all of which are critical for optimizing EV performance and efficiency.

Moreover, the ability of RNNs and LSTM networks to model and predict complex temporal patterns extends beyond individual vehicle performance to broader applications within the EV ecosystem. For example, these networks can be employed in smart grid management, where they help in forecasting energy demand and optimizing charging schedules based on historical usage patterns. By accurately predicting when and where EVs will need to be charged, RNNs contribute to more efficient energy distribution, reducing the load on the grid and minimizing energy costs. Additionally, in autonomous driving, RNNs can be used to model and predict vehicle trajectories, enabling more precise control and navigation in dynamic environments. By processing sequential sensor data, such as radar or lidar signals, RNNs can anticipate the movements of other vehicles and obstacles, thereby enhancing the safety and reliability of autonomous EVs. Fig 3 illustrated about the RNN for EV charging. The versatility of RNNs and their advanced variants like LSTMs make them indispensable tools in the evolving landscape of electric vehicles, where understanding and predicting temporal patterns are key to innovation and efficiency.

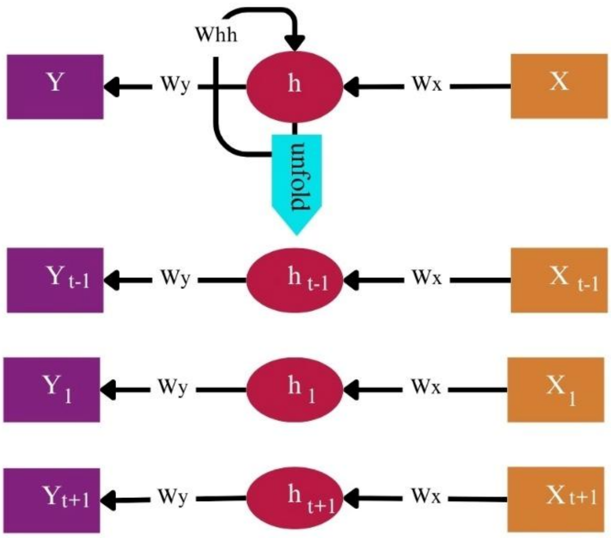

Fig 3. RNN for EV charging.

Generative Adversarial Network (GAN)

GANs are a powerful type of machine learning models that have gained popularity because they can produce artificial data that resembles real data in many ways which is illustrated in Fig 4. In the context of electric vehicles (EVs), GANs offer significant potential across various applications, from improving battery technology to enhancing autonomous driving systems. The core idea behind GANs is to pit two neural networks, a generator and a discriminator, against each other in a game-theoretic framework [73]. Through this adversarial process, the generator becomes increasingly adept at producing data that closely mimics real-world samples, leading to high-quality synthetic data generation. This capability is particularly valuable in the EV sector, where data-driven innovation is crucial for advancing technology and optimizing performance.

One of the most promising applications of GANs in the EV industry is in battery management and development. Battery performance and longevity are critical factors in the widespread adoption of EVs, and understanding the complex behaviours of batteries under various conditions is essential. However, gathering large amounts of high-quality battery data can be challenging, especially for rare or extreme conditions that are difficult to replicate in testing environments. GANs can be employed to generate synthetic battery data that closely resembles real-world data, allowing researchers to simulate and study battery behaviour under a wider range of conditions [74]. This synthetic data can be used to train machine learning models for battery state of charge (SOC) estimation, state of health (SOH) prediction, and fault detection, leading to more robust and accurate battery management systems. Additionally, GANs can aid in the design and testing of new battery materials by generating virtual datasets that can accelerate the discovery of materials with superior performance characteristics.

Beyond battery technology, GANs have significant applications in enhancing the capabilities of autonomous driving systems in EVs. Autonomous vehicles rely heavily on vast amounts of sensor data to navigate complex environments safely. However, collecting and labelling such data, particularly for rare or dangerous driving scenarios, can be both time-consuming and costly. GANs can generate realistic synthetic sensor data, such as images from cameras, lidar, and radar, to augment the training datasets used to develop autonomous driving algorithms. This approach allows for the simulation of a wide variety of driving conditions, including adverse weather, nighttime driving, and unexpected obstacles, without the need for extensive real-world data collection [75]. By improving the diversity and richness of the training data, GANs contribute to the development of more robust and reliable autonomous driving systems that can better handle the complexities of real-world driving.

Furthermore, GANs can be utilized in the design and optimization of EV infrastructure, such as charging stations and smart grid systems. Predicting and managing the demand for charging infrastructure is a complex task that requires understanding patterns of EV usage and energy consumption. GANs can generate synthetic data on EV charging behaviour, which can be used to simulate and optimize the placement and operation of charging stations. This synthetic data can help planners and engineers design more efficient and responsive charging networks that can accommodate the growing number of EVs while minimizing costs and environmental impact.

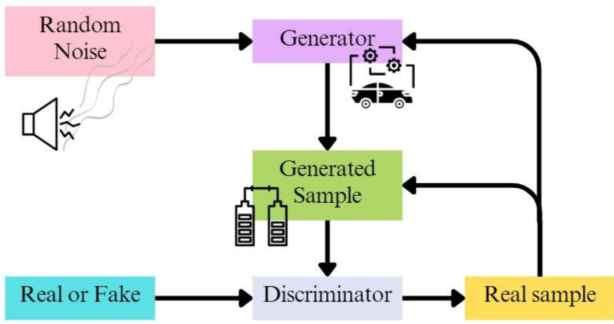

Fig 4. GAN basic architecture.

The fundamental idea of GAN is shown in Fig. The generator approximation and discriminator's nonlinear functions are denoted by the symbols (·) and G(z), respectively. The real sample distribution and random noise distribution are shown as and respectively. because the discriminator and generator have distinct training goals. Accordingly, the objective function is defined as follows in equation 2 and 3:

$$\min_G\{L_G(D,G)=E_{Z\sim P_n}[\log(1-D(G(z)))]\} \tag{2}$$

$$\max_D\{L_D(D,G)=E_{x\sim P_{\text{data}}}[\log D(x)]+E_{Z\sim P_n}[\log(1 \quad D(G(z)))]\} \tag{3}$$

where LD, G) and L (D, G) symbolize the generator's and discriminator's goal functions. As seen in equation, equations and may be incorporated into a single goal function for the GAN's entire training process.

Generative Adversarial Networks (GANs) offer transformative potential in the electric vehicle industry by enabling the generation of high-quality synthetic data that can drive innovation in battery technology, autonomous driving, and infrastructure development. In battery management, GANs can create synthetic datasets that simulate battery behavior under various conditions, improving the accuracy and reliability of battery models. In autonomous driving, GANs can generate realistic sensor data to enhance the training of algorithms, leading to safer and more robust autonomous systems. Additionally, GANs can aid in the design and optimization of EV infrastructure, ensuring that charging networks and smart grids are equipped to handle the demands of an increasingly electrified transportation system.

LSTM

LSTM network, categorized as a RNN, is specifically designed to tackle the challenge of the vanishing gradient problem prevalent in conventional RNN architectures. Its advantageous feature of being less affected by gap length sets it apart from traditional RNNs, hidden Markov models, and other sequence learning methodologies. LSTM is useful for understanding the long-term relationships between the deteriorated lithium-ion battery capacities. The LSTM model developed exhibits proficiency in capturing the inherent long-term dependencies within degraded capacities, ultimately constructing a robust RUL predictor oriented towards capacity which is showed in Fig 5. Its long-term learning performance is contrasted with models like the particle filter, support vector machine, and basic neural network. By using gating methods to control gradients and information flow, LSTM efficiently addresses the problem of disappearing gradients, enabling the network to learn and remember information across longer sequences. The forget gate, output gate, and input gate are the three fundamental gates included in the LSTM architecture.

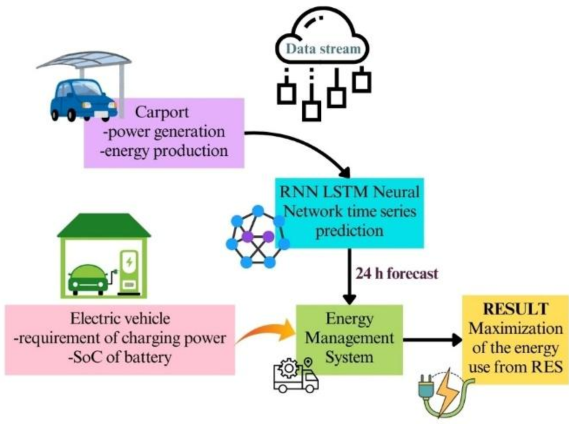

Fig 5 Deep RNN-LSTM neural network for EV charging.

Energy Consumption Prediction

RNNs have been widely used for predicting energy consumption in EVs, which is crucial for optimizing driving range and improving energy efficiency. Since energy consumption in EVs is influenced by various factors such as driving patterns, road conditions, and environmental factors, RNNs are ideal for capturing these temporal dependencies. For example, an LSTM network may be trained on previous driving data to forecast future energy usage, enabling more accurate range estimates and better energy management methods [34][35]. These predictions can be used to optimize route planning and charging strategies, thus enhancing the overall efficiency of EV operations. Moreover, by integrating RNN-based predictions with real-time data, EVs can adapt to changing conditions, such as traffic or weather, thereby improving the accuracy of energy consumption estimates [36].

Battery Aging and Degradation Analysis

RNNs are also used to model the aging and degradation processes of EV batteries, which are inherently sequential in nature. Battery degradation is influenced by the cumulative effects of charge-discharge cycles, temperature variations, and other operational factors. RNNs, especially LSTMs, are capable of learning these complex temporal relationships, making them well-suited for predicting battery life and planning maintenance schedules [37]. An LSTM network was employed in one study to analyse charge-discharge cycle history in order to forecast the remaining usable life (RUL) of EV batteries. The model was able to provide more accurate predictions compared to traditional methods, which often rely on simplistic linear models or rule-based approaches [38]. This improved accuracy is critical for ensuring the longevity and reliability of EV batteries, which are one of the most expensive components of the vehicle.

Driver Behavior and Adaptive Control

Another application of RNNs in EVs is in modelling and predicting driver behavior. Understanding and predicting driver behavior is essential for developing adaptive control systems that can optimize vehicle performance based on individual driving styles. RNNs can be trained on time-series data collected from various sensors within the vehicle, such as speed, acceleration, and steering angle, to predict future driver actions [39]. For example, an LSTM network could be used to predict aggressive driving behavior, allowing the vehicle's control systems to adjust power delivery and regenerative braking in real-time to enhance safety and efficiency. The development of autonomous driving features and advanced driver assistance systems (ADAS) depends heavily on this capacity [40].

While CNNs and RNNs have shown great promise in enhancing the capabilities of EVs, several challenges remain. The requirement for substantial datasets in order to properly train neural networks is one of the primary obstacles. It can take a lot of time and money to gather and identify such data, especially for applications involving autonomous driving [41]. Furthermore, real-time applications may be limited by the computational complexity of deep neural networks, especially CNNs, which need a large amount of processing power [42]. Another challenge is the generalization of models across different driving environments and battery chemistries. For instance, a CNN or RNN trained on data from one type of battery or driving condition may not perform well when applied to different scenarios. Therefore, future research should focus on developing more robust models that can generalize across various conditions and can be efficiently deployed in real-time systems [43]. To create more intelligent and adaptable control systems for EVs, there is also significant interest in integrating neural networks with other machine learning methods, such reinforcement learning. Furthermore, the use of transfer learning, which involves optimizing a model trained on one task for a related task, may assist reduce the amount of data needed and enhance model generalization [44].

Review Of Neural Networks for Ev Charging Behaviour

This evaluation regards session charging behavior $B_{session}$, given a charging session, as followed in equation 4.

$$B_{\text{session}}\,(t_{\text{con}}\,, t_{\text{full}}\,, t_{\text{discon}}\,, e) \qquad (4)$$

where e stands for the energy supplied to the car during the session, t for the time after which no charge was delivered, t_{discon} for the disconnection time (also known as the departure or end time), and t_{con} for the connection time (also known as the arrival or start time). This may define the session duration, S_{dur}, as follows based on the information provided in equation 5.

$$S_{dur} = t_{con} - t_{discon} \qquad (5)$$

Studies have also explored specific charging behaviors, such as the duration until the next plug-in, the likelihood of a vehicle charging the next day, and the charging speed. After covering the foundational concepts, a review of recent research utilizing deep learning (DL) for analyzing EV charging behavior will be conducted. The review will start by comparing various supervised learning techniques before exploring unsupervised learning methods. Although deep learning is often divided into supervised and unsupervised methods, owing to the recent accomplishments of deep learning models and the growing interest from the academic community, it will be covered in a distinct section. The goal of this framework is to make DL in this subject easier for researchers to access.

Comparative Analysis of Deep Learning Techniques for Analyzing Electric Vehicle Charging Behavior

A comparative study of deep learning methods for EV charging behavior analysis identifies unique advantages and disadvantages for each model. Methods like as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are excellent at detecting temporal relationships in charging patterns, which makes them very useful for predicting user behavior. Conversely, load forecasting and spatial data analysis are key components of grid management optimization, and here is where Convolutional Neural Networks (CNNs) shine. Autoencoders and Generative Adversarial Networks (GANs) offer robust simulation capabilities for charging infrastructure planning, while ensemble learning methods, such as those combining multiple models, have shown superior performance in handling complex, heterogeneous data sets. The choice of deep learning technique often depends on the specific application, with some models offering better accuracy in user behavior prediction and others excelling in load forecasting and anomaly detection, ultimately contributing to a more reliable and efficient EV charging ecosystem.

A range of studies have focused on predicting various aspects of electric vehicle (EV) charging behavior, utilizing different deep learning (DL) models to achieve varying levels of accuracy and impact. The study conducted by reference [45] aimed to predict the energy consumption and session duration for both residential and non-residential electric vehicle (EV) charging scenarios. The researchers employed an ensembled model that combined Random Forest (RF), Data Kernel Density Estimation (DKDE), and Support Vector Regression (SVR). The results of this model were promising, achieving a Symmetric Mean Absolute Percentage Error (SMAPE) of 10.4% for charging duration and 7.54% for energy consumption. Furthermore, this model demonstrated its practical use in improving EV charging procedures by reducing the peak strain by 27% and the charging cost by 4% when integrated into a scheduler.

In the research presented by reference [46], utilized a probabilistic Gaussian Mixture Model (GMM) to achieve this objective. The model's performance was quantified with a SMAPE of 12.25% for user duration and 12.73% for energy consumption. These results underline the effectiveness of the GMM in forecasting energy needs in public charging environments, providing a useful tool for managing energy consumption in such settings.

Furthermore, it explored the prediction of EV charging departure times. The researchers used regression models, including XGBoost (XGB) and Linear Regression (LR), to develop their predictive model. Among these, the XGBoost model delivered the best performance, with a MAE of 82 minutes for predicting the departure time. This outcome suggests that XGBoost can be a reliable method for estimating when an EV will finish charging, which is crucial for managing charging stations efficiently. The study focused on predicting the end time, start time, and energy consumption of EV charging sessions. Linear Regression (LR) was employed specifically for predicting energy consumption. However, the study did not report specific results or impacts from this model, leaving an area for further research and development in this domain [48].

Moreover, the research highlighted by reference [49] cantered around predicting the departure and arrival times of EVs on a university campus, a non-residential setting. Support Vector Machines (SVMs) were used to build the predictive model. The model achieved an average MAPE of 3.7% for departure time predictions and 2.85% for arrival time predictions. These low error rates indicate that the SVM model is highly accurate in forecasting charging schedules, which can be particularly beneficial in managing university campus charging facilities.

Based on a residential dataset, the research in [50] focused on predicting whether or not EVs will be charged the next day and identifying the exact hours that they would be charged. An ensembled model that incorporated Gradient Boosting, AdaBoost, RF, and Naive Bayes was used in the study. With a True Positive Rate (TPR) of 0.996 for predicting if the EVs will be charged and an accuracy of 0.724 for forecasting the charging hours, the findings were outstanding. This model provides a robust tool for predicting residential EV charging behavior, aiding in better planning and energy management.

In fact, the researchers' goal in the study reported in reference [51] was to forecast how much electricity a charging outlet on a college campus would need. They employed a k-Nearest Neighbors (KNN) model and found that setting k to 1 produced the best results (1-NN). The SMAPE of 15.27% was attained by the model. In addition, a smartphone application that incorporates the predictive model enables users to estimate the final charging time and energy usage in less than a second. This integration demonstrates how the model may be used practically in situations that occur in real time.

In the meanwhile, this research looked at how much electricity a university campus would use at a charging outlet over the course of the following 24 hours. PSF, SVR, and RF were among the machine learning models used in the study. With an average SMAPE of 14.06%, the PSF model produced the greatest results out of all of them. This model is a useful tool for controlling energy use in academic contexts because of its capacity to predict short-term energy demands [52].

The focus was on predicting the energy consumption of a single charging session. The researchers used a PSF-based model combined with k-Nearest Neighbors (kNN). The model achieved a SMAPE of 7.85%, indicating a high level of accuracy in estimating the energy consumption of individual charging sessions. This result demonstrates the model's potential for use in optimizing charging station operations [53]. The purpose of the study reported in [54] was to categorize drivers' propensity to use rapid charging. For this categorization job, binary logistic regression was used by the researchers. With an accuracy of 0.894, the model proved to be useful in forecasting rapid charging behavior. These forecasts are essential for maintaining charging station references and guaranteeing rapid charging availability as required.

Undoubtedly, [55] investigated how long it would take to anticipate the next home EV charging plug-in. SVR with a radial basis function kernel was used in the investigation. The model's performance was measured using an RMSE of 0.158 minutes and an MAE of 0.124 minutes. These low error rates suggest that the model is highly accurate in predicting the timing of the next plug-in, which can help in scheduling and managing residential charging loads. In the research presented by [56], the focus was on predicting charge profiles in a workplace setting. The study used Artificial Neural Networks (ANN), XGBoost, and Linear Regression (LR) as the predictive models. With an MAE of 126 watts, XGBoost produced the best results. Additionally, incorporating the model into scheduling practices led to a 21% increase in charging efficiency. This demonstrates the model's potential for improving workplace charging station management.

In light of this, [57] sought to create a model that could forecast charging speed in response to factors including temperature, connection duration, and State of Charge (SOC). The researchers employed Linear Regression (LR) for this task. While the study did not report specific results, the focus on these factors highlights the importance of considering environmental and operational conditions in predicting charging speed. Thus [58] examined the estimation of daily charging times and charging capacity. Random Forest (RF) was the prediction model employed in the investigation. When estimating the charging load over the next fifteen minutes, the findings showed a MAPE of 9.76% for individual stations and 12.8% for clusters of stations. These findings underscore the model's utility in forecasting short-term charging demands, which is essential for optimizing the operation of charging stations.

Another significant area where deep learning contributes is in the planning and optimization of charging infrastructure. Techniques like Autoencoders and Generative Adversarial Networks (GANs) are employed to simulate various charging scenarios, aiding in the strategic placement of charging stations to minimize user inconvenience and optimize the use of available resources. The integration of deep learning in EV charging also extends to security aspects. Deep learning models can detect anomalies in charging behavior, which could indicate potential security breaches or malfunctioning equipment. This is particularly important as EV charging systems become more interconnected and integrated with the smart grid, where cyber-attacks could have significant repercussions. Finally, deep learning models are also being used to offer personalized charging recommendations to users. By analyzing individual driving habits and charging history, these models can suggest optimal charging times and locations, helping users reduce costs and avoid peak demand periods. This personalized approach enhances the overall user experience and contributes to a more balanced and efficient energy distribution system.

In the study referenced by [56], researchers explored clustering behaviors in electric vehicle (EV) charging by using K-means clustering with squared Euclidean distance. The resulting model classified future data instances into six clusters, achieving a Silhouette score of 0.7, which indicates moderate clustering performance. Additionally, the K-Nearest Neighbors (KNN) algorithm was used for classification, yielding a precision of 0.5 and a recall of 0.47. Consequently, while the clustering provided some valuable insights, the classification results suggest room for improvement in predicting future behaviors.

Furthermore, this study focused on identifying distinct clusters in non-residential EV charging behavior through the use of a Gaussian Mixture Model (GMM). The study found that the Adjusted Rand Index (ARI) value was above 0.6 for all clusters except one, indicating a generally strong clustering performance. However, the exception highlights that some behaviors might be more challenging to cluster accurately, suggesting the need for more refined modeling approaches in complex environments [60]. Similarly, it applied GMM to create EV profiles that capture charging behavior based on existing data. This approach allowed for the identification of probabilistic patterns within the data, which are crucial for understanding and predicting charging trends. Notably, although the specific evaluation metrics were not provided, the use of GMM in this context underscores its effectiveness in modeling complex data distributions, making it a valuable tool for profiling EV charging behaviour [61]. Furthermore, [62] used a Beta Mixture simulate (BMM) to simulate the multi-modal probability distributions of variables like connection and idle times in order to study the behavior of EV charging. According to the survey, there are notable variations in the charging habits of weekdays and weekends. Weekends account for 25% of overall energy supply, and 50% of recharges are completed in less than four hours. Furthermore, it was found that idle periods lasted for almost four hours. As a result, the results illustrate the variety in charging behavior and the need of taking temporal elements into account when constructing charging infrastructure.

On the other hand, this study combined departure and arrival time data to identify EV charging habit groups using a Density-Based (DB) clustering technique. The analysis resulted in the identification of three distinct clusters. However, the study did not provide detailed cluster evaluation metrics, which limits the ability to fully assess the clustering quality. Consequently, while the study offers insights into charging patterns, the absence of performance evaluation necessitates caution in interpreting the results [63]. Furthermore, [64] employed K-means clustering with Euclidean distance to identify clusters in EV charging behavior, resulting in four distinct clusters. Unfortunately, the study did not include cluster evaluation metrics, making it challenging to validate the effectiveness of the identified clusters. Consequently, even though the strategy was effective in classifying the data, the absence of assessment measures is a serious drawback that has to be addressed in other studies.

On the other hand, [65] combined clustering and classification to analyze EV charging behavior. After identifying three groups using K-means clustering using Euclidean distance, the researchers employed KNN for classification, resulting in an Area Over the ROC Curve (AUC) of 0.99 and a classification accuracy of 97.9%. Consequently, these results demonstrate the high potential of this combined approach for accurately predicting future charging sessions, making it a powerful tool for EV charging behavior analysis. Additionally, [66] explored residential EV charging behavior by applying hierarchical clustering with the Ward linkage method. The study identified four distinct clusters and used the results to forecast charging loads with a Random Forest (RF) model, achieving a MAE of 4.9 kW. However, the absence of clustering evaluation metrics leaves some uncertainty regarding the clustering quality, although the successful load forecasting suggests that the clusters captured relevant patterns in the data.

Similarly, this study aimed to predict future EV charging behavior by first clustering the data using the Expectation-Maximization (EM) algorithm. The study identified four clusters of charging behavior and found that as prediction errors increased, the associated cost reduction and savings decreased. Consequently, this highlights the critical importance of accurate predictions in optimizing charging strategies, particularly in contexts where cost efficiency is a priority [67]. Furthermore, [68] used the Davies-Bouldin assessment criterion to calculate the number of clusters and K-means clustering to identify trends in EV charging characteristics across three UK counties. Three clusters in the West Midlands, six in Nottinghamshire, and five in Leicestershire were found by the research. Nevertheless, the lack of detailed cluster evaluation metrics limits the ability to fully validate these findings, suggesting that future research should include comprehensive evaluations to ensure the robustness of the identified patterns.

In contrast, reference [69] focused on predicting session duration and energy consumption using a DKDE model. The study found that the proposed DKDE method outperformed the traditional Gaussian Kernel Density Estimation (GKDE) method, as demonstrated through graphical plots. Consequently, this suggests that DKDE is a better option for modeling EV charging patterns as it offers a more realistic depiction of the underlying data distribution. Similarly, the below research examined the differentiation between intra-day and inter-day EV charging behaviors using the GKDE model. The study found that correlations were only noticeable when classifications were made into these two distinct groups. Consequently, this finding underscores the importance of distinguishing between different charging behaviors to enhance the accuracy of predictive models, particularly in contexts where temporal factors play a significant role [70].

Additionally, the research below developed a hybrid estimator that combined GKDE and DKDE methods to predict charging session duration and energy consumption. The study achieved a median stay duration of 0.75 hours and a median energy consumption of 0.68 kWh, indicating that the hybrid model effectively captured central tendencies in the data. Therefore, this approach highlights the benefits of integrating multiple estimation methods to improve prediction accuracy in EV charging behavior analysis [71]. Lastly, reference [72] forecasted parking lot recharging demand using an ARIMA time series model based on anticipated EV arrival and departure timings. Consequently, this demonstrates the substantial economic benefits of accurate demand forecasting in optimizing EV charging infrastructure, making it a valuable tool for large-scale planning.

Conclusion

The comparative review of neural network approaches for state of charge (SOC) estimation in electric vehicles (EV's) underscores the critical role that accurate SOC estimation plays in enhancing the efficiency and reliability of electric vehicle systems. As the global emphasis on environmental sustainability and carbon neutrality grows, the need for advanced battery management systems has become increasingly urgent. Lithium-ion batteries, which power the majority of modern EVs, require precise SOC estimation to ensure optimal performance, extend battery life, and maintain safety standards. This review has highlighted the importance of leveraging neural network models, given their ability to handle complex, nonlinear relationships and their superior performance in SOC estimation tasks.

The review also emphasizes the relationship between SOC estimation and battery aging, a crucial factor that directly impacts the accuracy and reliability of SOC predictions. As batteries age, their capacity and performance degrade, which can lead to significant deviations in SOC estimation if not properly accounted for. Neural network models, with their ability to adapt and learn from new data, offer a promising solution to mitigate the impact of battery aging on SOC estimation. However, further research is needed to refine these models, particularly in developing techniques that can accurately account for the aging process over the entire lifespan of a battery. In conclusion, while significant progress has been made in neural network-based SOC estimation, there is still ample room for improvement. Future research should focus on developing more efficient algorithms that require less computational power, improving the robustness of models under diverse operating conditions, and enhancing the ability to accurately estimate SOC as batteries age. Additionally, integrating these advanced neural network models into intelligent battery management systems will be key to unlocking the full potential of electric vehicles. By addressing these challenges, researchers and engineers can contribute to the development of next-generation EVs that are not only more efficient and reliable but also more aligned with global sustainability goals.

Author contribution

Author 1 designed the study, led the comparative analysis of past research, and drafted the manuscript, including ensuring the accuracy of grammar and Figures. Author 2 reviewed the literature, developed the theoretical background, and contributed to the overall structure and organization of the review.

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