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Neural Network Based Decision Support System for Forecasting the Power Needs of Electric Vehicle

S. Suganya[1], K. Padmapriya[2]
[1]*Associate Professor, Department of Electrical and Electronics Engineering,*
[2]*Assistant Professor, Department of Electronics and Communication Engineering,*
AAA College of Engineering and Technology, Sivakasi- 626005, Tamilnadu, India.

Abstract:- Global energy trends are undergoing significant changes, and the future of transportation will promote sustainable development by managing energy production and consumption while reducing vehicle emissions. Electric Vehicles (EVs) have the potential to reshape energy consumption patterns by mitigating environmental risks. In the upcoming years, Artificial Intelligence (AI)-based systems will be pivotal in the comprehensive energy management of EVs. Advanced EV technology and intelligent components will drive innovation in automotive power train design. However, several challenges like regional government support, user acceptance, vehicle range, battery technology, and charging infrastructure hinder widespread EV adoption. Therefore, understanding current conditions and emerging trends is crucial to expand EV penetration. This study explores existing charging technologies and standardization efforts to enhance EV adaptability, along with AI applications in advancing EV intelligence. Range and battery level estimation are critical for the safe and efficient operation of electric vehicles (EVs). This work proposes a Neural Network (NN)-based approach for battery level estimation in EVs. The findings indicate that the suggested neural network-based method can attain greater accuracy and quicker convergence compared to current techniques. This can lead to more efficient electric vehicle operation and enhanced battery lifespan.

***Keywords**:* Electric Vehicle, Artificial Intelligence based approach, Neural Network, Range and battery temperature estimation

1. Introduction

The use of rechargeable batteries is recommended for storing renewable and other types of energy. Lithium-ion (Li-Ion) batteries, known for their high energy density, reliable safety features, and environmentally friendly nature, lead the global battery market, especially in Electric Vehicles (EVs) and power banks [1-4]. The key parameter for lithium-ion batteries in information-based applications is the state of charge (Battery temperature). Battery temperature is influenced by various short-term and long-term factors and represents the ratio of the remaining capacity to the current rated capacity. Ensuring that the battery operates within a safe range benefits the battery management system (BMS). Therefore, accurately estimating the Battery temperature is crucial for determining the distance under load and the battery's intrinsic state of charge under mechanical load. Lithium-ion batteries perform optimally when their battery temperature is precisely measured.

Battery temperature contributes to optimal battery management, improved energy efficiency, and real-time battery monitoring, taking into account both long-term and short-term operating conditions [5,6]. This data can also be utilized by the vehicle's control system to optimize energy consumption and extend the vehicle's range. In renewable energy systems like solar or wind power, precise Battery temperature estimation is crucial for optimizing the use of stored energy and ensuring that there is enough energy available to meet demand.

The use of EVs is growing in popularity due to their potential for reducing greenhouse gas emissions and dependence on fossil fuels [7-13]. Accurate estimation Battery temperature of the battery is essential for the proper operation of an EV, as it indicates the amount of energy remaining in the battery and can affect the performance and range of the vehicle. Traditionally, Battery temperature estimation has been performed using mathematical models based on the electrochemical characteristics of the battery [14-20]. However, these models can be complex and may not accurately reflect the real-world behavior of the battery, especially in cases where the battery has aged or experienced other factors that can affect its performance.

1.1 Literature review

Battery temperature must be implicitly calculated based on observable battery characteristics and factors since it cannot be directly defined. Due to its relevance in predicting EV range, Battery temperature estimation is crucial [21-26]. Over the years, various Battery temperature estimation techniques have been developed and can be broadly categorized into four groups: lookup table approach, ampere-hour integral method, model-based estimation method, and model-free parameter estimation. The lookup table methods have known limitations and have gradually been replaced by more advanced techniques like the model-based estimation method. Researchers have combined these with nonlinear state estimation algorithms to enhance the estimation capabilities of Lookup Table (LUT), Coulomb-Counting, and model-based techniques [27-30]. Common algorithms in the literature include the Kalman filter, Luenberger observer, proportional integral viewer, and sliding mode viewer.

The traditional Kalman filter is sensitive to nonlinear processes, temperature, and battery charging/discharging as it is suitable only for linear systems. To address this, the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) have been effectively used to estimate Battery temperature [31-36]. Fuzzy logic, a popular AI approach, uses multi-valued logic to compute Battery temperature while considering various factors like age, temperature, and noise [37-40]. However, it requires extensive training data and long-term data collection experience to develop reliable rules. Support Vector Machines (SVM) and Gaussian Process Regression (GPR) perform well, especially in nonlinear battery modeling. Recent research has modified and improved these methods to handle multiple input parameters effectively. The Greenwald-Khanna method, which uses entropy weight and Kernel functions with genetic evolution, is recommended for clustering and battery state prediction, providing more accurate capacity, battery cell package clustering, and energy estimates [41-46]. However, complex computing remains a significant issue, hindering implementation in battery management systems (BMS).

Coulomb counting, a simple Battery temperature calculation technique, accumulates the net charge over time in ampere-hours (Ah). Its effectiveness depends on the accuracy of current sensors and the initial Battery temperature calculation [47-50]. As an open-loop estimator, it does not completely prevent the accumulation of measurement errors and ambiguities, nor can it account for initial Battery temperature variations due to self-discharging or identify the initial Battery temperature, leading to increasing estimation errors over time. Data-driven estimation approaches have also been employed to estimate Battery temperature. Techniques like Support Vector Machines, fuzzy control, and Artificial Neural Networks (ANN) are commonly used in classical machine learning applications, typically involving no more than two layers of processing [51,52]. ANN has gained attention for state estimations under various battery dynamics, fluctuating loads, and changing temperatures. The main advantage is that information fusion-based models accurately represent the nonlinear behavior of the battery discharging and charging process due to the training process. However, selecting the activation function for hidden nodes, determining the number of neurons in the hidden layer, and adjusting the learning rate pose challenges [53-58]. Traditional neural networks often involve complex computations and may be inaccurate when training data is scarce or get stuck in local minima with large training datasets.

Recent advancements have made traditional ANN more effective. Adding more computational layers, thanks to improvements in software and hardware, has significantly enhanced conventional ANN capabilities [59]. The deep neural network (DNN), an ANN with additional computational layers, excels in fields such as computer vision, speech recognition, and natural language processing with smarter training methods and adjustments [60-64]. Despite these advancements, accurate Battery temperature estimation remains essential to accommodate various conditions and the electrochemical properties of materials used in classical empirical techniques. Robust algorithms are crucial for collecting and analyzing data to improve Battery temperature estimation under diverse operating scenarios. Most existing models do not account for aging health factors and the cross-correlations of Battery temperature with interdependent nonlinearities in collected data [65-70]. Modern Battery temperature estimation is vital to equip EVs with accurate and reliable systems for monitoring and managing their batteries.

This paper is organized into five sections. Section 1 provides an introduction. Section 2 details the proposed technique designed to enhance the efficiency of Battery temperature estimation. Section 3 explains the drive cycle datasets used in this study, including their sources and characteristics. Section 4 presents the results obtained from the proposed technique and offers a comprehensive discussion of the findings. Finally, Section 5 concludes the study and summarizes the main findings.

2. Proposed Methodology

This paper presents a comprehensive study aimed at accurately predicting the battery temperature of Lithium-ion batteries in Electric Vehicles (EVs) across a range of low and high temperatures. The graphical abstract illustrating the proposed model can be found in Figure 1.

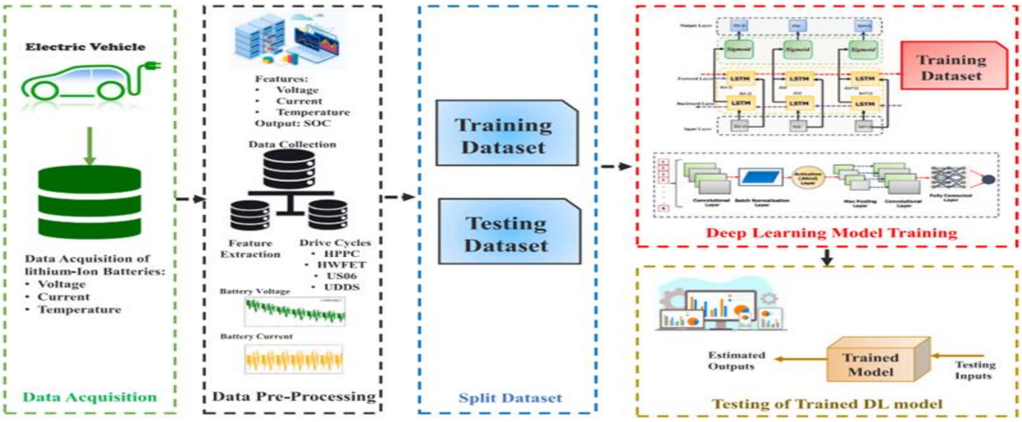

Figure 1: Proposed model for training and testing the data set

2.1. Aritificial Neural Network

Artificial Neural Network (ANN) is a type of deep neural network widely used in image and video recognition. It consists of multiple layers, each applying a set of filters to the input data to extract features. The input to a ANN is typically a multidimensional array, such as an image represented as a matrix of pixel values. The filters, or kernels/weights, used by each layer are also multidimensional arrays that are learned during training. The general structure of a ANN is depicted in Figure 2.

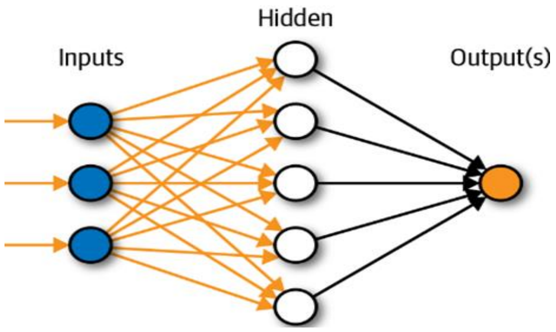

Figure 2: Architecture of Artificial Neural Network

A 1D ANN is a variant of Convolutional Neural Network (CNN) designed to process one-dimensional data, such as time series signals. It performs a convolution operation on the input data along one dimension, using a sliding window of fixed size to extract features from the signal. The input to a 1D ANN is typically a sequence of real values, represented as a one-dimensional array. The filters used by each layer are also one-dimensional arrays, known as kernels or weights, learned during training. The output of a convolutional layer in a 1D ANN is produced by applying a convolution operation between the input and the kernel along the time dimension.

3. Drive cycles of EV

Drive cycles are standardized driving patterns used to assess electric vehicle battery performance, particularly for State of Charge (Battery temperature) estimation. Common drive cycles include HPPC (Hybrid Pulse Power Characterization), HWFET (Highway Fuel Economy Test), UDDS (Urban Dynamometer Driving Schedule), and US06 (Supplemental Federal Test Procedure). HPPC applies pulse power loads to the battery, while HWFET and UDDS simulate highway and urban driving conditions, respectively. US06 is a more aggressive cycle with high-speed driving and frequent stops. These cycles play a crucial role in Battery temperature estimation by providing a uniform method to evaluate battery performance under various driving conditions. This standardization enables manufacturers to conduct accurate comparisons and tests, enhancing Battery temperature estimation algorithms and ultimately improving battery longevity and performance.

3.1 Battery temperature dataset

In this study, datasets from HPPC, HWFET, UDDS, and US06 drive cycles at temperatures ranging from -20°C to 25°C were used to train and test the proposed model. Data sourced from the CALCE Research Group included tests on a cylindrical LG 18650HG2 Li-ion battery cell, following standard charging and discharging protocols with constant current/constant voltage procedures.

3.2 Dataset Diversity

Dataset diversity was analyzed through correlation analysis, an essential step to understand how different features impact Battery temperature estimation using deep learning models. The correlation matrix revealed significant relationships among voltage, current, temperature, and Battery temperature at -20°C for various drive cycles. Identification of highly correlated features helped mitigate multicollinearity and instability in the model. By selecting and optimizing input variables based on these correlations, the study aimed to develop a more precise and reliable deep learning model for Battery temperature estimation. Use the state of charge and temperature to determine the battery's condition. To forecast the future temperature profile of the battery, analyze the load applied to the battery pack and have some data on its current temperature state. To gather this information, use the product of the battery's instantaneous current and voltage as the load. You can predict future temperatures with knowledge of just a few initial battery temperature states. NARX models are well-suited for these applications. This example demonstrates how to define a NARX model with a temperature delay over multiple timesteps during training.

3.3 Battery Research and Development

Continuous research and development in electric vehicle (EV) batteries are crucial due to their high cost and significant impact on vehicle performance. AI and machine learning (ML) methods are increasingly being studied to enhance battery performance and efficiency while reducing costs. Research has particularly focused on lithium-ion batteries, solid-state batteries, and metal-air batteries as promising technologies. Cutting-edge advancements are improving battery performance, energy management, and battery pack management. A review of AI applied to battery research highlights neural networks, decision trees, support vector machines, and k-nearest neighbors as the most commonly used AI and ML methods in battery R&D (Lombardo et al., 2021).

These methods reduce computational demands for material selection, formulation, and operational conditions. The scientific literature has explored AI applications for estimating battery State of Health (SOH), State of Charge (BATTERY TEMPERATURE), Remaining Useful Life (RUL), and similar parameters (Li et al., 2019; Semeraro et al., 2022). However, there are limited academic studies on new data-driven approaches in battery research and development.

4. Results and Discussion

In this section, we first evaluate various layer structures of Deep Neural Networks (DNN) using the drive cycle dataset. Based on comparative analysis, we select the 3-layer DNN structure for State of Charge (SoC) estimation, which is then tested across all drive cycle scenarios. Finally, we present a comparative analysis with competing techniques, demonstrating that our proposed Hybrid model excels in SoC estimation.

4.1 Range Estimation:

The range of the vehicle still depends on real world driving conditions. The range also depends on the driver profile, including when the driving pattern is agressive (demanding lots of instantaneous power) or relaxed (stable speeds, gradual acceleration). In this example, you use typical worst case driving profile scenarios to evaluate the range provided by a 400V battery pack.

Automotive manufacturers conduct standardized drive cycles to determine the range rating of battery electric vehicles (BEVs). The industry commonly employs three main cycles: NEDC (New European Driving Cycle), WLTC (Worldwide Harmonised Light Vehicle Test Cycle), and EPA (Environmental Protection Agency) cycle. These cycles are conducted in controlled laboratory conditions. The NEDC cycle typically consists of two phases simulating urban and non-urban driving scenarios, lasting 20 minutes with a maximum speed of 120 km/hr and it is depicted in Figure 3.

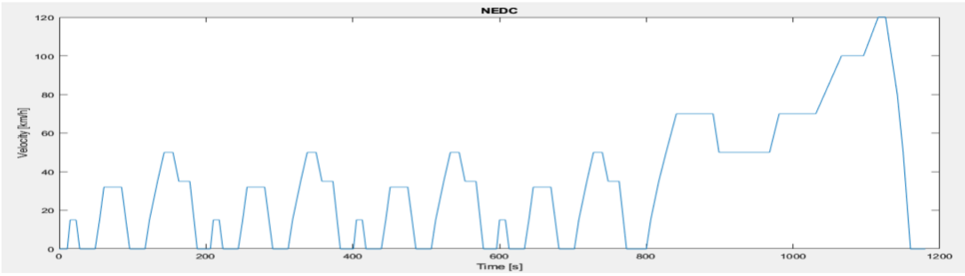

Figure 3: New European Driving Cycle

The typical WLTP (Worldwide Harmonised Light Vehicle Test Procedure) cycle comprises four dynamic phases: low, middle, high, and extra high speeds. It spans a duration of 30 minutes with a maximum speed reaching up to 131 km/hr as shown in Figure 4.

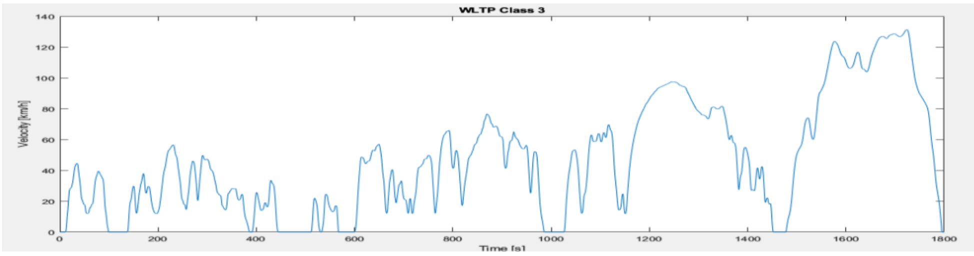

Figure 4: Worldwide Harmonised Light Vehicle Test Procedure

The EPA driving procedure involves subjecting the vehicle to multiple drive cycles. The two primary cycles utilized are UDDS (Urban Dynamometer Driving Schedule), designed for assessing urban fuel economy is shown in Figure 5, and HWFET (Highway Fuel Economy Driving Schedule), used to evaluate highway fuel economy as clearly explained in Figure 6.

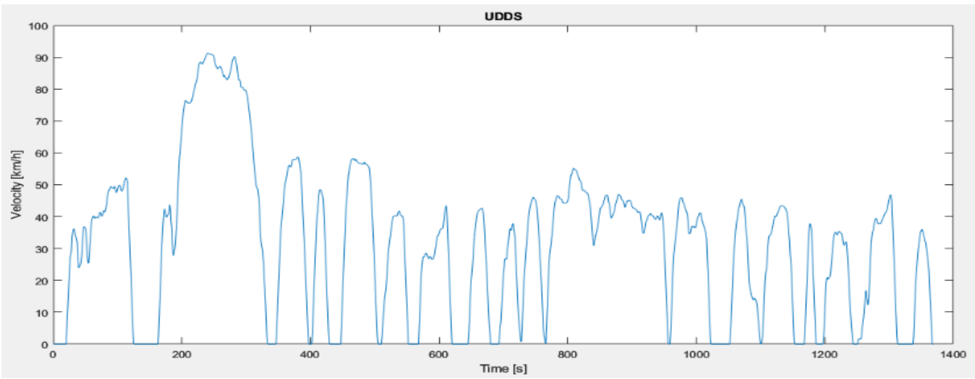

Figure 5: Urban Dynamometer Driving Schedule

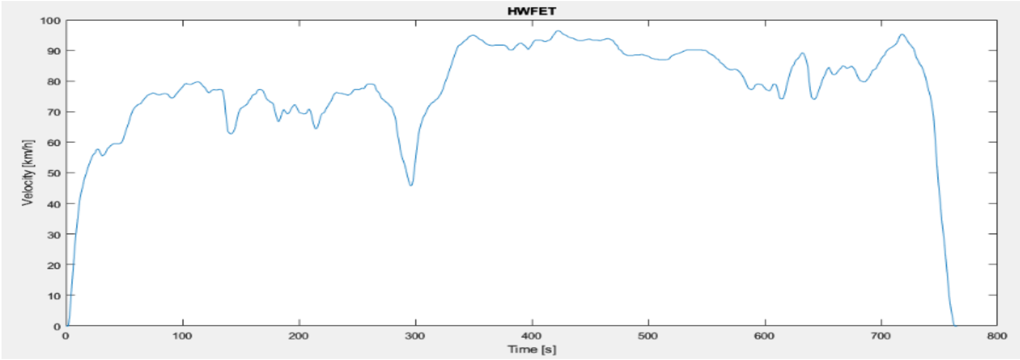

Figure 6: Highway Fuel Economy Driving Schedule

4.2 Battery Temperature Estimation

In automotive battery packs, sensors for pack voltage, current, and temperature relay measurement signals to the battery management system (BMS). These signals are crucial for battery control and logic implementation. Given the challenges of cost and installation complexity, especially in large battery packs, there's a need for alternative methods to estimate battery temperature numerically. This approach can either substitute or supplement sensors in the event of failure or malfunction, offering cost savings by eliminating the requirement for a thermocouple. The onboard numerical estimation of battery temperature relies on measurements from voltage and current sensors. For different gear ratio, the temperature of the winding and magnet is shown in Figure 7.

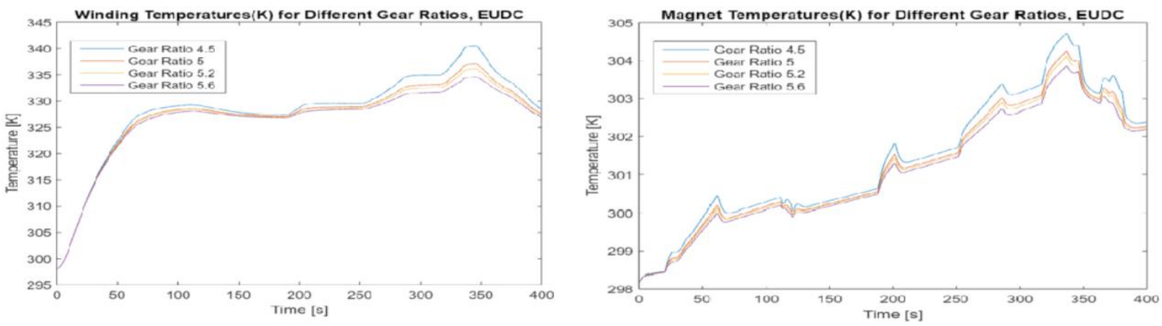

Figure 7: Winding temperature and magnet temperature for different gear ratio

The use of AI- and ML-based decision support systems for electric vehicle (EV) power requirements presents important managerial considerations. The temperature prediction in battery using the predicted and actual values is depicted in Figure 8.

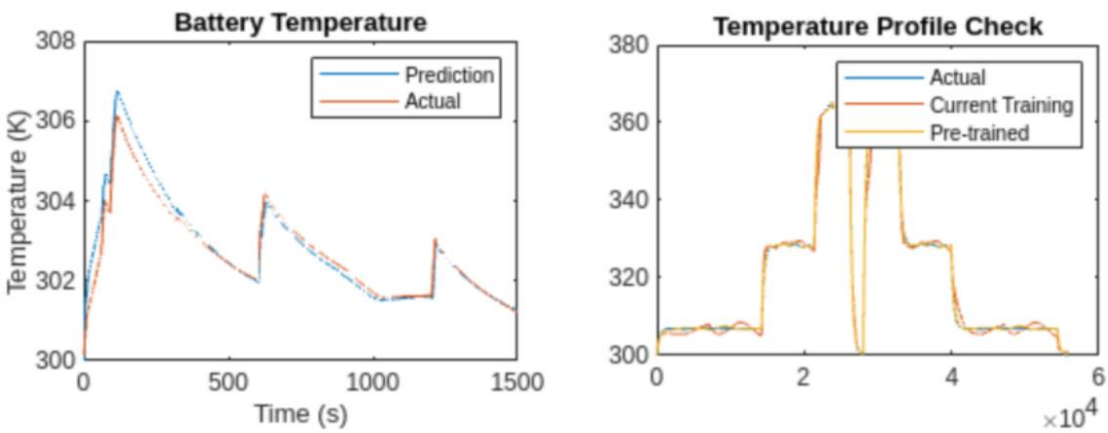

Figure 8: Temperature prediction and profile check

Integrating advanced forecasting technology offers significant advantages across various sectors. These sophisticated systems accurately predict EV electricity consumption patterns over different timeframes, from days to years. This foresight allows utilities to plan and schedule electricity generation and distribution more effectively, ensuring optimal resource allocation. Additionally, it helps utilities identify peak demand periods, enabling proactive management of electricity supply to meet the growing needs of EV users during these times. Furthermore, this technology facilitates the optimization of the placement and capacity of EV charging stations by analyzing data to identify regions with substantial EV demand.

Adopting this framework leads to tangible cost savings by optimizing EV charging schedules to align with periods of lower electricity rates. Organizations can reduce grid maintenance and operational expenses by utilizing off-peak charging hours, enhancing financial efficiency. Beyond economic benefits, this method strengthens the reliability of electrical power grids by proactively identifying and addressing potential issues before they escalate into disruptive outages, thereby enhancing the resilience of critical infrastructure and ensuring uninterrupted access to electricity for consumers. Additionally, this method aims to enhance the electrical grid's sustainability by minimizing fossil fuel usage. It promotes the efficient use of clean energy by coordinating EV charging with renewable energy sources.

For instance, EVs can be charged using wind power at night and solar power during the day, contributing to grid stability and the growth of renewable energy. Implementing AI and ML in decision support systems for predicting EV power requirements can significantly benefit electric car fleets by optimizing planning, scheduling, and charging infrastructure to reduce costs, increase reliability, and promote sustainability. Technologically, this method requires a system capable of processing, storing, and analyzing vast amounts of data in real-time. The system must also adapt to environmental changes, such as an increase in EV availability and the integration of renewable energy sources. Despite these challenges, AI- and ML-based decision support systems for determining EV power requirements show great potential for enhancing the efficiency and sustainability of electrical grids.

5. Conclusion and Future Research Directions

This study has developed a robust framework to identify the key characteristics of EV charging demand. By integrating artificial intelligence (AI) and machine learning (ML), the model uncovers latent features crucial for accurately calculating EV charging demand. The Demand Forecasting module effectively predicts power consumption across various locations and loads, spanning multiple timeframes. Implementing this model's strategies in managerial contexts enables the creation of feasible charging demand and load zone designs. For example, in areas with high charging demand, the model provides insights for optimizing power distribution through strategies like power swapping or augmentation. Its adaptable design is suitable for various scales, from smaller neighborhoods to entire countries, with only minor adjustments needed for different scenarios.

However, the effectiveness of the proposed model depends on several factors, such as localized weather conditions and the influence of marketing strategies on charging demand. A significant limitation of AI- and ML-based decision support systems is their dependence on data availability and quality. The reliability of these models is closely tied to the breadth and accuracy of the datasets they are trained on, necessitating careful attention to real-world representativeness. The complexity of AI and ML models also poses challenges in terms of interpretability and transparency, which are crucial for ensuring the validity and reliability of their conclusions. Additionally, AI and ML models are susceptible to biases, which can lead to skewed decision-making processes. Addressing these biases requires meticulous mitigation strategies. Security and privacy vulnerabilities are significant risks as battery temperature with AI and ML systems, highlighting the need for robust security measures and proactive risk mitigation strategies.

Future research should focus on improving data gathering and preparation methodologies, including techniques for data cleaning, anonymization, and handling missing data. This will ensure the integrity and utility of datasets. Developing accurate, robust, and interpretable AI and ML models requires exploring new methodological approaches and gaining a deeper understanding of their operational mechanisms. Transparent and interpretable models are essential for fostering trust and confidence in their outputs. Advancing model evaluation and validation techniques is critical for ensuring the reliability and applicability of AI and ML solutions. Comprehensive evaluation metrics and strategies for assessing accuracy and robustness are necessary for effectively gauging model performance. Addressing security and privacy concerns requires a multi-faceted approach, including the development of stringent security protocols, proactive threat detection mechanisms, and user education initiatives. Safeguarding AI and ML systems against potential vulnerabilities is paramount for upholding data integrity and user privacy.

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