

Research Paper

ANN-Based Fast Charging Control Strategy for Electric Vehicles with Intelligent Battery Thermal Management Using Renewable Energy Resources

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Abstract –

Automobile manufacturers have been incentivized to provide sustainable and eco-friendly transportation due to the increasing concern about atmospheric pollution. To hasten the broad adoption of battery-powered vehicles, rapid battery charging with a minimal recharging period aim is anticipated. This research presents a model for a rapid electric car charging system that uses renewable energy sources to power an autonomous DC microgrid. To address the issue of power demand management in dynamic situations, this study develops a novel DNN-based control strategy that combines model predictive control (MPC) with artificial neural networks (ANNs) instead of relying just on MPC. Fast direct current (dc) charging of electric vehicles (EVs) is supervised by an artificial neural network (NN) that uses energy available from renewable sources and battery backup devices. We recommend a battery temperature control method to keep EV batteries safe and efficient even under the most demanding situations. Results from simulation experiments under different operating situations demonstrate that the proposed ANN MPC system outperforms the MPC controller. Slide mode improved load power utilizing SMC in conjunction with ANN, and improved fuel cell power using SMC, are all possible when employing an ANN controller.

Keywords – Electric Vehicle, MPC, ANN, SMC, DNN.

1. INTRODUCTION

There is an increasing need to enhance energy efficiency and decrease emissions of greenhouse gases; EVs are quickly becoming one possible answer to this problem. An important step toward a more sustainable transportation system, EVs lessen our reliance on fossil fuels and cut pollution levels dramatically. The exceptional performance of wide-bandgap (WBG) semiconductor technologies in power electronics has propelled them to the forefront of research. Examples of such technologies are gallium nitride (GaN) and silicon carbide (SiC). Additionally, many EV owners rely on public charging stations to refuel their cars since they do not have the infrastructure to do so at home. Due to their high power consumption, large-scale electric vehicle integration will put a significant burden on the power supply infrastructure. Adding more stations for charging to the grid won't help the environment since most of the power comes from conventional power plants. The energy quality of the transmission network is negatively affected by rapid charging of electric vehicles. Unorganized rapid charging operations for electric vehicles are likely to worsen the already precarious state of power distribution centers. This research presents a novel charging technique

that reduces charging times, temperature rise, and power oscillations all at once; thus, using renewable energy sources with BESS is an incredibly effective way to control fast charging stations, since it overcomes a number of drawbacks, such as complicated computations and power fluctuations. Issue detection, voltage sag classification, short-term forecasting, low computational load, etc. are some of the many applications of ANN-based control units, a subset of AI and ML technology. Recent years have seen a surge in interest in using AI methods to power electrical devices, because to the rapid advancements in ML. It is possible to train ML systems to recognize trends in consumer behavior and charge demand by analyzing historical data. Such algorithms have the potential to provide statistical insight via accurate future prediction after a successful training phase. Then, a variety of algorithms, or only these predictions, might be used to enhance EV quick charging methods. This study proposes a new method of control that integrates the MPC with artificial neural networks (ANNs) trained on the MPC's rigid action. Instead of relying just on MPC to address the drawbacks of dc rapid charging, the proposed method incorporates ANNs to do away with them altogether, all while making use of

renewable energy sources and devices for storing energy. The duty cycles for PWM signals are swiftly sent to the power converters by the trained ANNs, and no computing effort is required. With the help of AI, the necessary forecasting and monitoring tasks may be completed much more quickly and accurately than with the MPC method. The instructions should include the converter's working range, which includes both no load and maximum load. Consistent distribution of instruction sets is necessary to prevent overfitting and underfitting. An overview of the study's aims is provided below. The primary obstacle to fast charging is temperature growth; an efficient AI-based thermal management framework for batteries is developed by combining phase-change materials with liquid cooling methods. Many are hesitant to buy EVs because they are worried about their range. With the ability to quickly increase their state of charge (SoC) from 20% to 90% using AI technology, customers will find electric vehicles more attractive and environmentally friendly. When electric vehicles (EVs) become widely used, the power system will be overwhelmed by the amount of power needed to charge them rapidly. To fully meet the need for rapid recharging, the authors proposed using devices for storing energy in conjunction with renewable energy sources. The controller can mitigate voltage variations caused by erratic EV as well as load demand with the help of an ANN. The AI controller has been shown to be more successful than the traditional MPC via both simulation and experimental investigation.

2. ENERGY STORAGE SYSTEMS

After going over the many ways in which an ESS might improve a microgrid, the next step is to determine which storage technologies are suitable for the chosen application, compare them, and then choose the one that works best. The criteria for an MG application formed the foundation for the comparison. This application's storage system must have a large power capacity with a rapid reaction time in order to maintain power balance. To maintain energy balance and enhance the integration of renewable energy sources, an extremely energetic capacity is also necessary. Additionally, the chosen ESS has to be very efficient and have a long lifespan. A huge penetration of DG into the main grid cannot be achieved without an ESS. Here we take a look at some of the additional advantages that a system to store energy may provide. We only consider technical gains and ignore economic ones. The three primary categories into which the technical benefits brought about by an ESS fall are those pertaining to power production and transmission, power system operation, and the integration of renewable energy sources. One or more energy storage devices may be integrated into a system to smooth out power fluctuations

from renewable resources. In order to power renewable energy producing systems, a wide range of energy storage technologies have been suggested. Pumped hydro storage is one kind of energy storage technology that can hold a lot of energy but takes a long time to respond, whereas SMES is one type of technology that can store less energy but react much faster. Superconducting magnetic energy storage, pumped hydro, batteries, flywheels, and supercapacitors are the many energy storage devices. Data from a variety of energy storage systems are shown in Table 1.

Table 1 Comparison of different energy storage devices

Storage Technology	Response Time	Energy Density (Wh/kg)	Power (W/kg)	Charge-Discharge Efficiency	Durability Cycle	Time Durability (Years)
PHES	Minutes	0.3	—	75%	—	>75
BESS	1 min	30–200	150–3000	65–100%	500–1000	2–10
FESS	15 s	100–110	1000	90%	>20,000	>20
CAES	—	10–30	—	50%	—	>40
SCES	1 s	Low	Very High	93%	10,000–100,000	—
SMES	Millisecond level	30	Very High	98%	—	—

3. SYSTEM MODELING

A fuel cell with hydrogen generator, energy storage units, a rooftop photovoltaic array, and an independently powered dc shunt motor attached to a PMSG that looks like a wind turbine are all part of the charger architecture concept shown in Fig.1. Electric vehicles (EVs) that come to the charging station are charged using the power that is made available by renewable energy sources. An LLC resonant dc-dc converter connects all of the renewable energy sources and the ESU to a DC bus bar. Many different types of electric vehicles will be able to use the charging the batteries station for rapid replenishment. An electrical charging facility uses renewable energy sources with battery backup devices to power itself as it is disconnected from the electrical grid. Here is one way to characterize the ability supply distribution framework:

$$P_{FCref} + P_{PVref} + P_{\omega ref} + P_{batref} = P_{Load}$$

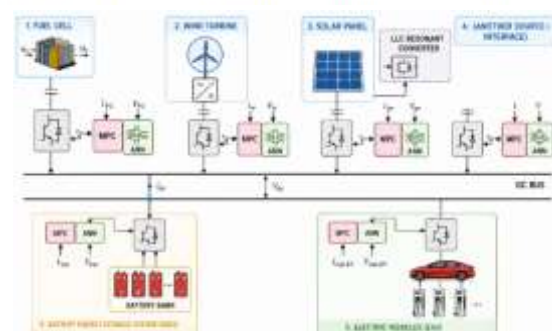


Fig. 1: Layout of fast battery charging scheme.

Constraints: The purpose of the charging process restrictions is to safely limit charging patterns that might damage batteries or create dangerous occurrences. The internal temperature must remain within a certain range to avoid overheating from charging or a charging current that

is too high and goes above the charging acceptance barrier. The two restrictions are detailed below:

$$P_{L,\min} \leq P_L(k+p) \leq P_{L,\max}$$

$$\text{SoC}_{\min} \leq \text{SoC}(k+p) \leq \text{SoC}_{\max}$$

$$T_{\min} \leq T(k+p) \leq T_{\max}$$

$$C_1: \text{SoC} \leq 90\%, \quad C_2: T \leq 50^\circ\text{C}.$$

The proposed method of charging control maintains the state of charge (SoC) within a specified range of 20% to 90%. The EMS keeps an eye on the system on a chip (SoC), and the battery keeps pumping out juice until the SoC hits its minimum level (SoCmin = 20%). Using the only weighted cost function that is provided below would get the best possible result for this multilayered optimal condition issue.

$$J_0 = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 J_3.$$

Design Consideration of LLC Resonant Converters: The project's resonant power converter, which was manufactured by Complete Bridge LLC. Throughout the sequential resonant tank of the proposed converter, there are four reactive components: L_r , C_r , and L_m . The other side of the coin is where C_o comes in; it converts the resulting ac signal to a flat dc signal. Depending on the locations of the full-bridge valves, the LLC conversion device provides two types of operation during resonant frequency operation. The most basic analog circuit for each operating mode is shown in the figures. When the toggle switches S1 along with S4 are turned on, as well as the converter's circuitry, the resonant tank receives the voltage V_{dc-nvo} . On the other hand, when S2 and S3 are activated, the resonant tank energy is defined by $nvo-V_{dc}$. It is possible to write by reformatting the equations in an optimal form and using Kirchhoff's rules.

$$V_{dc} = v_{Lr} + v_{Cr} + n v_{bat}$$

$$v_{bat}(t) = v_{bat}(t_k) + \left(\frac{n C_r}{C_0 + n^2 C_r} \right) \times (V_{dc} - n v_{bat}(t_k) - v_{Cr}(t_k)(1 - \cos(\omega_r t)))$$

$$i_{bat}(t) = \left(\frac{n C_0}{C_0 + n^2 C_r} \right) (V_{dc} - n v_{bat}(t_k) - v_{Cr}(t_k) \sin(\omega_r t)).$$

Machine learning (ML) is a method that gains knowledge by analyzing datasets, sometimes called "instruction data," which may be derived from either programming or the actual world. The following are some of the many reasons why ANN-based control systems are superior to traditional controllers.

- 1) Can be created without the need for specialist knowledge.
- 2) Does not need an exact computational description of the system.
- 3) When adjusted with the right data and input quality, it becomes much more effective.

Without a doubt, among the existing methods, a deep neural network (DNN) is the most successful in tackling the SoC

and SoT estimation issue. There are at least three layers in a DNN, as shown in Figure 2: input, hidden, then output.

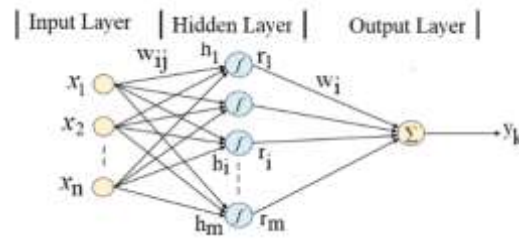


Fig. 2: DNN architecture.

Feedforward neural network (NN) designs often resolve detection and classification problems through the utilization of the Delta training principle. In this step, the supplied data is used to compare the actual result with the anticipated result of the suggested design. An mistake is represented as the difference between the two numbers. The goal of backpropagation is to decrease mistakes and enhance accuracy. The structure's weight factors are used to disperse the mistake after each loop. Since most real-world problems are unexpected and cannot be handled with a single-layer feedback approach, we used several-layer feed forward NN combining Levenberg-Marquardt backward propagation in this work. In order to collect data on input as well as output profiles, an LLC resonating converter is initially guided by MPC all through the DNN learning process. After the necessary information is collected, a wide range of input quality combinations are chosen. After been trained and shown to have outstanding model accuracy, the artificial NN model immediately produces the correct switching state required by the dc-dc converter.

4. SIMULATION RESULTS

Because different control systems predict, react to, and optimize thermal dynamics in different ways, the behavior of the battery temperature might vary when evaluating two controllers for rapid battery charging.

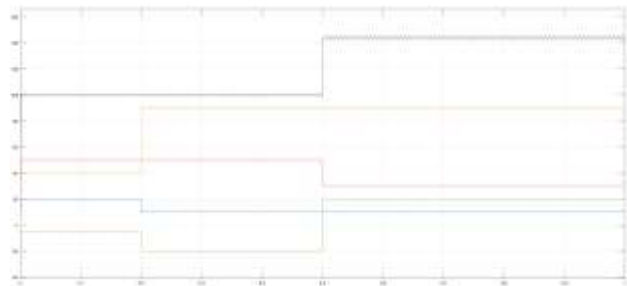


Fig. 3: Charging power dynamics for multiple EVs using controller under variable sources and increased load.

In this case, electric vehicles arrived at the charging station, connected to the priority and inexpensive connections, then a 100 kW power source was made available for sharing the charging, in addition to 10 kW for

charging storage batteries. Figure 3 shows that at half a second, the power consumption increased when the new EVs came to a charging station.

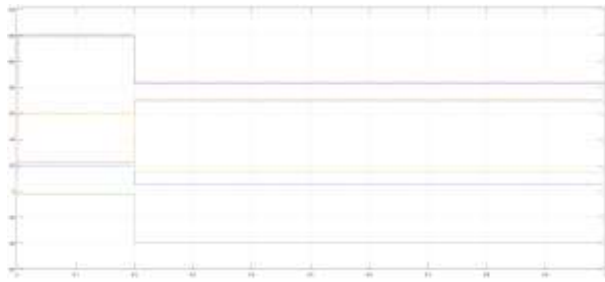


Fig. 4: Charging power dynamics for multiple EVs using controller under variable sources and decreased load.

When the energy imbalance is changed at 0.2 s by a decrease in EV use and fluctuations in sustainable power sources, the efficacy of the controller is assessed. As shown in Figure 4, an extra 20 kW was used to recharge storage battery packs without fuel cell power (PFC) as the energy generated by wind and solar energy was sufficient to meet the electric vehicle demand.

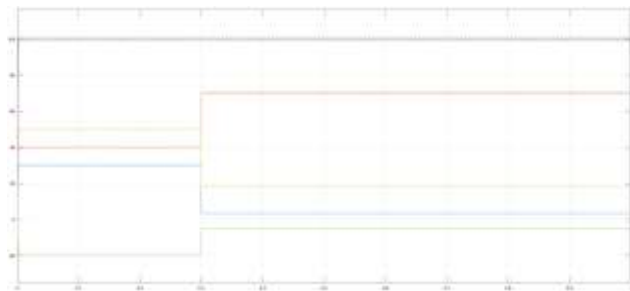


Fig. 5: Charging power dynamics for multiple EVs using controller under variable sources and constant load.

As seen in Figure 5, the correct charging outlets were occupied by electric vehicles with various systems on a chip (SoCs) as they arrived at the designated charging site. Recharging the battery packs required an extra 25 kW of electricity since the total charging demand was 100 kW as well as the power output from PPV, PW, as well as PFC sources was 60 kW, 40 kW, and 25 kW, respectively. Rapid changes in weather at 0.3 s led to 75 kW of solar power, 25 kW of wind power, with 10 kW of fuel cell power, respectively. The power balance was maintained by reducing the charge of the battery packs about 25 to 10 kW, as shown in Figure 5.

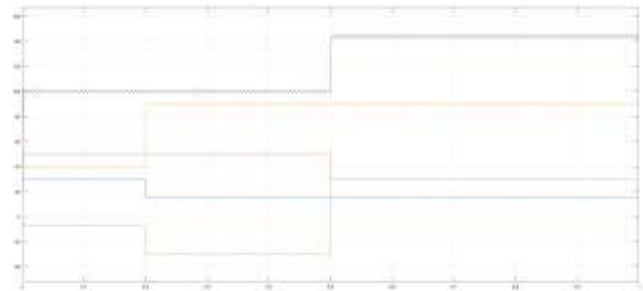


Fig. 6: Charging power dynamics for multiple EVs using controller under variable sources and increased load. (proposed system)

The new electric vehicles increased power consumption at 0.5 s as seen in Figure 6, when they reached charging. It stands for enhanced load power using SMC and ANN, as well as enhanced fc power using SMC.

CONCLUSION

Electric mobility is seen as a vital platform that influences national development, both the economy and the environment. Using clean and ecologically friendly power is one intentional way to decrease emissions globally. A novel managing electricity scheme that utilizes ANN as well as MPC for a Wind-FC-PV along with ESS-powered smart charging facility was proposed in the research article with the goals of reducing carbon emissions, improving charging infrastructure efficiency, and decreasing the time necessary for electric vehicles to generate electricity in remote locations. System resilience is of the utmost importance since the network is vulnerable to sudden shifts in sustainable power with their system of components. Longer wait times, especially during busy periods, are associated with charging infrastructure and waiting in line. Electric vehicles (EVs) may be controlled to start charging at certain times and with specific powers from various renewable energy sources in order to maximize the efficiency of dc rapid battery charging and reduce the overall time it takes to recharge. This would boost the proportion of energy accessible to nations, decrease emissions of carbon dioxide, and promote the broad usage of electric cars. At extreme ambient temperatures and throughout charge-discharge patterns, an active BTMS in combination with PCM with fluid refrigeration is proposed as a solution to the problems associated with battery thermal management. In comparison to MPC, driven by AI EV fast charging management is both more accurate and effective, according to modeling and testing data. Evaluating the present ANN model and organizing the cars in the most practical sequence for rapid wireless charging may be part of future research.

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