AI-Enabled Fast Charging with Intelligent Thermal Management for Renewable-Integrated Electric Vehicle Systems

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Abstract
Global electric vehicle (EV) sales exceeded 17 million units in 2025, representing nearly one in every five new vehicles sold worldwide, while the transportation sector contributes approximately 24% of global energy-related CO_2 emissions, highlighting the growing demand for sustainable charging infrastructures. The increasing penetration of renewable energy sources and the rapid deployment of fast EV charging stations require intelligent power management systems capable of maintaining stable operation under highly dynamic environmental and loading conditions. However, the existing Artificial Neural Network with Model Predictive Control (ANN-MPC) framework suffers from high computational complexity, slower real-time response, limited adaptability to highly nonlinear renewable energy dynamics, and increased processing overhead caused by continuous predictive optimization, thereby affecting DC bus voltage regulation, power-sharing efficiency, and battery charging performance. To address these limitations, this paper proposes a Deep Neural Network (DNN)-based intelligent control framework for a renewable energy-powered DC microgrid supporting fast EV charging. The proposed architecture completely replaces the ANN-MPC controller with distributed DNN controllers that directly regulate the fuel cell, wind turbine, solar photovoltaic system, battery energy storage system, and EV charging converter. The DNN is trained offline using measured operational data and subsequently deployed for real-time converter control, enabling rapid nonlinear decision-making without online predictive optimization. Consequently, the proposed framework improves DC bus voltage stability, renewable energy utilization, intelligent battery management, charging efficiency, computational performance, scalability, and overall reliability, making it highly suitable for next-generation sustainable fast electric vehicle charging infrastructures.

Keywords: Electric Vehicle Fast Charging, Deep Neural Network, DC Microgrid, Renewable Energy Integration, Battery Energy Storage System, Intelligent Energy Management

1. Introduction

The rapid growth of EVs has transformed the global transportation sector and accelerated the transition toward sustainable mobility. According to the International Energy Agency (IEA), global EV sales exceeded 17 million units in 2025, accounting for nearly 20% of all new vehicle sales worldwide. Governments across the world are promoting EV adoption through financial incentives, stricter emission regulations [1], and investments in charging infrastructure to reduce greenhouse gas emissions and dependence on fossil fuels. At the same time, renewable energy sources such as solar photovoltaic systems, wind turbines, and fuel cells are becoming increasingly important because they provide clean electricity with minimal environmental impact [2]. The integration of renewable energy into electric vehicle charging systems supports the development of sustainable transportation while reducing the burden on conventional electrical grids. As renewable energy generation continues to expand, efficient energy management within charging stations has become an important aspect of ensuring uninterrupted and reliable vehicle charging.

Modern EV charging stations are expected to deliver high charging power within a short duration while maintaining power quality, battery safety, and operational reliability. Renewable energy sources, however, are naturally intermittent because their output depends on environmental conditions such as solar irradiance and wind speed [3]. This variability creates continuous fluctuations in power generation, making energy coordination more challenging. Battery energy storage systems are widely incorporated to compensate for renewable intermittency and maintain a stable DC bus for charging operations. Industries involved in electric mobility, renewable energy generation, smart grid development, and public charging infrastructure require intelligent energy management systems capable of balancing multiple power sources and varying charging demands [4]. Consequently, renewable energy integrated DC microgrids have become an important research area because they improve energy utilization, reduce operating costs, support sustainable transportation, and enhance the overall efficiency of future charging infrastructures.

2. Literature Survey

Zhang et al. [5] designed a deep learning-based probabilistic forecasting framework for electric vehicle charging loads using a queuing model. They incorporated charging behavior uncertainty into the prediction process to estimate future charging demand distributions rather than single-point values. González-Rivera et al. [6] established an energy management system based on Model Predictive Control for optimizing the operation of a hybrid electric vehicle charging station. They coordinated photovoltaic generation, fuel cells, hydrogen storage, batteries, and grid power through predictive optimization to satisfy charging requirements. Abdullah et al. [7] reviewed Reinforcement Learning-based electric vehicle charging management systems for smart grid applications. They examined various reinforcement learning algorithms developed for charging scheduling, energy management, demand response, and Vehicle-to-Grid integration.

Nisha and Gaonkar [8] developed a three-level bidirectional converter controlled using Model Predictive Control for bipolar Direct Current microgrid-based electric vehicle fast charging stations. They regulated converter switching while maintaining voltage balance across the bipolar DC bus during charging and discharging operations. Jiao et al. [9] formulated an online optimal dispatch strategy for a microgrid containing an electric vehicle charging station using combined robust and stochastic Model Predictive Control. They incorporated uncertainties arising from photovoltaic generation, wind power, electric vehicle charging demand, and load variations into a two-stage optimization framework. Zhang et al. [10] developed an adaptive dynamic surface control strategy with disturbance observers for battery and supercapacitor-based hybrid energy sources in electric vehicles. They estimated external disturbances and compensated their influence through adaptive control to improve energy source coordination.

Shanmuganathan et al. [11] developed a Deep Learning-based Long Short-Term Memory (LSTM) recurrent neural network for predicting electric vehicle charging demand. They utilized historical charging records, temporal information, and user behavior to train the recurrent learning model for long-term demand estimation. Zhou et al. [12] implemented a Bayesian deep learning framework for forecasting electric vehicle charging station loads. They incorporated probabilistic learning to quantify uncertainty associated with charging demand while improving prediction reliability under varying operational conditions. Apaydin Ozkan and Erol-Kantarci [13] introduced an electric vehicle charging and discharging strategy supported by complementary renewable energy sources and incentive mechanisms. They coordinated charging schedules by considering renewable energy availability, electricity pricing, and user incentives to improve energy utilization.

Gao et al. [14] established an enhanced electrochemical model for the simultaneous estimation of battery State-of-Charge and State-of-Health. They combined electrochemical battery modeling with estimation algorithms to improve monitoring accuracy throughout battery operating conditions. Li et al. [15] presented an adaptive ensemble-based electrochemical and thermal degradation estimation framework for lithium-ion batteries. They integrated electrochemical and thermal characteristics into an adaptive ensemble model to evaluate battery degradation under different operating environments. The developed estimator continuously updated degradation states to improve battery health prediction and operational reliability. Their approach enhanced battery lifetime assessment through comprehensive degradation analysis. The study did not investigate intelligent energy management or converter control within electric vehicle charging systems.

Li et al. [16] developed a rapidly reconfigurable Direct Current battery architecture for electric vehicle drivetrains. They designed a flexible battery topology capable of dynamically reconfiguring cell connections to improve energy utilization, fault tolerance, and drivetrain efficiency. Abuelrub et al. [17] conducted a feasibility analysis of electric vehicle operation within a renewable energy integrated microgrid. They evaluated the interaction between renewable generation, battery storage, and charging demand under various operating scenarios using system-level simulations. Zhao et al. [18] reviewed the application and integration of Grid-Connected Battery Energy Storage Systems within modern power networks. They analyzed battery storage technologies, integration approaches, operational strategies, and grid support services for renewable energy applications. The review discussed the role of battery storage in improving power quality, renewable energy utilization, frequency regulation, and system stability. Their work summarized recent advancements and implementation challenges associated with large-scale battery storage deployment. The review did not present a practical intelligent controller for electric vehicle charging applications.

3. Proposed System

Although the existing renewable energy integrated EV charging system provides effective coordination between renewable sources and battery storage, several limitations reduce its overall performance. The system experiences increased computational complexity during real-time operation, resulting in slower controller response under rapidly varying environmental conditions. The control strategy demonstrates limited capability in accurately modeling highly nonlinear renewable energy dynamics, thereby affecting power-sharing accuracy and DC bus voltage regulation. Furthermore, simultaneous coordination of multiple renewable energy sources and battery storage devices increases computational overhead, reducing scalability for large charging infrastructures. Variations in renewable generation and charging demand also affect battery charging performance, leading to reduced energy utilization efficiency, increased thermal stress, and degraded overall system reliability.

To overcome the limitations of the existing renewable energy-based EV charging infrastructure, an intelligent control framework capable of rapidly learning complex nonlinear system dynamics while providing fast real-time decision-making is required. The proposed DNN-based control system directly learns the relationship between renewable energy generation, battery storage behavior, converter operation, and charging demand, enabling accurate converter control without computationally intensive online optimization. This improves DC bus voltage regulation, renewable energy utilization, battery management, charging efficiency, and overall system stability while reducing computational complexity and enhancing scalability for future high-power EV charging applications.

3.1 DNN Based Renewable Energy System

Figure 1 illustrates the proposed DNN-based renewable energy integrated DC microgrid for fast EV charging. Unlike the existing ANN-MPC framework, the proposed architecture eliminates the MPC and employs standalone DNN controllers for all renewable energy sources, battery energy storage, and EV charging units. The DNN controllers directly regulate the power electronic converters connected to the fuel cell, wind turbine, solar PV system, BEES, and EV charging station. By learning complex nonlinear relationships among system variables, the DNN provides faster decision-making, reduced computational complexity during online operation, improved DC bus voltage regulation, enhanced renewable energy utilization, and efficient power distribution under dynamic operating conditions.

Step 1: Fuel Cell Power Generation and DNN Control: The fuel cell operates as one of the primary energy sources by converting chemical energy into electrical energy. The generated DC power is supplied to the common DC bus through a DC-DC converter. A dedicated DNN continuously monitors the fuel cell voltage and current and directly generates optimal converter switching signals. The DNN rapidly adapts to load variations and maintains stable fuel cell operation without requiring predictive optimization algorithms.

Step 2: Wind Turbine Energy Conversion: The wind turbine converts available wind energy into electrical power through an electrical generator. Since wind speed varies continuously, the generated power changes dynamically. The proposed DNN controller receives wind voltage and current measurements and directly regulates the interfacing converter. Its deep learning capability enables accurate adaptation to fluctuating wind conditions, thereby maximizing energy extraction while maintaining stable DC bus operation.

Step 3: Solar Photovoltaic Energy Management: The solar photovoltaic array supplies renewable electrical energy to the DC microgrid through an LLC resonant converter. The DNN controller receives photovoltaic voltage and current measurements and immediately determines the appropriate converter control signals. By accurately modeling nonlinear photovoltaic characteristics under varying solar irradiance and temperature, the DNN maximizes solar energy utilization while ensuring efficient voltage regulation.

Step 4: Common DC Bus Regulation: The outputs from the fuel cell, wind turbine, and photovoltaic system are integrated into a common DC bus that serves as the central energy distribution platform. The coordinated operation of multiple DNN controllers continuously regulates power flow from each renewable source to maintain a constant DC bus voltage despite renewable intermittency and varying charging demand. This stable voltage provides reliable operation for all connected converters and charging equipment.

Step 5: BEES Management: The BESS functions as an energy buffer for balancing renewable power fluctuations. Through a bidirectional DC-DC converter, the battery bank can either absorb excess renewable energy or supply stored energy whenever renewable generation becomes insufficient. The DNN continuously monitors battery voltage and current and intelligently determines charging or discharging actions, thereby improving battery utilization while preventing overcharging and deep discharge.

Step 6: Electric Vehicle Fast Charging Control: The electric vehicle charging station receives regulated DC power directly from the common DC bus through a dedicated converter controlled by another DNN. The controller monitors the EV battery voltage and charging current and dynamically adjusts converter switching to provide safe and rapid charging. The DNN ensures accurate current regulation, minimizes charging time, and protects the EV battery under different operating conditions.

Step 7: Intelligent Energy Coordination: Each renewable energy source, battery storage unit, and EV charging interface possesses an independent DNN controller. These distributed DNN controllers operate cooperatively by continuously analyzing real-time system measurements and coordinating power flow among renewable sources, battery storage, and charging loads. This decentralized intelligence enhances system flexibility, scalability, and robustness under rapidly changing environmental conditions.

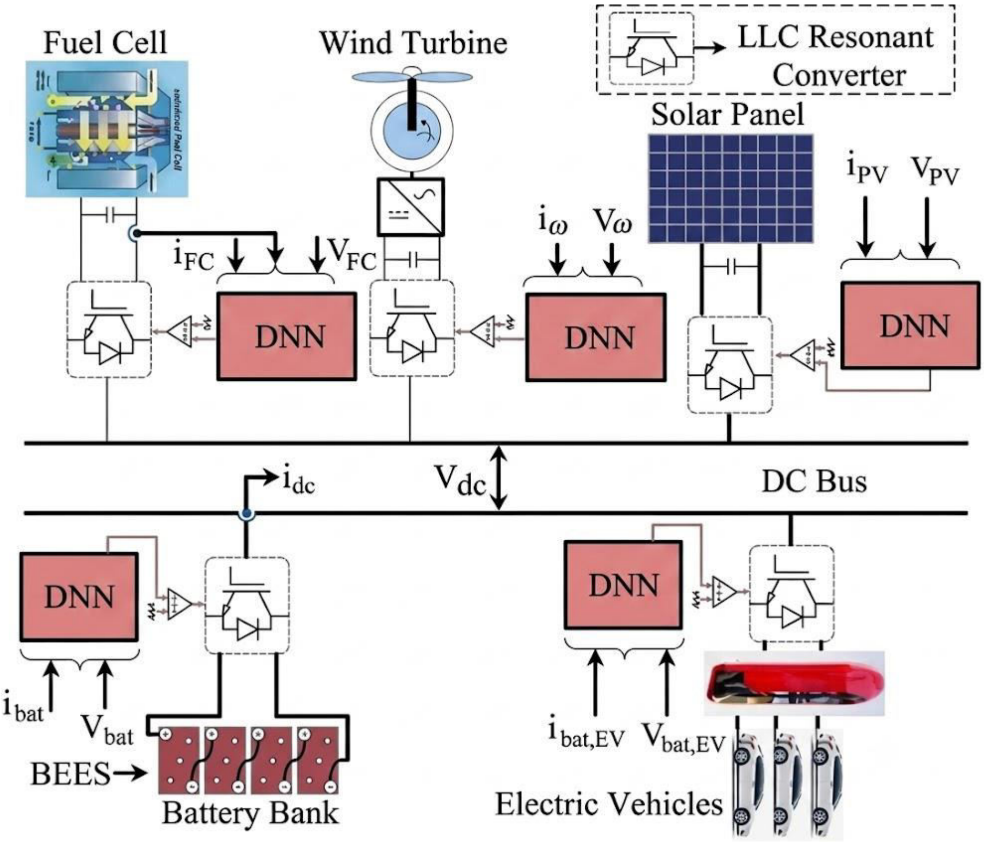

Figure 1. Proposed DNN Based Renewable Energy Integrated DC Microgrid for Fast Electric Vehicle Charging

3.2 DNN-Based Offline Training and Online Control Framework

Figure 2 illustrates the proposed DNN-based control framework comprising (a) Offline Training Phase and (b) Online Test Phase for renewable energy-powered DC microgrid operation. Unlike the existing ANN-MPC approach, the proposed framework eliminates the MPC during both training and online execution. During the offline phase, measured data collected from the photovoltaic system, battery bank, and DC bus are directly utilized to train the Deep Neural Network, enabling it to learn the complex nonlinear characteristics of renewable energy generation and energy storage. Once the training process is completed, the trained DNN model is deployed during the online phase to directly control the LLC resonant converters in real time. This fully DNN-based architecture provides faster decision-making, reduced computational complexity, improved DC bus voltage regulation, enhanced renewable energy utilization, and intelligent battery management for high-performance electric vehicle fast charging.

Step 1: Offline Measurement Data Collection: The offline training phase begins by collecting operating measurements from the photovoltaic system, battery energy storage system, and common DC bus under different environmental and loading conditions. The collected data include photovoltaic voltage, photovoltaic current, battery voltage, battery charging current, DC bus voltage, solar irradiance, and temperature. These measurements represent various operating scenarios required for training the deep neural network.

Step 2: DNN Training: The measured operating data are directly supplied to the DNN for supervised learning. Unlike conventional approaches that depend on a Model Predictive Controller to generate reference control actions, the proposed DNN independently learns the nonlinear relationships between system measurements and optimal converter control signals. Through iterative learning, the DNN develops a generalized control model capable of accurately representing the dynamics of the renewable energy system.

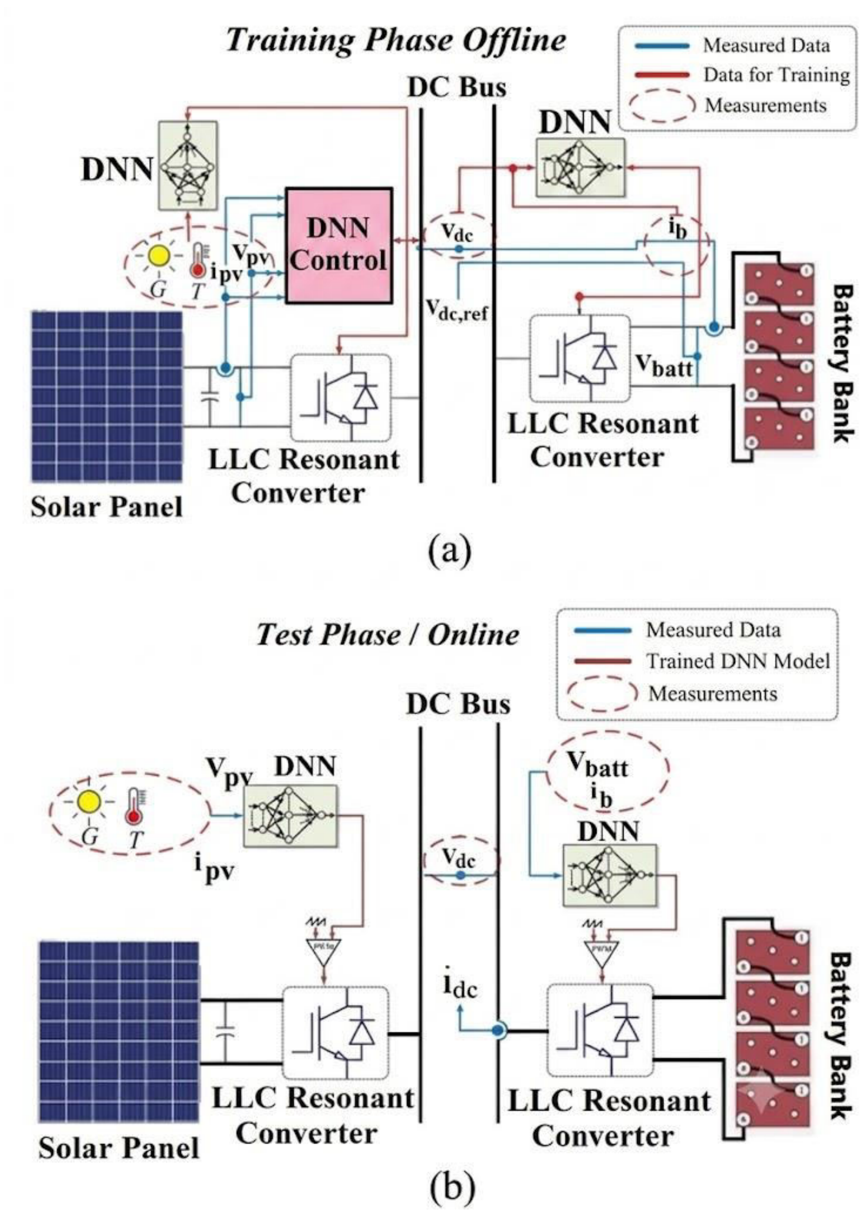

Figure 2. Proposed DNN-Based Offline Training and Online Control Framework for Renewable Energy DC Microgrid

Step 3: Photovoltaic Converter Learning: The photovoltaic subsystem utilizes an LLC resonant converter to interface the solar panel with the common DC bus. During offline training, photovoltaic voltage, current, solar irradiance, and temperature are continuously analyzed by the DNN. The network learns how environmental variations influence converter operation and determines the optimal converter control strategy for maximizing solar power extraction while maintaining stable DC bus voltage.

Step 4: Battery Energy Storage Learning: The battery energy storage system is connected to the DC bus through another LLC resonant converter. Battery voltage, charging current, and DC bus voltage measurements are used to train a dedicated DNN model. The network learns the appropriate charging and discharging behavior under varying renewable generation and load demand, thereby ensuring efficient battery utilization and long-term operational reliability.

Step 5: Development of the Trained DNN Model: After sufficient training iterations, the Deep Neural Network develops an optimized control model capable of accurately predicting converter control actions from real-time operating measurements. The trained DNN captures complex nonlinear system behavior without requiring explicit mathematical modeling or predictive optimization algorithms, enabling highly adaptive and intelligent controller operation.

Step 6: Online Deployment of the DNN Controller: Following the completion of offline training, the trained DNN model is deployed for real-time operation. During the online phase, only the trained DNN receives real-time measurements from the photovoltaic system, battery storage unit, and DC bus. Based on these measurements, the DNN directly generates converter switching commands without performing computationally intensive optimization, thereby significantly reducing controller execution time.

Step 7: Photovoltaic Control: During online operation, the DNN continuously monitors photovoltaic voltage, current, solar irradiance, and temperature. Using the knowledge acquired during offline learning, the DNN directly controls the LLC resonant converter connected to the solar panel. This enables rapid adaptation to changing weather conditions, maximizes renewable energy harvesting, and maintains stable power delivery to the DC bus.

Step 8: Battery Energy Management: The trained DNN simultaneously monitors battery voltage and charging current to determine appropriate charging and discharging actions. By directly controlling the battery-side LLC resonant converter, the DNN efficiently balances renewable power generation and load demand while protecting the battery from excessive charging, deep discharge, and abnormal operating conditions.

3.3 Operating Modes of the Proposed LLC Resonant Converter

Figure 3 illustrates the operating principle of the LLC resonant converter employed in the proposed DNN-based renewable energy integrated DC microgrid for battery charging applications. The converter transfers regulated power from the common DC bus to the battery bank through high-frequency resonant energy conversion, providing galvanic isolation, high conversion efficiency, and reduced switching losses. The LLC resonant converter operates in two complementary switching intervals. During the first interval, switches S1 and S4 conduct simultaneously, whereas during the second interval, switches S2 and S3 conduct. These alternating switching states generate a high-frequency AC excitation for the resonant tank, enabling efficient energy transfer through the transformer to the battery while maintaining soft-switching operation and minimizing switching stress.

Step 1: DC Input Supply: The LLC resonant converter receives regulated DC power from the common DC bus of the renewable energy microgrid. This DC input serves as the primary energy source for charging the battery bank. The converter transforms the DC voltage into high-frequency AC power before transferring energy through the isolation transformer.

Step 2: Formation of the Resonant Tank: The resonant tank consists of the resonant inductor (Lr), resonant capacitor (Cr), and transformer magnetizing inductance (Lm). These passive components establish the resonant operating condition that enables soft switching. Energy oscillates between the inductor and capacitor while the magnetizing inductance regulates transformer excitation, thereby reducing switching losses and improving converter efficiency.

Step 3: Mode-I Operation (S1 and S4 Switched ON): As illustrated in Figure 3(a), switches S1 and S4 are turned ON simultaneously, while S2 and S3 remain OFF. Under this switching condition, the input DC voltage is applied across the resonant tank, allowing resonant current to flow through the resonant inductor, resonant capacitor, and transformer primary winding. The transformer transfers energy to the secondary side, where the rectifier delivers regulated charging current to the battery bank. During this interval, the resonant components operate under soft-switching conditions, significantly minimizing switching losses and improving overall power conversion efficiency.

Step 4: Energy Transfer Through the Transformer: The high-frequency transformer provides electrical isolation between the DC bus and the battery bank while simultaneously performing voltage transformation according to the turn’s ratio. The secondary-side rectifier converts the high-frequency AC output back into regulated DC voltage suitable for battery charging. The output capacitor smooths voltage ripple before delivering power to the battery.

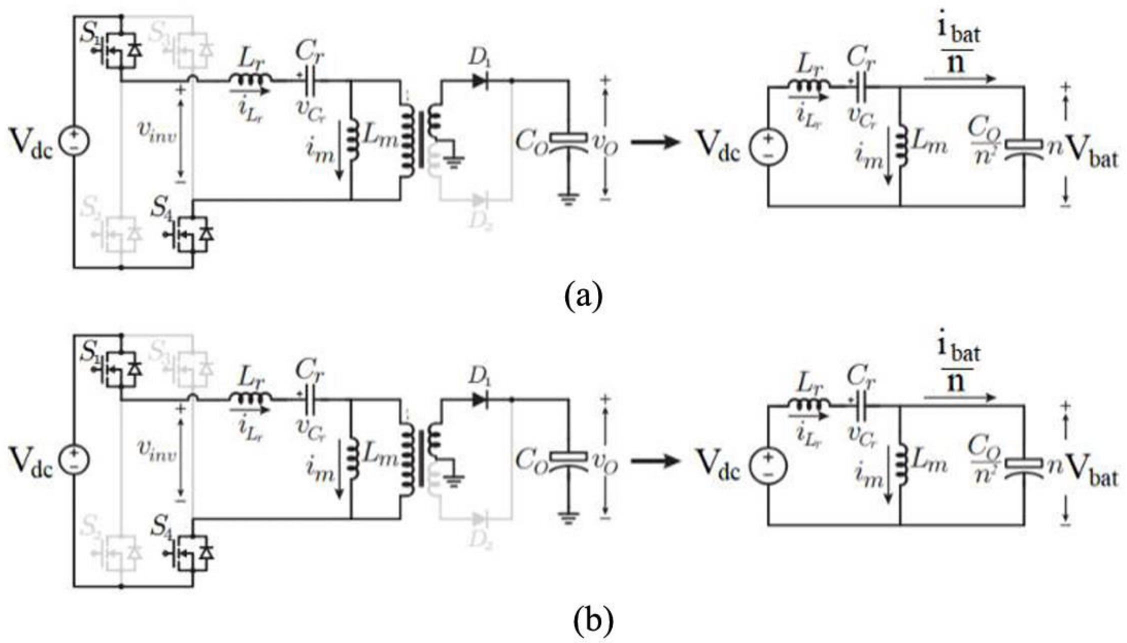

Figure 3. Operating Modes of the Proposed LLC Resonant Converter: (a) S1 and S4 ON State, (b) S2 and S3 ON State.

Step 5: Mode-II Operation (S2 and S3 Switched ON): As shown in Figure 3(b), switches S2 and S3 are turned ON while S1 and S4 are switched OFF. The polarity of the applied voltage across the resonant tank reverses, causing the resonant current to flow in the opposite direction. The transformer continues transferring energy to the secondary side, and the rectifier maintains continuous DC power delivery to the battery bank. This complementary switching action ensures uninterrupted energy transfer and balanced converter operation.

Step 6: Soft Switching Operation: Throughout both switching intervals, the resonant behavior of the LLC tank enables Zero Voltage Switching (ZVS) for the primary switches and near Zero Current Switching (ZCS) for the secondary rectifier devices. These soft-switching characteristics substantially reduce switching losses, electromagnetic interference, and thermal stress while improving overall converter reliability and extending component lifetime.

Step 7: Battery Charging Process: The regulated output of the LLC resonant converter supplies controlled charging current to the battery bank. The proposed DNN controller continuously supervises converter operation by monitoring battery voltage, charging current, and DC bus voltage. Based on these measurements, the DNN adjusts the converter switching frequency and control signals to maintain stable charging conditions, maximize charging efficiency, and protect the battery against overvoltage, overcurrent, and abnormal operating conditions.

4. Results and Discussion

Figure 4 illustrates the complete MATLAB/Simulink implementation of the renewable energy integrated DC microgrid for electric vehicle fast charging. The model integrated a fuel cell source, wind generation system, photovoltaic (PV) array, Battery Energy Storage System (BESS), and electric vehicle charging subsystem through a common DC bus. Individual source modules were interconnected using transmission resistances (R, R1, R2, and R3) to regulate power flow among distributed energy resources. Figure 5. presents the photovoltaic energy conversion subsystem controlled using the proposed DNN. The PV array operated under a solar irradiance input of 1000 W/m² and an ambient temperature of 27°C to generate electrical energy. A full-bridge converter comprising four switching devices (Q1–Q4), an LLC resonant network, high-frequency transformer, and output rectifier converted the PV output into a regulated DC voltage.

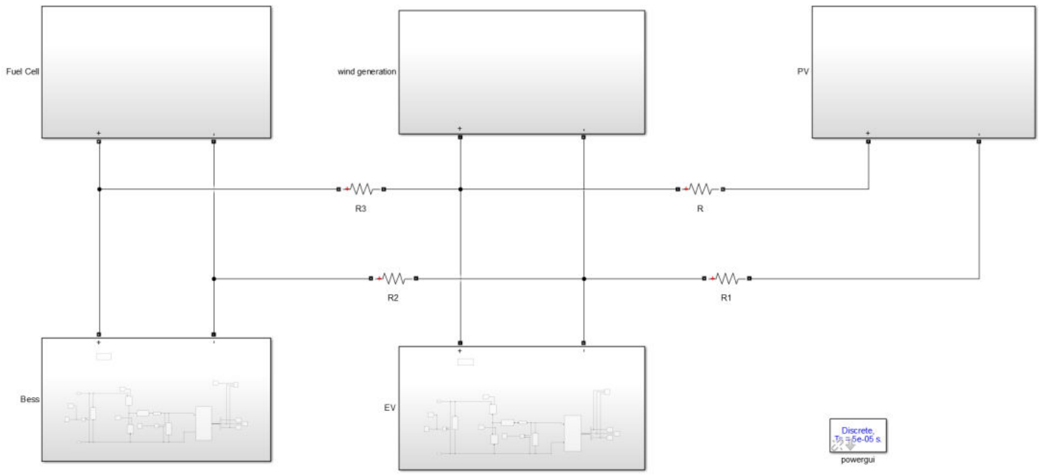

Figure 4. Overall Simulation Model of the Renewable Energy Integrated DC Microgrid for EV Fast Charging

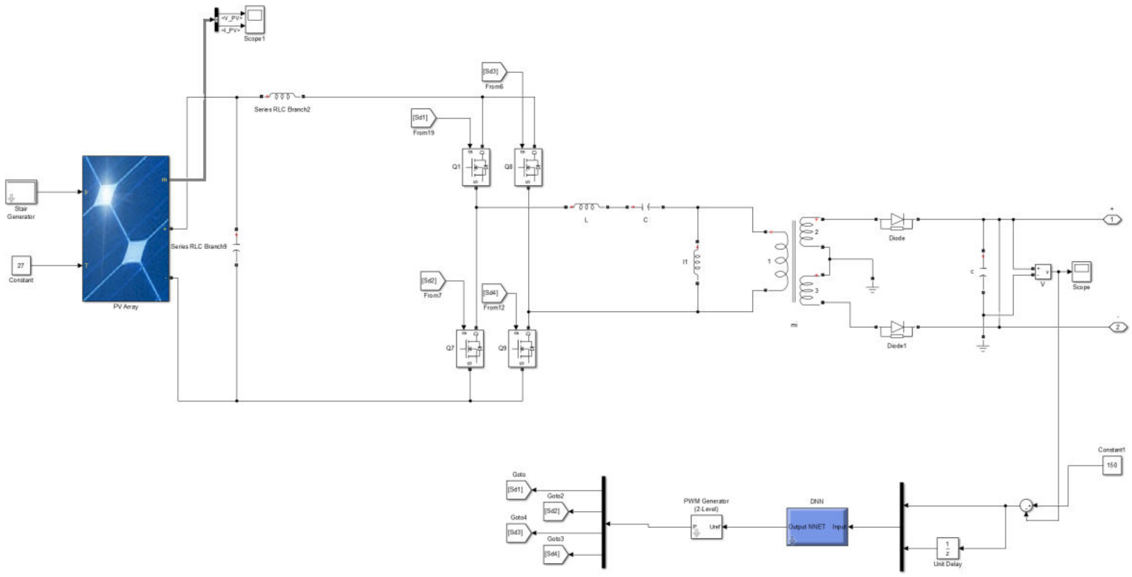

Figure 5. DNN-Based Photovoltaic Power Converter

Figure 6 illustrates the wind energy conversion subsystem integrated with the DC microgrid. The model consisted of a wind turbine, Permanent Magnet Synchronous Generator (PMSG), three-phase voltage source converter, PWM controller, and DC output stage. The wind turbine operated at a wind speed of approximately 15 m/s with a machine speed close to 860 rpm to generate electrical power. The generated three-phase output was converted into regulated DC power through the converter controlled by the switching devices S1–S6. Figure 7 shows the fuel cell power conditioning subsystem controlled using the proposed DNN. The fuel cell stack supplied low-voltage DC power, which was boosted using a DC–DC converter consisting of a MOSFET switch, inductive filtering components, output diode, and capacitor network. The DNN controller generated switching pulses based on the voltage error and reference voltage of 150 V to regulate the converter output.

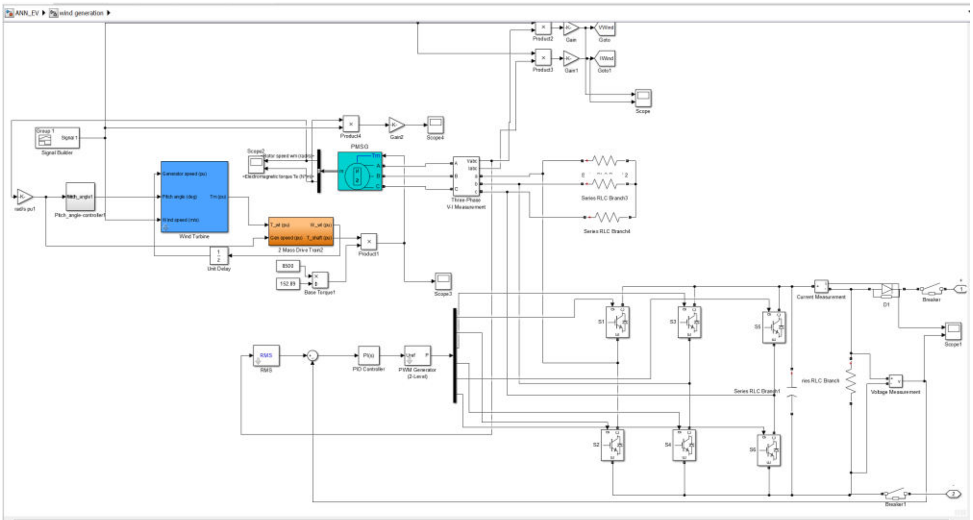

Figure 6. Wind Energy Conversion System with Power Electronic Interface

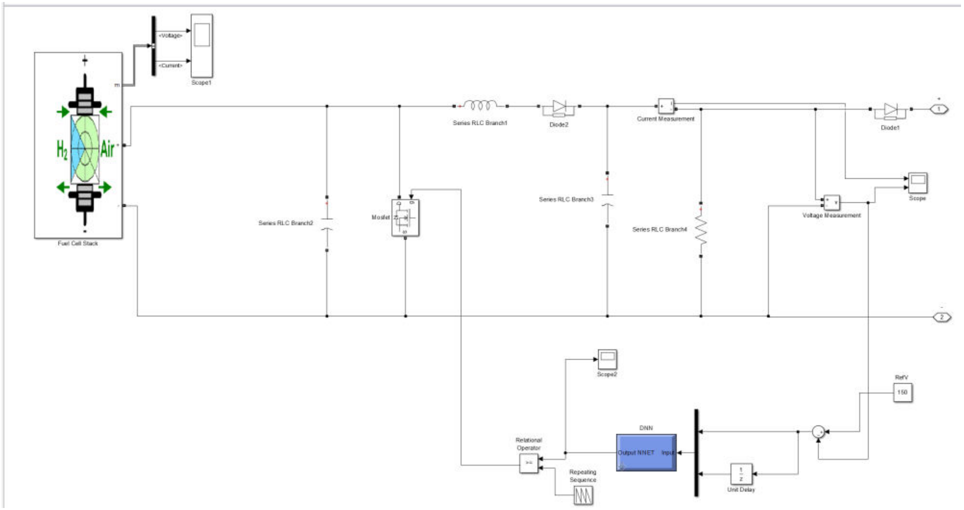

Figure 7. DNN-Based Fuel Cell Power Conditioning Circuit

Figure 8 illustrates the BESS integrated into the renewable energy DC microgrid. The battery module was connected through a bidirectional DC–DC converter employing two MOSFET switches, inductive filtering elements, and resistive-capacitive compensation circuits. The subsystem continuously monitored battery voltage, charging current, and State of Charge (SOC) using dedicated sensing blocks connected through the bus selector.

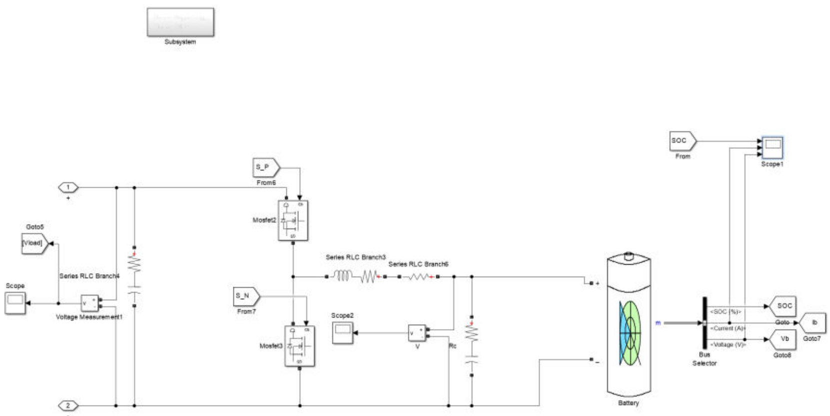

Figure 8. BESS Model

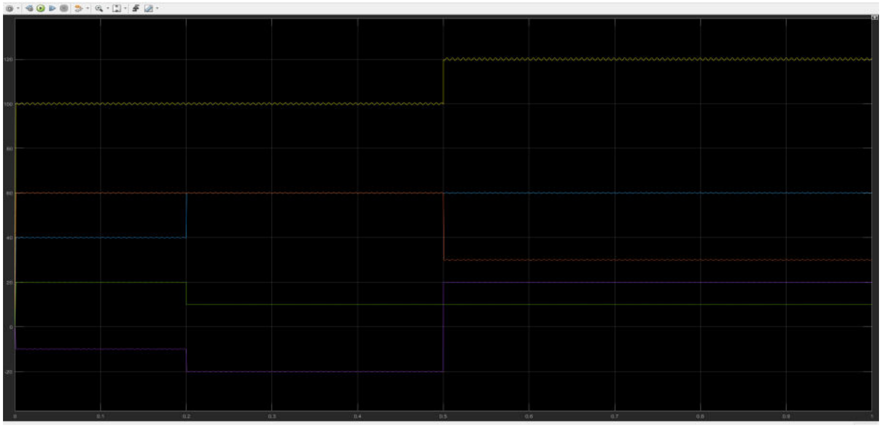

Figure 9. Charging Power Dynamics for Multiple Electric Vehicles Using DNN Under Variable Sources and Increased Load

Figure 9 illustrates the charging power allocation of the proposed DNN-based energy management system under variable renewable energy sources with an increased charging demand. Initially (0–0.2 s), Electric Vehicle 1 (blue) received approximately 40 kW, Electric Vehicle 2 (orange) received 60 kW, Electric Vehicle 3 (green) received 20 kW, Electric Vehicle 4 (purple) operated at −10 kW, while the total available charging power (yellow) remained close to 100 kW. At 0.2 s, the charging demand increased, resulting in Electric Vehicle 1 receiving 60 kW, Electric Vehicle 2 decreasing to 30 kW, Electric Vehicle 3 reducing to 10 kW, and Electric Vehicle 4 decreasing to −20 kW while the total charging capacity remained around 100 kW. At 0.5 s, additional renewable power became available, increasing the total charging capacity to nearly 120 kW. The DNN controller immediately redistributed the available energy by maintaining Electric Vehicle 1 at 60 kW, Electric Vehicle 2 at 30 kW, Electric Vehicle 3 at 10 kW, and increasing Electric Vehicle 4 to 20 kW. Figure 10 presents the charging power dynamics of the proposed DNN controller when renewable sources varied under a decreased charging load. During the initial operating interval (0–0.2 s), the available charging capacity remained approximately 120 kW, with Electric Vehicle 1 supplied by 50 kW, Electric Vehicle 2 by 50 kW, Electric Vehicle 3 by 20 kW, and Electric Vehicle 4 by 10 kW. At 0.2 s, the overall charging demand decreased, causing the DNN controller to reduce the total charging capacity to approximately 100 kW. Simultaneously, Electric Vehicle 1 increased to nearly 70 kW, Electric Vehicle 2 reduced to 30 kW, Electric Vehicle 3 reduced to 10 kW, and Electric Vehicle 4 shifted to approximately −40 kW, indicating controlled bidirectional power regulation.

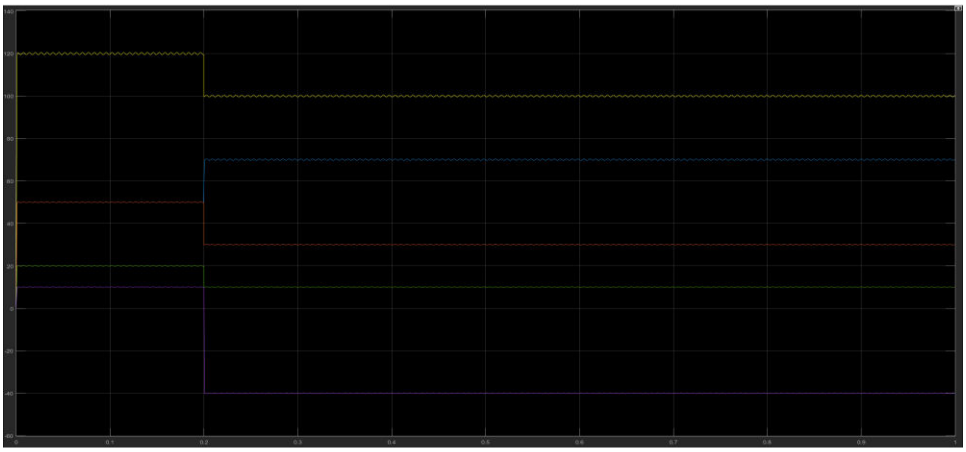

Figure 10. Charging Power Dynamics for Multiple Electric Vehicles Using DNN Under Variable Sources and Decreased

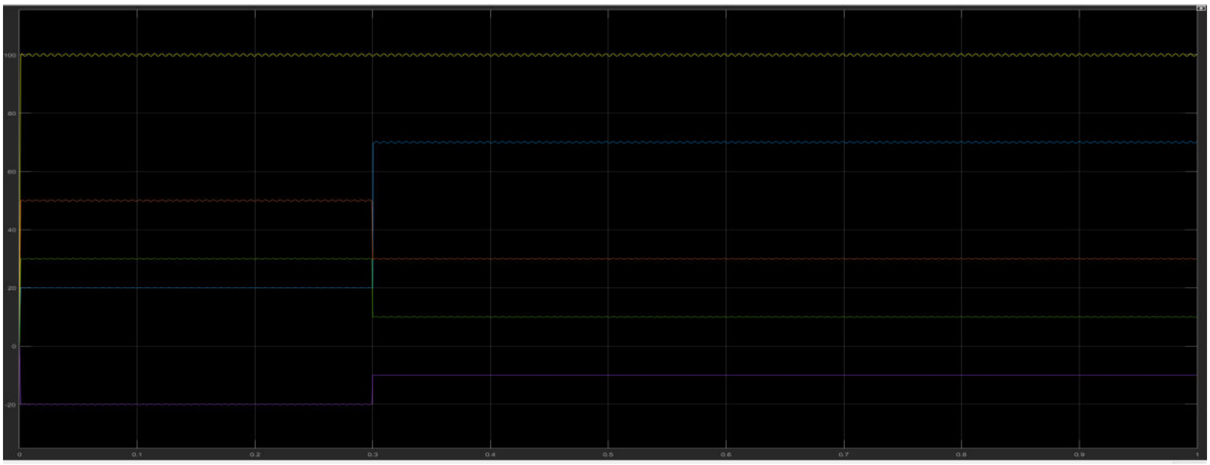

Figure 11. Charging Power Dynamics for Multiple Electric Vehicles Using DNN Under Variable Sources and Constant Load

Figure 11 illustrates the charging power distribution of the proposed DNN-based controller under variable renewable energy sources while maintaining a constant charging load. From 0 to 0.3 s, the available charging capacity remained nearly 100 kW, where Electric Vehicle 1 received approximately 20 kW, Electric Vehicle 2 received 50 kW, Electric Vehicle 3 received 30 kW, and Electric Vehicle 4 operated at −20 kW. At 0.3 s, renewable source availability changed while the overall charging demand remained constant. The DNN controller immediately redistributed the charging power by increasing Electric Vehicle 1 to approximately 70 kW, reducing Electric Vehicle 2 to 30 kW, lowering Electric Vehicle 3 to 10 kW, and adjusting Electric Vehicle 4 to approximately −10 kW, while maintaining the total charging capacity close to 100 kW throughout the simulation.

5. Conclusion

The proposed DNN-based renewable energy integrated DC microgrid for electric vehicle fast charging demonstrated significant improvements over the existing ANN-MPC approach. Unlike the ANN-MPC framework, which depended on repeated predictive optimization and incurred higher computational complexity, the proposed DNN controller performed direct intelligent decision-making with faster convergence and improved adaptability under varying renewable energy generation and charging demand. Consequently, the proposed DNN-based framework provided higher operational reliability, greater scalability for future charging infrastructure, and superior overall performance compared with the existing ANN-MPC-based energy management system. Future research will focus on implementing the proposed DNN controller on real-time embedded hardware platforms such as Field Programmable Gate Arrays and Digital Signal Processors for practical deployment in commercial charging stations. The framework will also be extended by integrating Vehicle-to-Grid services, battery health prediction, and cyber-secure communication for intelligent smart grid applications. Further investigations will incorporate advanced reinforcement learning and federated learning techniques to improve autonomous energy management in large-scale renewable energy integrated electric vehicle charging networks.

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