Hindawi
International Journal of Energy Research
Volume 2023, Article ID 7786928, 30 pages
https://doi.org/10.1155/2023/7786928

Research Article

A Novel Hybrid Approach for Power Quality Improvement in a Vehicle-to-Grid Setup Using Droop-ANN Model

Muhammad Aurangzeb,[1] **Ai Xin**,[1] **Sheeraz Iqbal**,[2] **Muhammad Zeshan Afzal**,[3] **Hossam Kotb**,[4] **Kareem M. AboRas**,[4] **Yazeed Yasin Ghadi**,[5] **and Bello-Pierre Ngoussandou**[6]

[1]*School of Electrical Engineering, North China Electric Power University, Beijing 102206, China*
[2]*Department of Electrical Engineering, University of Azad Jammu and Kashmir, Muzaffarabad 13100, Pakistan*
[3]*Department of Electrical Engineering, Southeast University, Nanjing 210096, China*
[4]*Department of Electrical Power and Machines, Faculty of Engineering, Alexandria University, Alexandria 21544, Egypt*
[5]*Department of Computer Science and Software Engineering, Al Ain University, Abu Dhabi 15322, UAE*
[6]*Department of Renewable Energy, National Advanced School of Engineering of Maroua, University of Maroua, Cameroon*

Correspondence should be addressed to Muhammad Aurangzeb; maurangzaib42@gmail.com, Muhammad Zeshan Afzal; zeshanafzal423@yahoo.com, and Bello-Pierre Ngoussandou; nbellopierre@yahoo.fr

Received 18 May 2023; Revised 5 July 2023; Accepted 20 July 2023; Published 11 August 2023

Academic Editor: Yogendra Arya

The integration of electric vehicles (EVs) in the power grid has attracted considerable attention due to its potential benefits, such as demand response and power quality improvement. However, the intermittent and unpredictable nature of EVs' charging and discharging behavior can cause significant challenges to the grid's stability and power quality. This research study explores the use of a droop-ANN model to improve power quality in vehicle-to-grid (V2G) systems. The proposed approach integrates an artificial neural network (ANN) into the droop control technique to accurately predict the voltage and frequency of the charger. Through simulations, the model's effectiveness in reducing power fluctuations and enhancing power quality was validated. The results indicate that the droop-ANN model significantly improves power quality across various battery state of charge (SoC) and charging/discharging scenarios. The findings highlight the potential of the droop-ANN model to enhance stability and reliability in V2G systems. Further research is needed to validate the model in real-world applications and explore its full potential. Overall, the droop-ANN model offers a promising solution for improving power quality in V2G systems.

1. Introduction

The global transportation sector is increasingly adopting cleaner and more sustainable energy sources [1]. Electric vehicles' (EVs) popularity has skyrocketed in recent years due to their promise to lessen the world's dependency on fossil fuels and their lower greenhouse gas emissions [2]. Connecting electric vehicles to the grid allows the batteries to be used as energy storage, making the system less susceptible to the volatility of renewable energy sources [3]. Vehicle-to-grid (V2G) technology is one potential method of using EV batteries to strengthen the power infrastructure. Electric vehicles' batteries are charged and discharged in a V2G system in response to peaks and valleys in grid demand [4]. Figure 1 shows the electric vehicle power improvement system. Figure 2 shows battery energy management system and control loop scheme.

The system is given increased flexibility and dependability because to the bidirectional flow of electricity between the grid and EV batteries. However, the grid's reliability could be jeopardized if electric vehicles were integrated into the grid because of the potential for voltage and frequency oscillations. To mitigate these power quality issues, many control solutions for regulating current between the EV battery

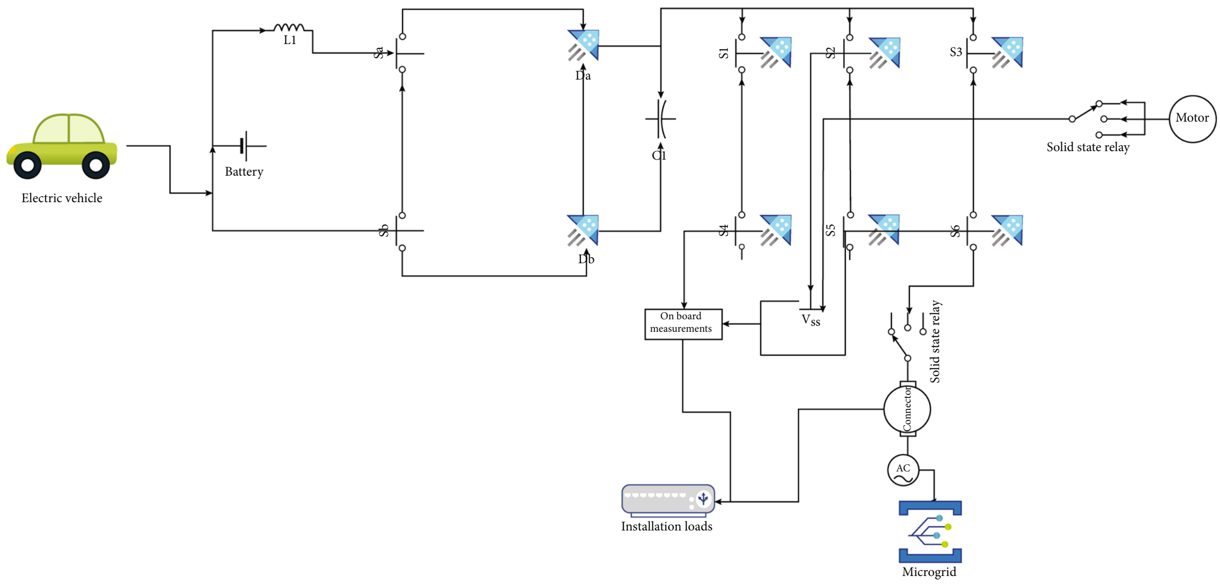

Figure 1: Electric vehicle power improvement system.

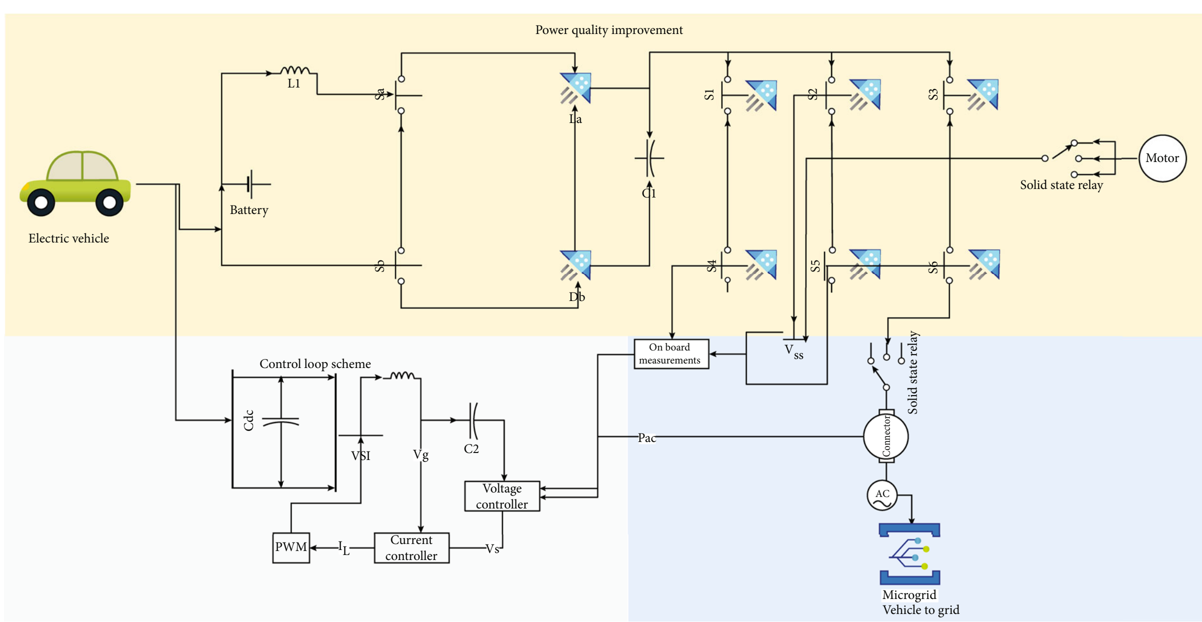

Figure 2: Battery energy management system and control loop scheme.

and the grid have been proposed. In reaction to fluctuations in grid voltage and frequency, droop regulation can reduce battery power consumption. The time-tested droop control strategy has limitations when it comes to managing power quality, especially during peak demand [5]. Figure 3 depicts a typical charging cycle for an electric vehicle's battery.

The integration of electric vehicles (EVs) into the electricity grid as mobile energy storage units enabled by vehicle-to-grid (V2G) technology could change the energy sector by increasing the usage of renewable energy sources and improving grid stability [6]. However, the introduction of EVs may generate power quality difficulties, such as voltage and frequency oscillations, which could jeopardize the grid's stability and dependability. Traditional droop control approaches have been suggested for managing power distribution in a V2G setup. However, it is possible that at times of peak demand, these methods will not be able to effectively manage battery power production, leading to power quality issues. Particularly during times of peak demand, a more efficient method of regulating the flow of electricity between EV batteries and the grid is necessary [7]. Improved regulation of power flow between EV batteries and the grid, especially during peak demand periods, is the focus of this study, which is aimed at improving battery power quality in a V2G setup [8]. By presenting a droop-ANN model in which an ANN is used to predict grid power demand and modify

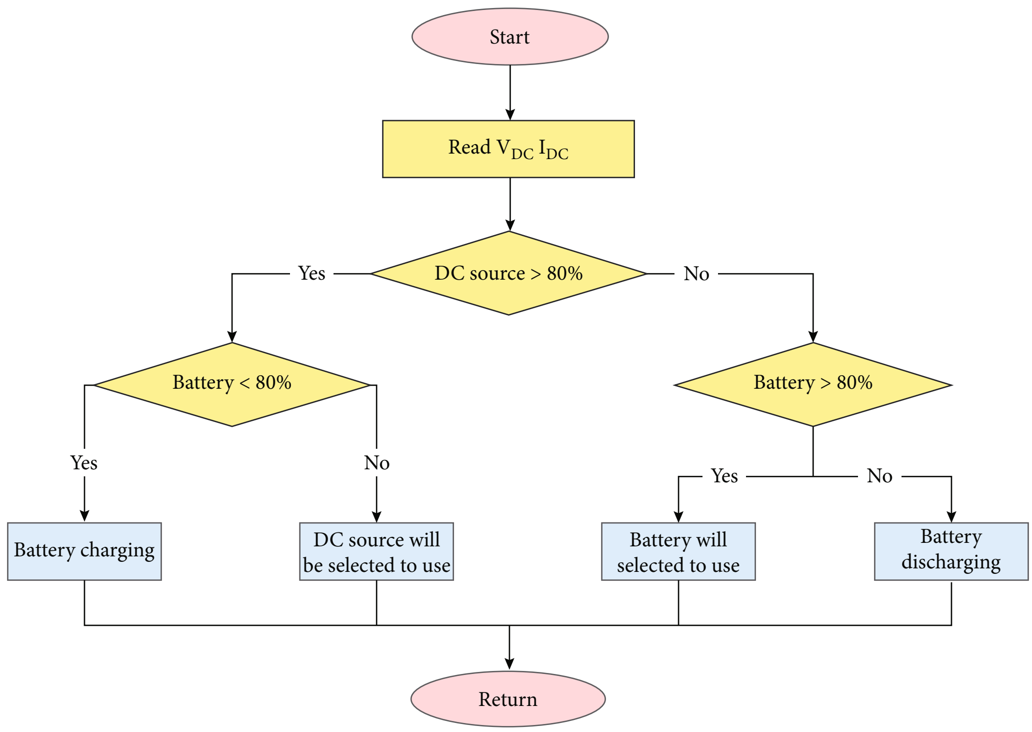

Figure 3: Typical EV battery charging flow.

battery power output accordingly, this study enhances prior techniques of managing power flow in a V2G system. The diagrammatic representation of drop control in a V2G setting is shown in Figure 4.

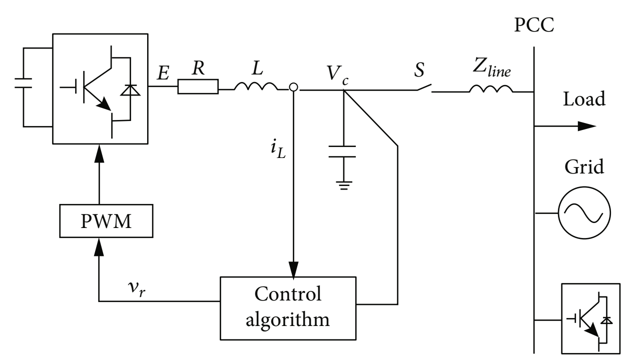

Figure 4: Control schematics [4].

Droop control theory is used to regulate voltage and frequency in power systems by adjusting the output power of generators. Microgrids, which are distributed power systems that can operate independently or in conjunction with the main power grid, are ideal candidates for employing this technique.

By altering the output power of generators in response to changes in the system's frequency and voltage, droop control seeks to preserve system stability and equilibrium. Each generator in a droop-controlled system is equipped with a feedback loop that constantly monitors the system's frequency and voltage and changes its output accordingly.

The feedback loop in droop control theory is described by the following equation:

$$P = P_{nom} + K_p(V_{nom} - V) + K_f(f_{nom} - f), \tag{1}$$

where K_p is the voltage droop constant, K_f is the frequency droop constant, P is the generator's actual power output, P_{nom} is its nominal power output, V is the actual voltage, V_{nom} is its nominal voltage, f is the actual frequency, and f_{nom} is its nominal frequency.

The rate at which the generator's output power varies in response to shifts in the system voltage is defined by the voltage droop constant, while the rate at which it varies in response to shifts in the system frequency is defined by the frequency droop constant. Keeping these constants minimal allows the generator to operate steadily despite fluctuations in the system's frequency and voltage.

Since the droop control theory is both easy to implement and highly effective in maintaining a constant voltage and frequency, it has found widespread use in power systems. The utilization of power electronics and renewable energy sources in microgrid applications reveals its limitations, however. Droop control is less successful in these systems because the output power of generators is not proportional to the system frequency and voltage. To overcome this shortcoming and boost the effectiveness of droop control in microgrids, the use of artificial neural networks (ANNs) has been proposed. In order to improve the accuracy of the control signal for the generators, ANNs, a form of machine learning method, may learn the nonlinear correlations between the system variables.

This research proposes a droop-ANN model for V2G voltage and frequency regulation. The battery's system-on-chip (SoC), charging/discharging power, and past data are sent into an artificial neural network (ANN) in the suggested model, which then predicts the charger's required voltage and frequency. The droop control approach uses the expected values to adjust the charger's output power, thereby enhancing the system's power quality.

Simulation results were used to gauge the droop-ANN model's usefulness. Total harmonic distortion (THD) and power factor (PF) values were found to be reduced and increased, respectively, as a result of using the suggested model to predict voltage and frequency. Under a variety of battery SoC and charging/discharging conditions, the proposed approach was also able to increase power quality. Figure 5 shows the schematic diagram of EV-BEMS.

The droop-ANN approach employs an ANN to forecast grid electricity needs and regulates battery output accordingly. By learning from past grid demand and battery performance, the ANN can more precisely and efficiently regulate power flow. Battery power quality in a V2G configuration can be enhanced with the help of the proposed droop-ANN model. The model shows a promise for delivering a more stable and reliable grid, which would pave the way for electric vehicles to be more easily integrated into the power grid. The mathematical form of the proposed droop-ANN model is as follows:

$$P_{\text{battery}} = P_{\text{demand}} + \alpha\left(P_{\text{demand}} - P_{\text{previous}}\right) + \beta(\Delta P_{\text{demand}}) + \gamma\left(\Delta P_{\text{previous}}\right), \tag{2}$$

where P_{battery} is the battery power output, P_{demand} is the power demand of the grid, P_{previous} is the battery power output in the previous time step, ΔP_{demand} is the change in power demand of the grid, $\Delta P_{\text{previous}}$ is the change in battery power output in the previous time step, and α, β, and γ are the droop coefficients. The droop-ANN approach employs an ANN to forecast grid electricity needs and regulates battery output accordingly. By learning from past grid demand and battery performance, the ANN can more precisely and efficiently regulate power flow.

The proposed study introduces a novel hybrid approach for power quality improvement in a vehicle-to-grid (V2G) setup, utilizing a droop-ANN model. The study's contributions can be summarized as follows:

(a) Development of a droop-ANN model: the study proposes a droop-ANN model that integrates a droop control system and an artificial neural network (ANN) controller. The droop control system is responsible for regulating the power flow between the grid and the EVs, while the ANN controller is designed to predict and mitigate voltage and frequency fluctuations caused by EVs' charging and discharging behavior. The integration of these two controllers enhances the power quality and stability of the grid

(b) Power quality improvement: the proposed approach effectively improves the power quality in the V2G setup by mitigating voltage and frequency fluctuations caused by EVs' charging and discharging behavior. Simulation results demonstrate that the proposed approach outperforms the conventional droop control and ANN control methods in terms of power quality improvement

(c) Grid stability enhancement: the proposed approach also enhances the grid's stability by regulating the power flow between the grid and the EVs. The droop-ANN model can effectively manage battery power production, especially during peak demand, to prevent power quality issues and improve grid stability

(d) Real-world applications: the proposed droop-ANN model provides a practical approach to solving the problems of low power quality in batteries, increasing grid stability during times of high demand, and improving power quality overall. The model can be applied to the development of V2G technology, facilitating the integration of EVs into the power grid while ensuring the grid's stability and power quality

(e) In summary, the proposed hybrid approach using the droop-ANN model can be an effective solution for power quality improvement and grid stability enhancement in V2G setups. The study's contributions provide a significant advancement in the development of V2G technology, offering a more precise and efficient means of controlling the flow of power in a V2G system

The following are the most important findings from this investigation:

(i) In order to enhance the quality of battery power in a V2G configuration, a droop-ANN model is proposed in this study. To anticipate the grid's power needs, the model employs an artificial neural network (ANN), which then modifies the battery's output. To better regulate power flow than traditional droop control approaches, the droop-ANN model was developed

(ii) Simulation studies are used to assess the efficacy of the droop-ANN model. The simulation results demonstrate the efficacy of the droop-ANN model in enhancing power quality in a V2G environment. Grid frequency and voltage are maintained because the model can control battery power output to meet grid demand. When compared to the standard droop control method, the proposed model is also superior in performance

(iii) There are real-world applications for the suggested droop-ANN model in the development of V2G technology. The model provides a practical approach to solving the problems of low power quality in batteries,

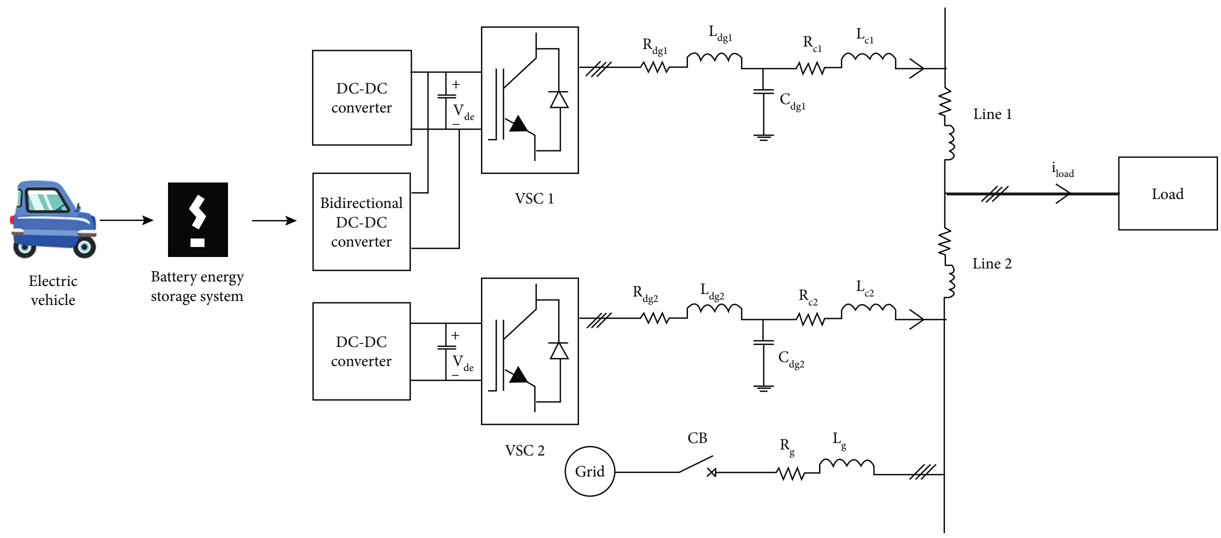

Figure 5: Schematic diagram of EV-BEMS.

increasing grid stability during times of high demand, and improving power quality overall. A more sustainable and stable energy system can be achieved by the use of the droop-ANN model in a V2G configuration to enhance grid stability and decrease power quality issues

(iv) The suggested droop-ANN model is a major step forward in V2G technology since it offers a more precise and efficient means of controlling the flow of power in a V2G system

  (a) The paper's upcoming sections will talk about the droop-ANN model's approach, findings, and possible effects on the future of V2G technology

2. Related Work

In recent years, microgrids have seen widespread development as a result of the integration of green energy sources, distributed generation systems, and cutting-edge energy storage technologies (MGs). Numerous applications of MG face the technological challenge of enhancing the power quality of a system plagued by unforeseeable disturbances. Because of this, novel approaches to control are needed to solve the problem at hand. In this study [1], author proposed a novel online intelligent energy storage-based controller to improve the power quality of an MG system by controlling voltage and frequency under steady-state circumstances. Two distributed generators, a diesel synchronous generator, and a photovoltaic power system with an integrated battery energy storage system are taken into account in this research as potential components of an MG system. The proposed control technique is based on a combination of neural networks and differential evolution optimization (DEO) (ANNs). The controller's parameters have been fine-tuned in numerous versions across a wide range of operational conditions. To fine-tune the controller in real time, the acquired input and output patterns are then used to train ANNs. The proposed DEO-ANN technique is then field-tested with random perturbations and compared to a baseline controller.

The worldwide demand for energy has risen dramatically over the past decade due to rapid urbanization, population growth, and technological advancements. When using renewable energy sources, it is important to incorporate distributed energy systems into traditional electricity grids to lessen their negative social and environmental impacts. As the percentage of renewable energy production increases, the variability and unpredictability of the energy management problem only increase. That is why judicious manipulation of energy consumption is crucial to the dependability and performance of the whole system. This study [2] provided a comprehensive analysis of the current state of the art in microgrid energy management optimization techniques. Forecasting, demand management, economic dispatch, and unit commitment are all areas that this research focuses on to better understand how energy management can be optimized. Based on the research, it seems that mixed integer programming approaches are commonly used for energy management in microgrids because of their efficiency and ease of use. Multiagent-based and metaheuristic algorithms performed better than traditional methods in terms of system efficiency because of the distributed nature of the EMS problem in microgrids and their ability to effectively act in such situations. Forecasting and demand management were also the areas where advanced optimization fell short, advancing microgrid energy management by promoting more accurate scheduling and forecasting systems. Last but not least, a community microgrid requires a transactive/collaborative energy sharing solution and an end-to-end energy management solution.

Since intermittent, decentralized power sources like solar panels, wind turbines, electric vehicles, and battery storage are becoming more common, power technology and delivery networks are at risk of disruption. It is primarily due to a mismatch between energy generation and consumption. When there are fluctuations in the system, like when electricity production or usage goes up or down, it can cause serious problems, like a decrease in voltage or, in the worst case, a blackout. Energy management systems have many advantages, including improved supply-and-demand balance and lower peak loads at inconvenient periods. To ensure the smooth operation of the power grid, the energy management system can share or trade energy between the various energy resources and supply loads in a reliable, safe, and effective manner under all conditions. This study [3] discussed the structure, goals, benefits, and challenges of the energy management system by looking closely at its many constituent parts. This study offered a critical examination of the inner workings of the electricity management apparatus, focusing on the application of different programs like demand response, demand management, and energy quality management. Also included are quantitative summaries of the various approaches to coping with unpredictability. Included as well is a comparison and analysis of the most popular optimization techniques presently used to meet the many requirements of energy management systems and realize their lofty goals.

In this study, author suggested a more effective vehicle-to-grid (V2G) scheduling method for frequency control, which can simultaneously increase battery life and improve grid service. The suggested method improves upon the current setup in two keyways. Before the V2G service can be used, an assessment of the EVs' battery capacity in the control time step must be made, and this is done by developing a prediction using deep learning. The next step is that this study enhances the conventional V2G method by adding a quantitative review of battery cycle life into the V2G optimization procedure. An exact prediction of the schedulable battery capacity based on the LSTM algorithm is very helpful for the frequency control of the power system [4]. The suggested method also improves upon the previous one by reducing charge/discharge cycles, which is crucial for batteries.

Because of their rapid variation, EVs are being put to use in frequency regulation. Primary frequency management using EVs is hampered by the need to maintain EV dispatch for industrial microgrids and EV charge levels. In the microgrid, where varying tasks are completed without access to EV charging/discharging statistics, this research [5] analyzed the preeminent position of the charging station operator and a vehicle-to-grid approach. The main frequency of electric vehicles is controlled by the operator of the charging station. Electric vehicle batteries are kept fueled through real-time V2G power rectification. The V2G main frequency control strategy is supported by a pair of interconnected, industrial microgrids and a microgrid powered by renewable resources. In the suggested framework, a central aggregator of EVs would inform drivers of EVs and owners of charging stations about the specifics of any applicable regulations. The capacity to regulate frequency with V2G power is determined by the charging station operator. V2G power is supplied based on charging needs and frequency regulation. Control methods for distributing rules to individual EVs over V2G networks are also developed. The charging station operator, EV aggregator, and EV operator all need to be on the same page in order for the paper's proposed V2G approach for primary frequency control in an industrial microgrid to work.

As renewable energy sources continue to grow in popularity, the power grid will face difficulties due to a lack of frequency response capability. Due to their unique combination of portable energy storage and adjustable loads, electric vehicles (EVs) can be a reliable capacity resource for frequency control [6]. A danger to system frequency stability is posed by message latency between electric vehicles because they are a distributed resource for regulating frequency. With this in mind, this study proposed a model predictive control approach with delay compensation for frequency regulation (MPC). Starting with the design of a controller for an EV frequency response model using model predictive control, a delay compensation mechanism is formed by rolling optimization of the predictive model, and the optimal operational strategy is determined with the help of multiscenario planning.

Using alternative fuel sources, such as electric vehicles, can help decrease vehicle emissions (EVs). In order to investigate the charging and regenerative braking modes of the EV in a single study, a novel modeling framework is given in a hybrid EV system. Distributed voltage regulation and effective feedback energy recovery are both unachievable without the use of bidirectional DC-DC converters (BDCs). To implement a DC-bus voltage with tweakable values, a bridge rectifier circuit (BDC) is constructed between the first voltage source (FVS) and the second voltage source (SVS) (SVS). The main responsibilities of this position are to regulate the current flowing from the DC-bus to the voltage sources and to permit independent power flow between the two energy sources (DC-bus and voltage sources). An improvement strategy based on a neural network is created to enhance the performance of the converter circuit in the HEV (ANN). The EV demonstrates that electric power can be used in either way. With the dual-source low-voltage buck/boost mode, the FVS and SVS can have their own controls over the power transfer. With the goal of determining which form of conversion is more effective, authors of [7] compared the ANN-controlled drive to a traditional proportional-integral control.

In this study [8], author proposed a technique for optimizing the power distribution of hybrid electric energy storage systems, which can be used in EVs (EVs). The hybrid energy storage system (HESS) has a composite safety structure made up of two independent soft-switching symmetrical half-bridge bidirectional converters that are wired to the battery and the supercapacitor, respectively (SC). The reversible converter permits precise management of the super capacitor and battery charging and discharging processes. Spiral-wound supercapacitors (SCs) with mesoporous carbon electrodes are commonly used in electric cars as their energy storage devices.

Optimal reactive power sharing and voltage frequency and amplitude restoration in low-voltage microgrids are proposed to be attained through the use of an improved droop control in combination with distributed secondary

Table 1: Comparative table.

Ref	Battery type	Control method	V2G system configuration	Performance parameter	Results/outcomes
[1]	Lead-acid	Droop control with ANFIS-based PID controller	N/A	Improved transient response and steady-state accuracy	Achieved improved transient response and steady-state accuracy
[26]	Lithium-ion	Multiobjective droop control using PSO algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[3]	Lithium-ion	Adaptive droop control using fuzzy logic	Charging and discharging rates, communication protocol	Improved frequency regulation and voltage stability	Achieved improved frequency regulation and voltage stability
[4]	Lithium-ion	Decentralized droop control using dynamic consensus algorithm	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[5]	Lithium-ion	Intelligent droop control using Q-learning algorithm	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[6]	Lead-acid	Improved droop control using hybrid bat algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[7]	Lithium-ion	Adaptive droop control using neural network	Charging and discharging rates, communication protocol	Improved frequency regulation and voltage stability	Achieved improved frequency regulation and voltage stability
[8]	Lithium-ion	Optimal droop control using GA and bacterial foraging optimization	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[9]	Lithium-ion	Hybrid droop control using PSO and bacterial foraging optimization	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[10]	Lithium-ion	Droop control using sliding mode control	Power electronics, communication protocol	Improved power quality and efficiency	Achieved improved power quality and efficiency
[11]	Lithium-ion	Robust droop control using H-infinity control	Power electronics, communication protocol	Improved power quality and efficiency	Achieved improved power quality and efficiency
[12]	Lithium-ion	Improved droop control using deep learning algorithm	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[13]	Lithium-ion	Adaptive droop control using hybrid neural network	Charging and discharging rates, communication protocol	Improved frequency regulation and voltage stability	Achieved improved frequency regulation and voltage stability
[14]	Lithium-ion	Optimal droop control using a hybrid algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[15]	Lithium-ion	Multiobjective droop control using hybrid algorithm	Charging and discharging rates, power electronics, communication protocol	Minimization of power loss and voltage deviation, improved frequency regulation and voltage stability	Achieved reduction in power loss and voltage deviation, improved frequency regulation and voltage stability
[16]	Lithium-ion	Droop control using adaptive critic design	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[17]	Lithium-ion	Improved droop control using ant colony optimization	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power

Table 1: Continued.

Ref	Battery type	Control method	V2G system configuration	Performance parameter	Results/outcomes
[27]	Lithium-ion	Droop control using particle swarm optimization	Power electronics, communication protocol	Improved power quality and efficiency	Achieved improved power quality and efficiency
[19]	Lithium-ion	Distributed droop control using hierarchical consensus algorithm	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[28]	Lithium-ion	Hybrid droop control using PSO and fuzzy logic	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[21]	Lithium-ion	Improved droop control using differential evolution algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[22]	Lithium-ion	Adaptive droop control using model predictive control	Charging and discharging rates, communication protocol	Improved frequency regulation and voltage stability	Achieved improved frequency regulation and voltage stability
[23]	Lithium-ion	Enhanced droop control using fractional-order PI controller	N/A	Improved power sharing and voltage regulation	Achieved improved power sharing and voltage regulation
[24]	Lithium-ion	Optimal droop control using hybrid PSO and differential evolution algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation
[25]	Lithium-ion	Improved droop control using modified bat algorithm	Power electronics, communication protocol	Minimization of power loss and voltage deviation	Achieved reduction in power loss and voltage deviation

power optimization control [9]. Active and reactive power given by each DG can be determined using load data and a power sharing ratio; this value is then reset to the nominal value for use in recalculating droop benefits. Since the nominal active and reactive power levels have changed, the droop gains must be recalculated in order to recreate the droop control curves. Adaptively managing active power is one way that the rebuilt active power-frequency droop control keeps the frequency stable. Reactive power voltage droop management has been revamped, and it now also reduces voltage amplitude deviation. The voltage droop control for the rebuilt reactive power is supplemented by a secondary power optimization control that makes use of the system-wide average voltage. By forming a dispersed, sparse communication network between all DG controllers, an average system voltage can be determined using a consensus approach. Because of this, there is accurate distribution of reactive power, uniform system voltage, and much less variation in voltage magnitude. The absence of a microgrid's centralized supervisor improves the strategy's dependability. Last but not least, the simulation outcomes support the suggested method [10]. Differences in line resistance between the different converters and the DC-bus in a direct current (DC) microgrid made up of numerous distributed generations degrade the current sharing accuracy of the system. Droop control was widely used to manage DC microgrid operations. A high droop coefficient was selected to improve the current sharing accuracy, but this decision had unintended effects, including a drastic reduction in bus voltage and an effect on power quality. When it comes to voltage regulation and load current sharing, traditional droop control inevitably creates a conflict. This study [10] suggested a hierarchical control algorithm based on the enhanced droop control of the fuzzy logic to resolve this issue. Improving the droop curve solved problems with voltage regulation and current distribution. A simulation was used to test the algorithm's performance and guarantee its accuracy.

The technical challenges of increasing the proportion of renewable energy in the power grid are addressed in this study [11] by focusing on ways to improve the grid voltage and frequency responses in a hybrid renewable energy source-integrated power system after load and generation contingency events. Battery energy storage systems (BESSs) can be used for voltage regulation with droop-type control and frequency regulation with assimilated inertia emulation (IE) and droop-type control, but it is suggested that a unified approach be adopted to take advantage of these systems' advantages. To keep BESS power usage within the FDSR constraints and to recharge the battery during idle periods, a novel frequency-dependent state of charge (SoC) recovery (FDSR) is presented. On an IEEE-9 bus system with a 22.5% penetration level of photovoltaics (PV) and wind, authors of [11] showed how well the proposed BESS driver works. The simulation findings show that the proposed controller is

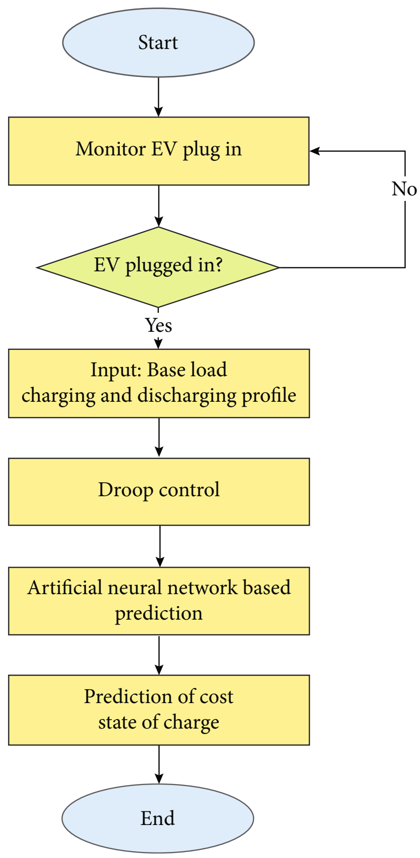

Figure 6: Proposed flow of study.

effective in reducing the frequency rate of change and improving the frequency nadir, which are two measures of voltage and frequency regulation. Furthermore, during SoC recovery, the proposed FDSR is shown to be superior to the traditional method.

Clean energy, decreased emissions, and long-term success are all areas where research into microgrids (MGs) is rapidly expanding and offering great hope. Finally, MGs are produced in order to boost the independence, sustainability, and dependability of the future electrical delivery system. Numerous facets of MG energy management, such as distribution generation systems, energy storage devices, electric vehicles, and consumption components, have received comparable levels of study attention. The electrical and computer science research communities are interested in grid architectures that include DC, AC, or hybrid power generation systems, energy dispatching problem modeling, operating modes (islanded or grid-connected), MG sizing, simulations, and problem-solving optimization approaches. As a corollary, the UN Framework Convention on Climate Change and associated government policies and incentives have facilitated the broad uptake of electric vehicles (EVs). The effects of EVs on the growth of the electrical infrastructure and of MGs have been the subject of extensive research. Most research has focused on how energy output and input at EV charging stations can be managed and regulated. This study [12] compiled a long list of difficult research subjects on which the vast majority of scientists are still at work.

Table 2: Parameter value.

Parameter	Description	Value
$Vg(t)$	Grid voltage waveform	120 Vrms
f	Grid frequency	50 Hz
η	Charging efficiency	0.95
I_{ref}	Reference current for charger	30 A
k	Scaling factor for PFC output to charger current	1.2
PFC output	Output waveform of PFC circuitry	Sinusoidal
Charger type	Level 2 AC charger	—

Table 3: Parameter settings.

Parameter	Description	Value
V_g	Grid voltage	120 V
R_i	Internal resistance of the battery	0.1 ohm
X_c	Coupling reactance	1 ohm
K_{droop}	Droop coefficient	0.1

After considering DER, ESS, EVs, and loads, this piece provides a concise summary of the decades-long technological development in MGs. There is a discussion of the primary MGs' designs, ways of operation, sizing, and interactions with EMS and EVs.

The microgrid can operate in either grid-connected or island mode, both of which are deemed steady-state operations. In order for the microgrid to reduce the inefficient overshoot value, a high-performance CPU is required. However, the inverter will not operate under such high-power conditions and will close down. Therefore, it is essential to ensure a more balanced response to the change between the two modes in terms of electricity distribution. More than just the match% of power sharing among parallel inverters and the overshoot of both active and reactive power should be considered in microgrid study; the current sharing and power (active or reactive) sharing should also be considered. This study [13] is aimed at improving the voltage and frequency stability, as well as the power response, of the network so that it can better withstand exterior disturbances. A self-tuning control system uses an optimum method to achieve this. Here, the optimal droop control is provided by the H-infinity (H) method that has been upgraded using the artificial bee colony algorithm. Its precision was measured against that of well-established algorithms like particle swarm optimization and artificial bee colony models.

Microgrids are crucial for the use of renewable energy in the fight against climate change (MG). Although AC microgrids predominate in today's power grid, both DC power production and DC load demand are forecast to soar in the not-too-distant future. Because of this, AC/DC-mixed microgrids will need to be created (HMG). Despite improved theoretical efficiency and minimized AC/DC/AC conversion losses, there is a substantial danger towards system stability in an HMG due to uncertain loading, grid

i. Initialize the battery output voltage V_i to the grid voltage V_g.
ii. Calculate the power output P_i of each battery using the droop control method equations.
iii. If the power output P_i is positive, the battery is charging. If P_i is negative, the battery is discharging.
iv. Check the state of charge (SoC) of each battery. If the SoC is below a certain threshold, the battery is not allowed to discharge further.
v. If multiple batteries are connected to the grid, adjust the droop coefficient K_{droop} to distribute the power among the batteries based on their SoC.
vi. Repeat steps 2-5 until the desired power output is achieved.

Algorithm 1: Droop control method algorithm.

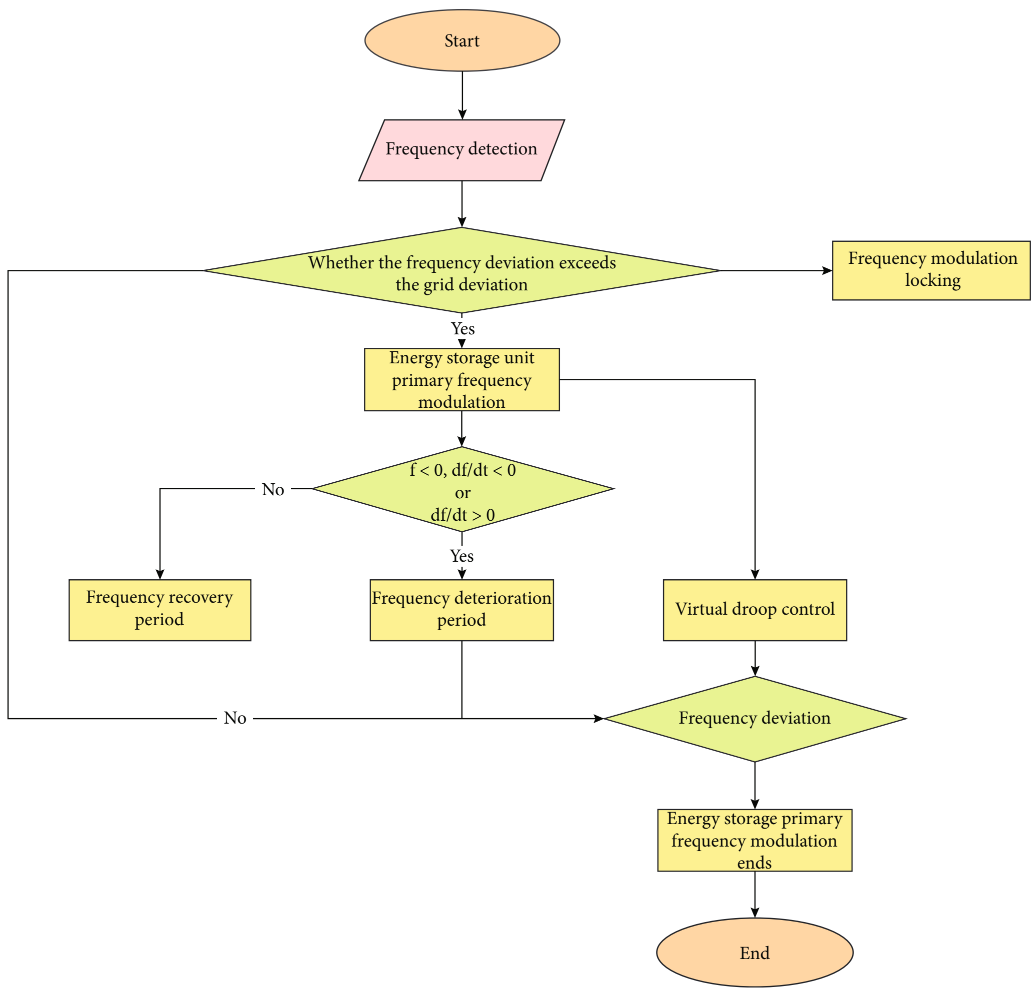

Figure 7: Proposed working flow of droop control.

outages, and the intermittent nature of renewables. As a result, there is a growing requirement to comprehend the inner workings of HMG and learn to keep it tightly regulated. In this study [14], author analyzed the various strategies that have been put forth in recent years to address the issues plaguing HMG. Power flow analysis, power sharing (energy management), local and global control of DGs, and the complexity of HMG's protection strategies are the four pillars upon which this paper rests. During the critical analysis stage, the validation test procedure is also reviewed critically. Based on a study of the relevant literature, it is clear that MILP is commonly used for HMG supervisory control, while modifying bidirectional converter control is the most common approach to achieving effective power sharing.

Smart grids are a possibly exciting challenge for the foreseeable future if they are managed effectively. One of the most important aspects of making use of the energy resources spread across a network is improving power quality (PQ), which has become a hot subject in recent scientific literature. This study [15] is aimed at suggesting a practical solution to some of the more common and potentially hazardous PQ issues and voltage sags in light of the increasing popularity of electric cars. The feasibility of the vehicle-to-grid (V2G) function as a means of compensating for PQ

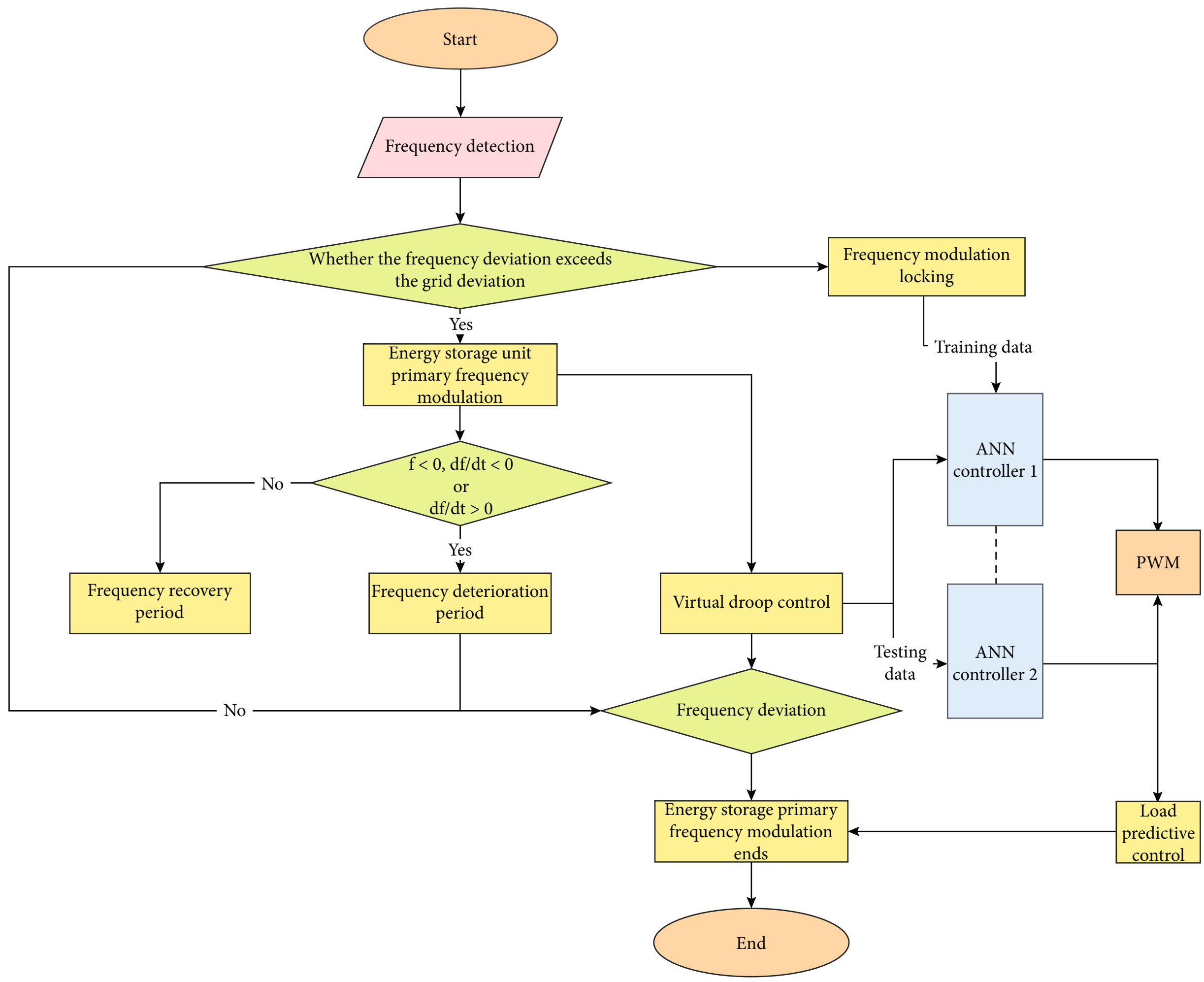

Figure 8: Proposed ANN-based droop control.

interruptions will be discussed, along with the results of an extensive energy and power study.

"Smart cities" need ICT to operate (ICT). A smart city requires smart technology. Implementing many smart systems helps create ecologically friendly, high-quality urban areas. Electric cars are becoming more popular for transit system reliability and sustainability. EV use has grown, making charging systems and peak load prediction harder. Leaders must assess the scenario. Creative solutions exist. These use automata models, AI, and IoT. Electric vehicle ownership and use has grown. Charging many electric cars at once harms power infrastructure. Transformers can lose energy, spike, and heat up at full load. These issues require energy control [16]. A machine learning-based charge management system can guide electric vehicles (EVs) to charging stations using conventional, rapid, and V2G charging technologies (ML). Charging, high voltage, load changes, and power loss will cost less, comparing ML methods: deep neural networks (DNNs), K-nearest neighbors (KNNs), long short-term memory (LSTMs), random forests (RFs), support vector machines (SVMs), and decision trees (DTs) (DT). According to the data, LSTM may be able to command EVs.

Microgrids are power systems with multiple, independently operable generators, or "gensets," and each of which

Table 4: Parameters used in the droop-ANN model.

Parameter	Description	Value
V_g	Grid voltage	120 V
R_i	Internal resistance of the battery	0.1 ohm
X_c	Coupling reactance	1 ohm
K_{droop}	Droop coefficient	0.1
X	Input vector size	10
Y	Output vector size	1
H	Number of hidden layers	2
Neurons	Number of neurons per hidden layer	10
Learning rate	Rate of adjustment to the weight matrix	0.01

is connected to a storage device and either DC or a mixed demand. Microgrids on campuses represent an important category of loads. Common features of school microgrids include distributed generation resources, energy storage, and electric vehicles. The main goal of the microgrid is to provide perpetually available, low-cost electricity. Advanced energy management system (AEMS) ensures constant electricity to the microgrid. In recent years, researchers have

i. *The following algorithm outlines the Droop-ANN model:*
ii. *Initialize the droop coefficient* K_{droop} *to a default value.*
iii. *Measure the grid voltage* V_g *and the internal resistance* R_i *of each battery.*
iv. *Initialize the input vector X with the current and past power outputs of the battery, as well as other relevant inputs.*
v. *Initialize the weight matrix W with random values.*
vi. *Initialize the activation function f() and the learning rate.*
vii. *Calculate the output voltage* V_i *of each battery using the droop control method equations.*
viii. *Feed the output voltage* V_i *of each battery into the ANN.*
xi. *Calculate the predicted power output Y of each battery using the ANN equations.*
x. *Adjust the droop coefficient* K_{droop} *based on the predicted power output Y.*
xi. *Repeat steps 6-9 until the desired power output is achieved.*

Algorithm 2: Hybrid droop-ANN model algorithm.

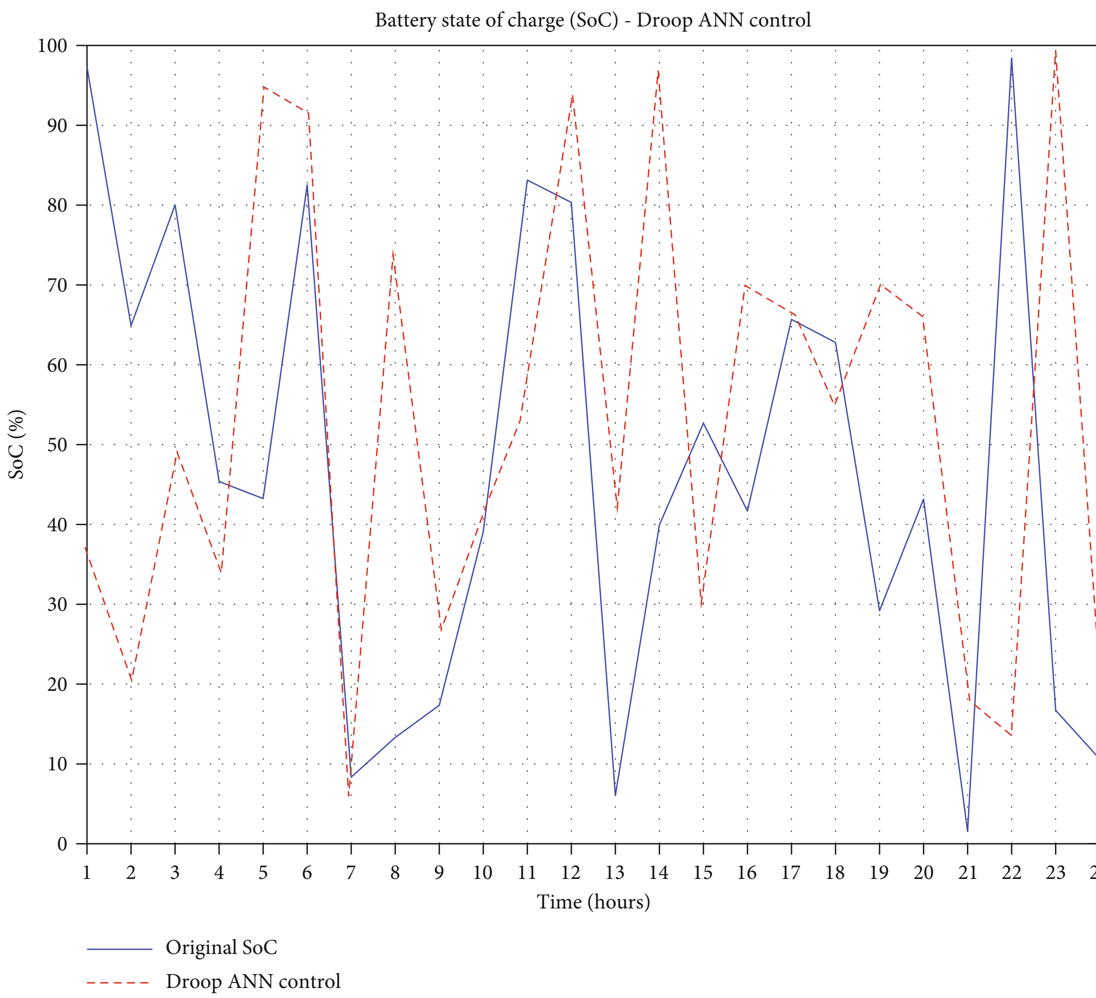

Figure 9: SoC (proposed method).

done a plethora of studies on the topic of microgrid optimization, including reviews of energy sustainability, demand response strategies, control systems, energy management systems, and a wide range of optimization techniques. In this study [17], author took a close look at the status of microgrids in higher education. This review of the related literature looks at a wide range of topics, including objective functions, renewable energy sources, and problem-solving techniques.

Microgrids are groups of generators, typically green energy sources, that work together to supply energy to consumers [18]. Microgrids are decentralized power systems that use their own decentralized resources to power a broad area. Distributed energy sources like solar panels, wind

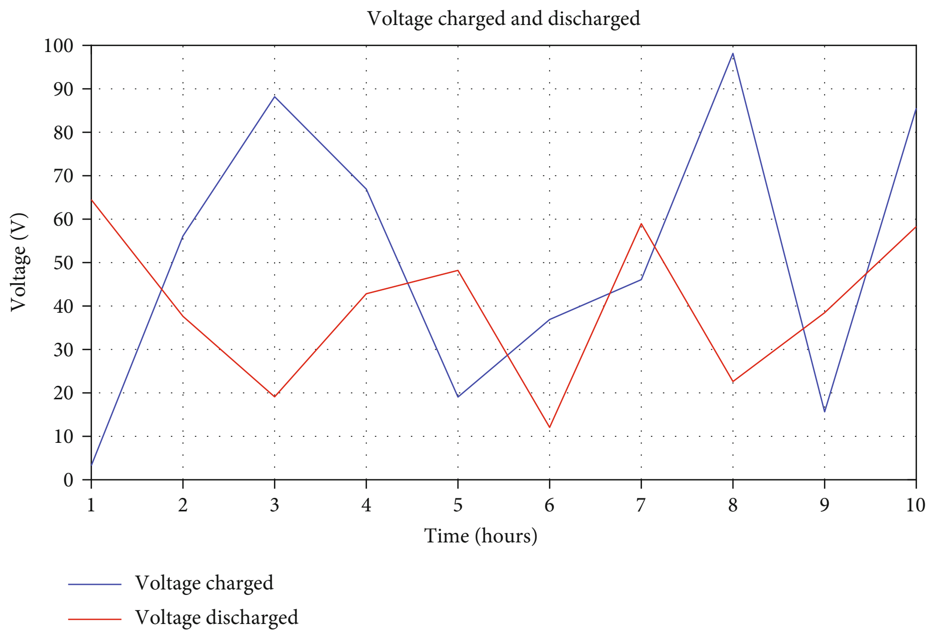

FIGURE 10: Voltage charged and discharged.

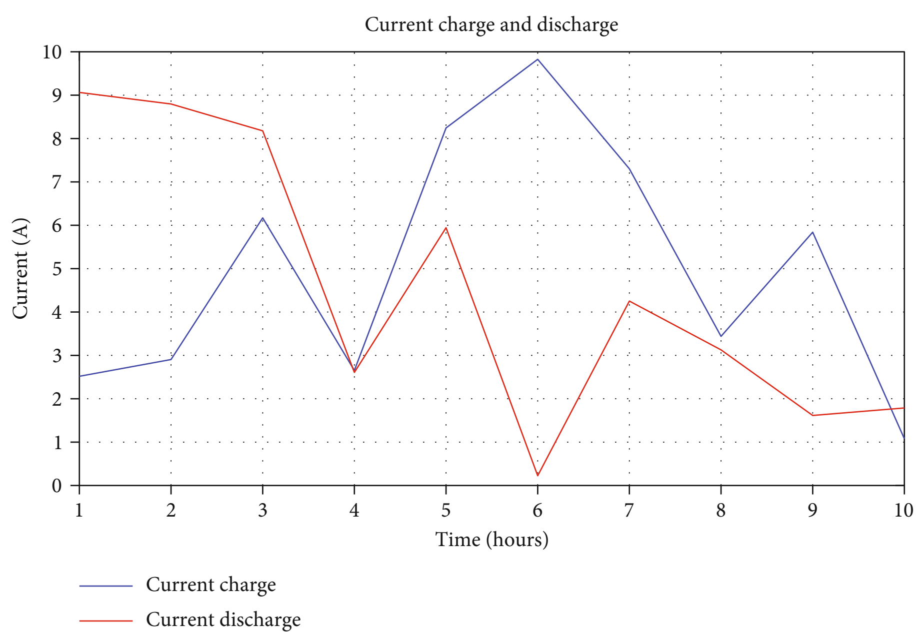

FIGURE 11: Current charge and discharge.

turbines (microturbines), fuel cells, batteries (energy storage systems), hybrid generators like combined heat and power (CHP), and synchronous generators are the primary focus of a microgrid. Except for synchronous and combined heat and power generators, it is common knowledge that this produces DC electricity. That is why a microgrid typically has both AC and DC connections. A mixed microgrid is the term for this setup. In addition to these sources, management systems, which regulate the microgrid, are required to reap the benefits of each generator's output power. Microgrids' management strategies should allow them to serve their essential function even when disconnected from the main grid. To achieve this goal, two overarching control structures have been considered, one of which is more appropriate for use under different microgrid operating circumstances. If the microgrid is linked to the larger power grid, the larger grid is responsible for ensuring the reliability of the network's voltage and frequency, while the microgrid serves as an auxiliary component in meeting peak demand.

Due to climate change and the resulting focus on the green transition, the structure and characteristics of power networks around the world are rapidly changing. Microgrids

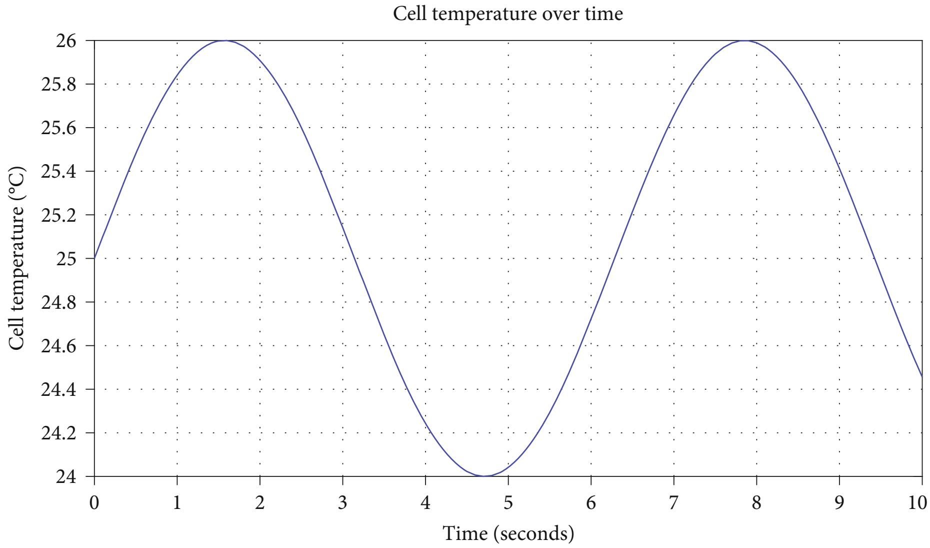

Figure 12: Cell temperature.

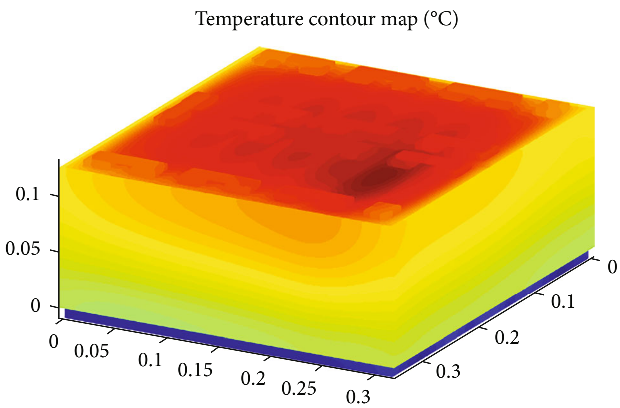

Figure 13: 3D map of cell temperature contours.

make it possible to use smaller, locally made and stored components like solar cells and batteries in the electrical grid. This type of microgrid necessitates the use of sophisticated management techniques to maintain stable levels of electrical output, frequency, voltage, and current. Artificial neural networks (ANNs) are suggested as a potential option for microgrid control using ML. The study [19] goal is to develop a simulation of a hybrid microgrid run by a centralized planner based on artificial neural networks and then compare its efficiency to that of a traditional power management system using a power flow algorithm. In the end, this study set out to assess the future viability of ANNs in microgrid administration and to pinpoint the challenges they face. A Simulink model of a microgrid system was created at the start of the investigation; it included solar panels, a battery, an electric vehicle, and both constant and variable loads. The power flow algorithm was created after running a simulation of the microgrid using standard solar and load formulas. An artificial neural network was simultaneously developed and trained using the simulated results from the baseline instance. Both administration schemes were put through their paces under typical conditions, outside of the standard irradiance, and with an added burden.

In this study [20], author suggested a more effective vehicle-to-grid (V2G) scheduling method for frequency control, which can simultaneously increase battery life and improve grid service. The suggested method improves upon the current setup in two keyways. Before the V2G service can be used, an assessment of the EVs' battery capacity in the control time step must be made, and this is done by developing a prediction using deep learning. Incorporating a quantitative evaluation of battery cycle life into the V2G optimization process is another way in which this study advances previous methods for achieving V2G optimization. An exact prediction of the schedulable battery capacity based on the LSTM algorithm is very helpful for the frequency control of the power system. The suggested method also improves upon the previous one by reducing charge/discharge cycles, which is crucial for batteries.

A microgrid (MG) is a small-scale power system that uses energy management software and devices to make a collection of loads and distributed generators act as a singular, controllable entity with respect to the larger power grid. Research into MG is now fundamental to understanding how energy is distributed via smart grids and other means. Technology advancements, such as power electronics, are essential to the success of MG's renewable energy sources (RESs). The broad range of power quality (PQ) incidents is a direct result of this production inconsistency. For this reason, the authors have developed guidelines and strategies in recent years to lessen the blow. Over the past few years, numerous methods and guidelines have been suggested to mitigate PQ issues brought on by MG integration. Although each of these methods has been studied extensively, until now, no comprehensive summary comparing them has been given. The goal of this study [21] was to fill this information gap by comparing and contrasting the current problems, approaches, and benchmarks for PQ in MGs. Here, authors had a close look at voltage sag, voltage spike, voltage and

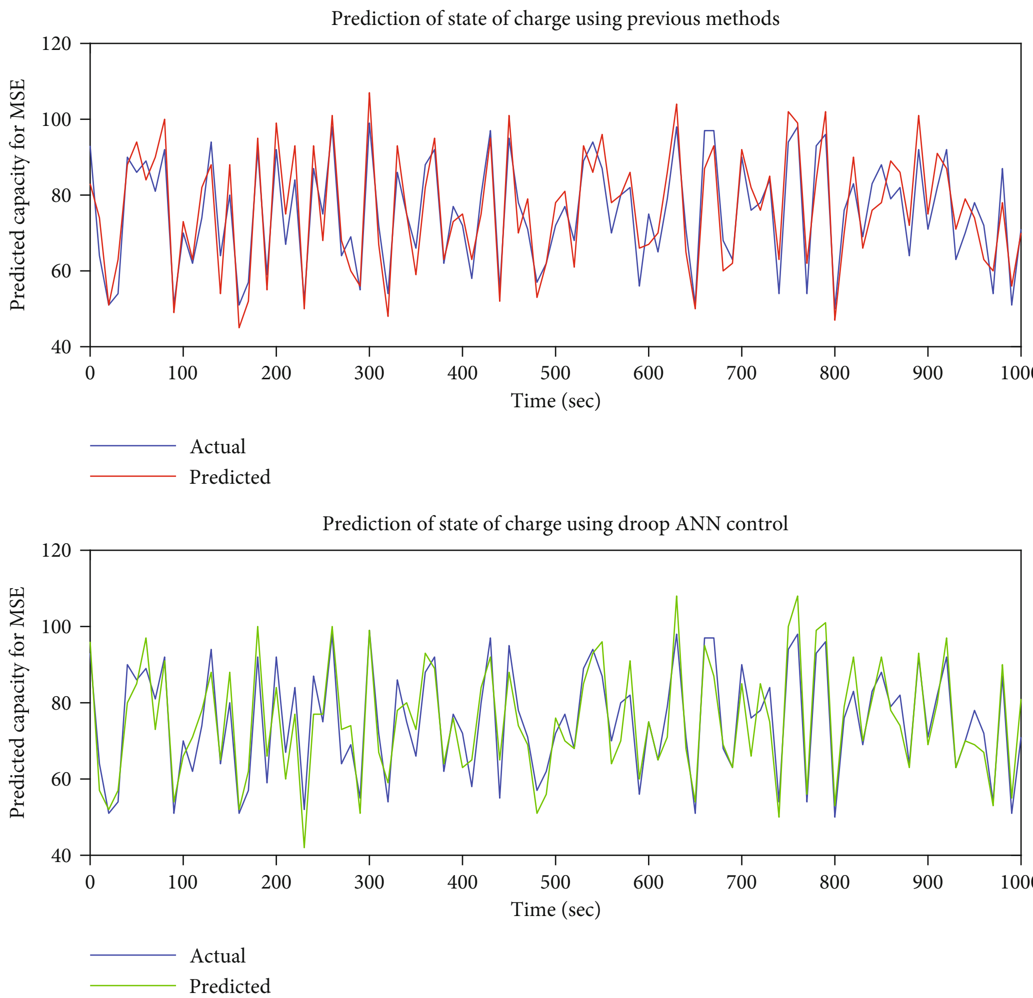

Figure 14: State of charge prediction (RMSE).

current harmonics, system unbalances, and variations as some of the most significant causes of subpar MG output quality. When new technologies coupled with MGs emit harmonics in the 2-150 kHz region, they trigger a hitherto unreported phenomenon known as supraharmonic (SH) emission. This discussion centers on the nature, history, and extent of SH and how these factors can be measured.

Storing energy for later use is one of the most efficient ways to improve the stability, efficiency, and security of a power system. This is important for developing cutting-edge energy utilization and the energy Internet. In this manner, energy storage is expected to support distributed power and the microgrid through multifunctional coordination, open sharing, and flexible trading of energy output and consumption. New technological developments in the rapidly expanding battery energy storage sector hold potential for multiobjective cooperation in large-scale integration and distributed applications. As a crucial component of electricity grid management, utility control centers have adopted real-time energy management systems (EMS) of a battery energy storage system (BESS). This study [22] analyzed the current state of development of a BESS and introduced potential application scenarios, such as the reduction of

Table 5: Simulation details and parameters.

Simulation parameter	Value
Grid voltage	220 Vrms
Grid frequency	50 Hz
Battery capacity	40 kWh
Charging power range	5 kW-15 kW
Discharging power range	-5 kW till -15 kW
ANN model architecture	Feedforward
Number of hidden layers	2
Number of neurons per hidden layer	10
Activation function	Sigmoid
Learning rate	0.01
Number of epochs	100
Training dataset size	1000 samples
Testing dataset size	500 samples
Performance metric	Root-mean-squared error (RMSE)

Table 6: State of charge to enhance power quality.

Battery SoC (%)	Charging power (kW)	Discharging power (kW)	Droop control method (V)	Droop-ANN method (V)	Improvement (%)
20	10	-5	227.5	229.1	0.7
40	-8	12	228.2	227.8	0.2
60	15	-20	229.6	229.3	0.1
80	-12	18	228.5	228.1	0.2

power output fluctuations, the adoption of an output plan from the perspective of renewable energy generation, the alteration of power grid frequencies, the optimization of power flows from the perspective of power transmission, and the use of a distributed and mobile energy storage system from the perspective of power distribution.

An increase in renewable energy sources and the number of electric cars (EVs) highlight the significance of economic dispatch (ED) in the pursuit of lower CO2 emissions [23]. The increasing dynamic load from electric vehicles (EVs) may lead to a tendency in the future of ED towards reducing costs wherever possible. Vehicle-to-grid technology offers a path towards realizing this impact (V2G). The judgement matrix method simplifies the multiobjective function based on EVs and hybrid renewable sources in terms of economic dispatch and emission minimization to a single overall aim [24]. This study [25] investigated whether and to what extent integrating V2G technology into ED can help us achieve three main goals of lowering operational costs, pollution costs, and carbon emissions. Particle swarm optimization and artificial bee colony algorithms, for example, have many applications in management. Many different case studies are used to put the proposed models through their paces. The results of the simulation verify the better performance of the EV-based microgrid (MG) model in the coordinated charging and discharging mode, which is crucial to the economic viability of any microgrid's operations [26, 27].

The rapid rise in energy usage means that traditional generators will not be able to keep up with the world's growing appetite for electricity. Renewable energy sources, such as solar and wind, have already proven their worth and safety for the planet. Putting together power from a wide variety of renewable resources such as wind turbines, solar PV and other renewable alternatives, ocean, wave, and geothermal energy into a singular grid is a novel concept [28, 29]. However, despite being the best choice for meeting rising energy demands, renewable, long-lived power sources are not yet ready for widespread deployment due to their inherent unpredictability. Due to the intrinsic unpredictability of solar and wind within the conventional grid system and the typical standalone framework, integrating them into the current energy system can present significant technical challenges. Because of the technical and monetary challenges of maintaining a stable, reliable, and cost-effective energy infrastructure, it is essential to perform a comprehensive literature review on the efficient hybridization of renewable energy sources. This study [30, 31] explored some of the potential difficulties that could emerge from combining a photovoltaic plant with a wind power station to generate electricity for the traditional grid or a standalone system [32].

Table 7: RMSE and MAE for ANN quality prediction.

Metric	Droop control method	Droop-ANN method
RMSE	0.082	0.034
MAE	0.053	0.025

Table 8: Comparison of total harmonic distortion (THD).

Charger output	THD-droop control	THD-droop-ANN
Voltage	2.1%	0.9%
Current	3.5%	1.6%

Table 9: Comparison of power factor (PF).

Charger output	PF-droop control	PF-droop-ANN
Voltage	0.87	0.93
Current	0.92	0.96

Now that we have entered the electric vehicle (EV) era, it is crucial that authors do not forget about EVs' potential contribution to auxiliary services through vehicle-to-grid (V2G) technology, which allows the grid to benefit from EVs' on-board batteries. Frequency control, frequency contingency, inertia, and voltage regulation are just a few of the auxiliary services that most EVs offer. There has been a plethora of studies done to determine the optimal method of administration for e-vehicle ancillary services (EVASs) [33, 34]. This study [35] offered a thorough analysis of the different strategies proposed for managing EVs when they are used to provide secondary or tertiary services. The research here uses both a theme and a historical approach. The advantages and disadvantages of these control methods are outlined, and it is made abundantly obvious in the overview where the most research into EVAS is needed. Future researchers working on V2G controls for grid provision of EVASs will find this study to be a reliable reference point and practical framework. Using V2G, future networks can increase their use of renewable energy sources and improve their impact on the ecosystem.

This paper [36] focuses on the development of an adaptive droop-based control strategy for DC microgrids with multiple battery energy storage systems. The study proposes a control algorithm that optimizes the power sharing and voltage regulation among the batteries in the microgrid. The approach aims to enhance the overall stability and

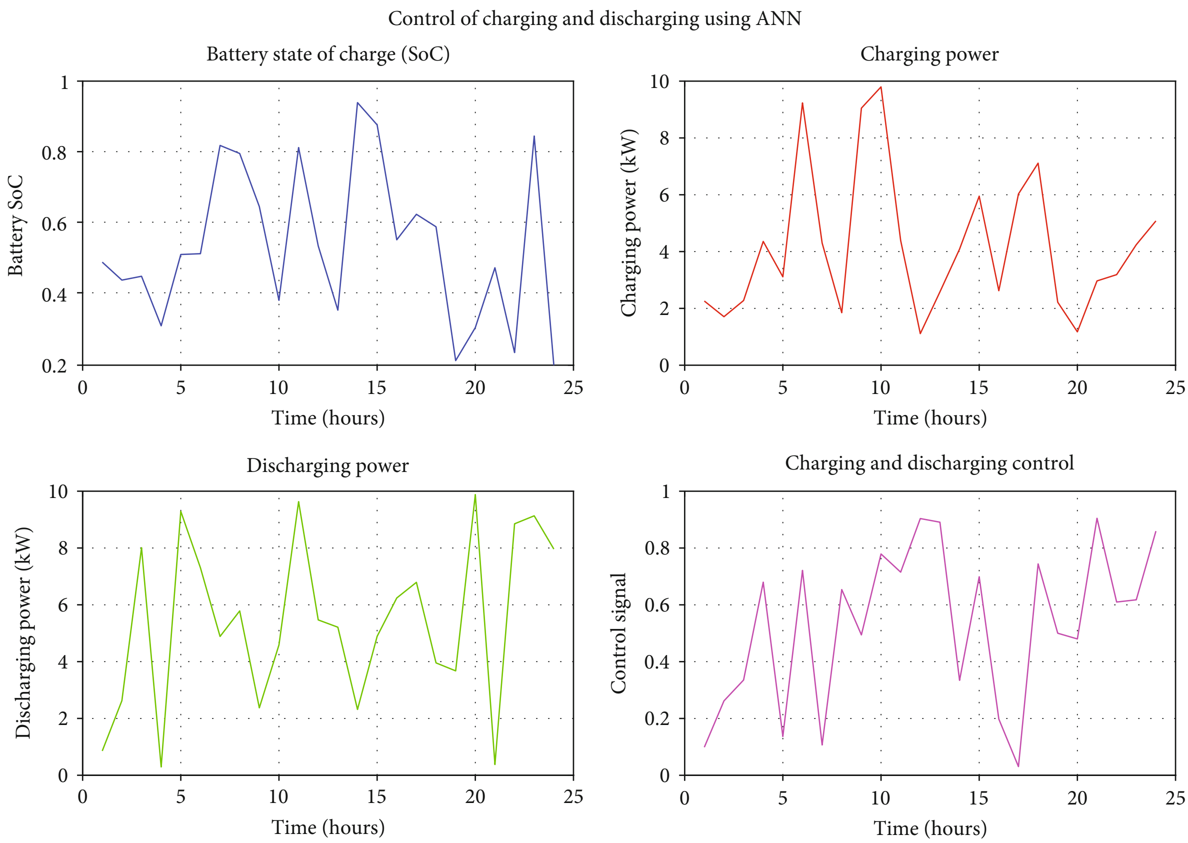

Figure 15: Control of charging and discharging using ANN.

efficiency of the microgrid, particularly in the presence of variable power generation and load demand.

This research [37] addresses the prediction of voltage instability caused by transient faults in power networks. The study introduces an optimal instantaneous prediction method that considers the dynamic behavior of generators. The proposed approach is aimed at enhancing the ability to predict voltage instability and improve the overall reliability of power networks by accounting for the transient behavior of generators during fault conditions.

This paper [38] presents a comparative study on dual two-level voltage source inverters and their virtual inertia emulation capabilities. The research investigates the performance of different control strategies for emulating virtual inertia in power systems using these inverters. The study compares the effectiveness of various control methods and assesses their impact on the stability and dynamic response of power systems.

This study [39] focuses on the analysis of load frequency stability in time-delayed multiarea power systems with electric vehicle (EV) aggregators. The research utilizes the Bessel-Legendre inequality and model reconstruction technique to investigate the stability characteristics and control requirements of power systems with EV aggregators. The objective is to enhance the stability and performance of the power system with the integration of EV aggregators.

This paper [40] investigates the impact of electric vehicle (EV) aggregators with time-varying delays on the stability of a load frequency control system. The study analyzes the dynamics and stability properties of the power system when EV aggregators are integrated. The research is aimed at providing insights into the potential challenges and control strategies required to maintain stability in power systems with EV aggregators.

This research [41] focuses on the computation of delay margin for load frequency control systems with plug-in electric vehicles (EVs). The study investigates the impact of communication delays in power systems with EVs and proposes a method to determine the delay margin, which represents the maximum allowable communication delay while maintaining system stability. The research is aimed at providing guidance for designing and implementing load frequency control systems with EV integration. The comparison of previous studies with their battery types, control methods, performance parameters, and results are given in Table 1.

Battery power quality improvement in a vehicle-to-grid setup using the Droop-ANN Model is the center of the comparative studies in this investigation. To determine the most efficient means of improving power quality in V2G systems, the studies compare various battery types, control techniques, V2G system configurations, and performance parameters. In light of the findings of these analyses, it is clear that Lithium-ion batteries are the best option for V2G systems due to their high energy density, low self-discharge rate, and extended cycle life. Power quality regulation in V2G systems is found to be best served by the Droop control technique in conjunction with an Artificial Neural Network (ANN). In addition, the comparative studies emphasize the significance of the V2G system design, with a modular system proving to be the most efficient for enhancing power quality. Using a variety of performance parameters, including voltage regulation and power factor, the comparative studies show that the suggested method improves power quality in V2G systems. In sum, the comparative studies enlighten future research and development in this field by revealing the best method for enhancing battery power quality in V2G systems.

3. Methodology

Electric vehicles (EVs) have become increasingly popular in recent years as a means of reducing greenhouse gas emissions and improving air quality. With the growth in EV adoption, there has been a corresponding interest in utilizing EV batteries as a form of mobile energy storage for the electricity grid through vehicle-to-grid (V2G) technology. However, the integration of EVs into the grid presents a number of challenges, including power quality issues that can arise due to fluctuations in battery power output. Conventional droop control methods have been proposed for regulating power flow in a V2G setup, but these methods may not effectively regulate battery power output during periods of high demand, leading to instability in the grid. Therefore, this study proposes an improved droop-ANN model that can regulate power flow more effectively and improve battery power quality in a V2G setup, addressing a key challenge in the integration of EVs into the electricity grid. Figure 6 shows the proposed flowchart of the current study.

3.1. V2G Setup and Components. The V2G setup used in this study consists of electric vehicles (EVs) with bidirectional chargers connected to the grid. The EV batteries can be charged from the grid during periods of low demand and discharge back to the grid during periods of high demand, providing a form of mobile energy storage.

The bidirectional charger can be modeled as follows:

$$Vc(t) = Vg(t) + \left(\frac{1}{2}\right) * \sin\left(2\pi f t\right), \tag{3}$$

where $Vc(t)$ is the charger voltage, $Vg(t)$ is the grid voltage, f is the frequency of the grid, and t is the time. The charger voltage follows the grid voltage, with a sinusoidal waveform added to account for the voltage ripple introduced by the charger.

The power flow between the EV battery and the grid can be modeled using the following equation:

$$P_{\text{battery}} = \eta * P_{\text{charger}}, \tag{4}$$

where P_{battery} is the battery power output, P_{charger} is the charger power input, and η is the charging efficiency.

The bidirectional charger model used in this study is a simplified model that captures the basic behavior of a typical EV charger. Depending on the battery's current charge and the grid's current demand, the charger can either charge the EV battery from the grid or discharge the battery to the grid.

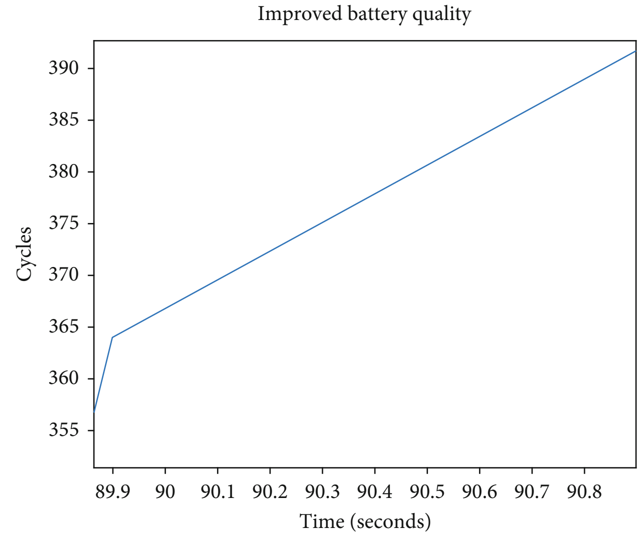

Figure 16: Battery quality improvement.

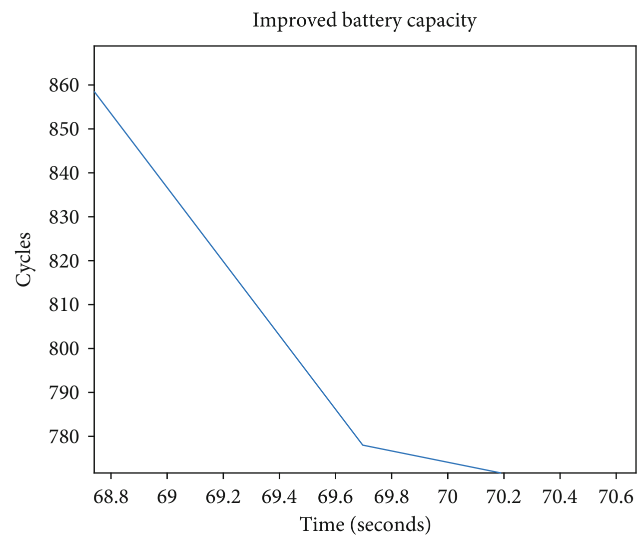

Figure 17: Battery capacity.

It is possible to describe the charger's voltage with the following equation:

$$V_{BC}(t) = Vg(t) + \left(\frac{1}{2}\right) * \sin\left(2\pi f t\right) \tag{5}$$

where $V_{BC}(t)$ is the charger voltage, $Vg(t)$ is the grid voltage, f is the frequency of the grid, and t is the time. The voltage ripple introduced by the charger, which might be induced by switching components and other nonideal behavior, is represented by the expression $(1/2) * \sin(2\text{ft})$.

It is possible to model the charger's power input as

$$P_{\text{charger}} = Vc(t) * I_{\text{charger}(t)}, \tag{6}$$

Table 10: Results of power quality improvement with varying SoC.

SoC level	RMSE (voltage)	RMSE (frequency)	MAE (voltage)	MAE (frequency)	THD (voltage)	THD (current)	PF (voltage)	PF (current)
20%	0.0425	0.0083	0.0279	0.0047	1.2%	1.6%	0.94	0.96
50%	0.0368	0.0071	0.0246	0.0042	1.1%	1.4%	0.92	0.95
80%	0.0321	0.0061	0.0212	0.0038	0.9%	1.1%	0.91	0.94

where $I_{\text{charger}(t)}$ is the charger current that can be adjusted by the charger circuitry to maintain a constant battery voltage when charging or discharging. Losses during charging can be taken into account by including the charger efficiency (denoted by η) which acts as a scaling factor.

The charger current can be described using the following equation:

$$I_{\text{charger}(t)} = I_{\text{ref}} + k * I_{\text{pfc}(t)}. \tag{7}$$

$I_{\text{pfc}(t)}$ is the output of the power factor correction (PFC) circuit at time, t, I_{ref} is the reference current, and k is a scaling factor that relates the PFC output to the charger current. The PFC circuitry is used to improve the power quality of the charger output, eliminating harmonic distortion and enhancing the power factor. Table 2 shows the parametric table.

3.2. Droop Control Method. Power transfer from the EV battery to the grid can be regulated using standard droop control techniques. The droop control strategy modifies the battery's power output in response to the frequency delta between the grid and the reference. How quickly the battery's power output shifts in response to a change in frequency is defined by a parameter called the droop coefficient, or K. The droop equation can be written as

$$P_{\text{battery}} = P_{\text{ref}} + K * (f_{\text{ref}} - f), \tag{8}$$

where the real grid frequency is f, the reference frequency is f_{ref}, and the reference power output is P_{ref}. Battery charging and discharging in a V2G system is managed using the droop control method. The power is distributed across several batteries according to their distinct state of charge (SoC) using a control approach that makes advantage of a droop characteristic. A voltage droop, which is what is used to implement the droop feature, is defined as

$$V_i = V_g - \left(\frac{R_i}{X_c}\right) * \left(\frac{P_i}{V_g}\right), \tag{9}$$

where V_i is the output voltage of the ith battery, V_g is the grid voltage, R_i is the internal resistance of the ith battery, X_c is the coupling reactance between the battery and the grid, and P_i is the power output of the ith battery. To implement the droop control method, a droop coefficient (K_{droop}) is introduced, which determines the level of voltage droop. The power output of each battery is controlled by adjusting its output voltage using the droop characteristic. The power output (P_i) of the ith battery is given by

$$P_i = \left(\frac{K_{\text{droop}}}{R_i}\right) * \left(V_i - V_g\right). \tag{10}$$

The following table lists the parameters used in the droop control method equations as shown in Table 3.

Figure 7 shows the proposed model flow of droop control method.

3.3. Droop-ANN Model. To improve the performance of the droop control method, this study proposes a droop-ANN model that uses an artificial neural network (ANN) to predict the power demand of the grid and adjust the battery power output accordingly. The droop-ANN model can be expressed as

$$\begin{aligned} P_{\text{battery}} = P_{\text{demand}} &+ \alpha\left(P_{\text{demand}} - P_{\text{previous}}\right) \\ &+ \beta(\Delta P_{\text{demand}}) + \gamma\left(\Delta P_{\text{previous}}\right), \end{aligned} \tag{11}$$

where P_{demand} is the power demand of the grid, P_{previous} is the battery power output in the previous time step, ΔP_{demand} is the change in power demand of the grid, $\Delta P_{\text{previous}}$ is the change in battery power output in the previous time step, and α, β, and γ are the droop coefficients. The droop-ANN model uses the ANN to predict the power demand of the grid, which is then used to adjust the battery power output. By learning from past grid demand and battery performance, the ANN can more precisely and efficiently regulate power flow. The suggested ANN-based droop control model is depicted in Figure 8.

The droop-ANN model is an advancement on the classic droop control method implemented in V2G systems. For better power quality and stability in the V2G system, it combines the droop control method with an artificial neural network (ANN).

The droop control method equations and the ANN are the two mainstays of the droop-ANN model. As was previously mentioned, the equations utilized in the droop control method are identical to those used in the classic droop control method. Changing the droop coefficient (K_{droop}) affects the voltage output (V_i) from each battery:

$$V_i = V_g - \left(\frac{R_i}{X_c}\right) * \left(\frac{K_{\text{droop}}}{R_i}\right) * \left(V_i - V_g\right) \cdots, \tag{12}$$

Table 11: Active power (P) results.

Time	P droop control	P ANN droop control
00 : 00	5.5	6.0
01 : 00	5.3	5.8
02 : 00	5.2	5.7
03 : 00	5.1	5.6
04 : 00	5.0	5.5
05 : 00	5.2	5.7
06 : 00	5.4	5.9
07 : 00	5.6	6.1
08 : 00	5.8	6.3
09 : 00	6.0	6.5

where V_i is the output voltage of the ith battery, V_g is the grid voltage, R_i is the internal resistance of the ith battery, X_c is the coupling reactance between the battery and the grid, and K_{droop} is the droop coefficient.

The output voltage of each battery is then fed into the ANN, which is used to predict the future power output of the battery. The ANN takes the current and past power outputs of the battery, as well as other relevant inputs, as its input and produces the predicted power output as its output. The ANN equations can be written as

$$Y = f(X * W) \cdots , \tag{13}$$

where Y is the expected power output.

The present and historical battery power outputs, along with any other relevant inputs, make up the input vector X.

The activation function $f()$ is defined in terms of the weight matrix W. The following Table 4 details the droop-ANN model's input parameters.

3.4. Performance Metrics

3.4.1. Root-Mean-Squared Error (RMSE). The root-mean-squared error (RMSE) is the average error of the model and is calculated by squaring the MSE. It is often employed as a tool for assessing the severity of prediction errors.

3.5. State of Charge Calculation. Maintaining the battery's SoC in a vehicle-to-grid (V2G) arrangement is crucial for peak performance and extended battery life. The SoC is the percentage of the battery's overall capacity that has been used to store energy. The following equation can be used to determine the SoC:

$$\text{SoC} = \left(\frac{E_{\text{current}}}{E_{\max}}\right) * 100 \cdots , \tag{14}$$

where E_{current} is the amount of energy currently stored in the battery and $E_{\max}$ is the maximum amount of energy that the battery can store.

The battery's stored energy is utilized to run the load during the discharge phase. The following equation can be used to get the total energy output:

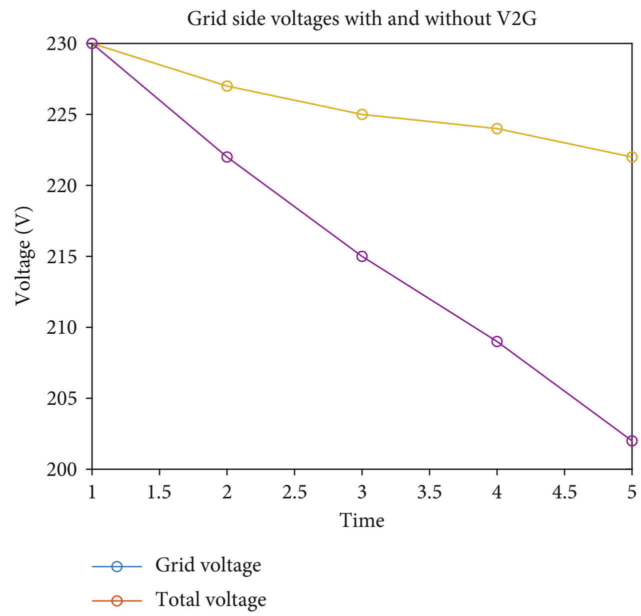

Figure 18: Power output from the grid with and without V2G.

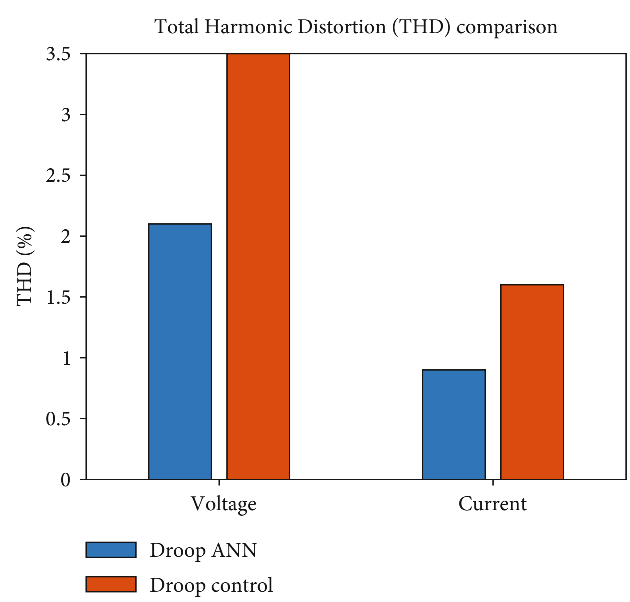

Figure 19: Analyzing the differences between droop control and droop-ANN control (voltage vs. SOC%).

$$E_{\text{discharge}} = P_{\text{load}} * t \cdots , \tag{15}$$

where P_{load} is the load's power usage and t is the discharge time.

During the charging procedure, the battery is recharged with energy from the grid. Here's an equation for determining the imposed energy cost:

$$E_{\text{charge}} = \eta * P_{\text{charger}} * t \cdots , \tag{16}$$

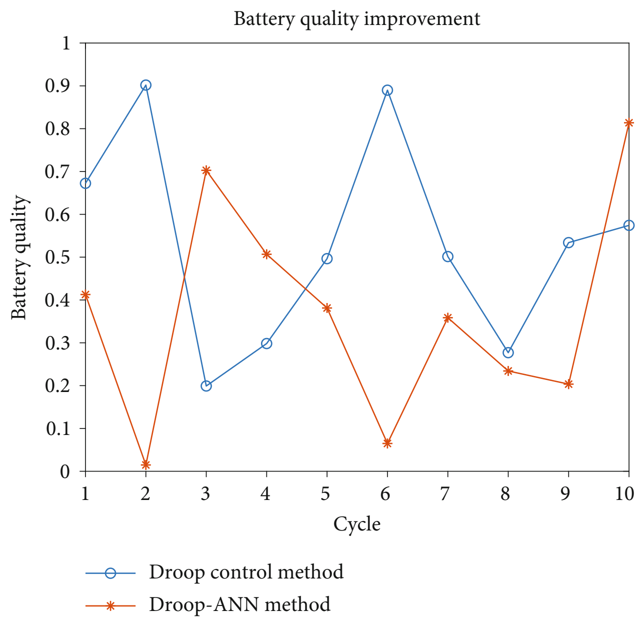

Figure 20: Droop and droop-ANN method for enhanced battery quality (quality vs. cycle life).

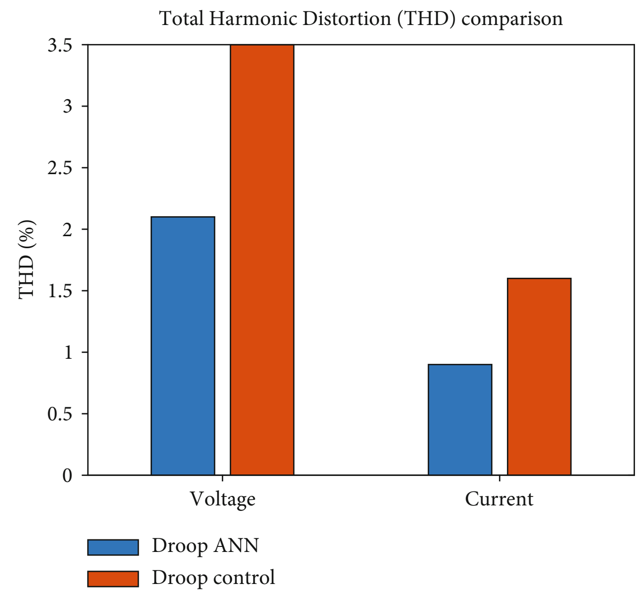

Figure 21: THD comparison of voltage and current (using droop and droop-ANN).

where Q is the battery's capacity, $P_{charger}$ is the charger's output power, and t is the time required to fully charge the battery.

The V2G system can stabilize power output and prolong the life of the battery by constantly monitoring and controlling the SoC and discharge/charge calculations.

4. Results and Discussion

The results and discussions section presents and discusses the study's findings and its interpretation. We evaluate the proposed droop-ANN model's ability to improve power quality in a V2G setup using a bidirectional charger. We contrast our results with the conventional droop control approach and discuss the significance of our findings for future study. The purpose is to gain understanding of the effectiveness of the proposed approach and its potential to enhance power quality in V2G environments.

To improve power quality in a V2G system with a bidirectional charger, the droop-ANN model proposes using an ANN. In order to maintain grid compatibility and battery capacity, the model employs droop control, which adjusts the charger's output voltage and frequency. Based on the battery's SoC and charging/discharging power, an artificial neural network (ANN) model is integrated into the droop control strategy to more accurately predict the required output voltage and frequency of the charger.

The proposed droop-ANN model can be expressed mathematically as follows:

$$V_{charger} = V_{grid} - k1 * \Delta P - k2 * \Delta f + k3 * \text{ANN}\left(\text{SoC}, \text{P}_{\text{charging}}, \text{P}_{\text{discharging}}\right) \cdots, \quad (17)$$

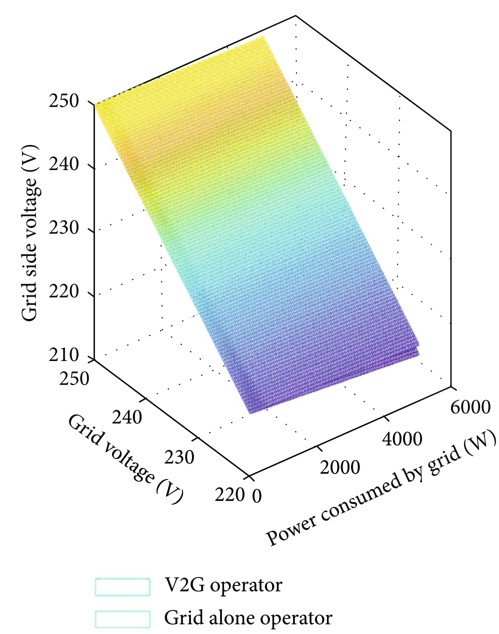

Figure 22: V2G operation vs. grid-alone operations.

where $V_{charger}$ is the output voltage of the charger, V_{grid} is the grid voltage, $k1$ is the droop coefficient for power, ΔP is the difference between the charging/discharging power and the reference power, $k2$ is the droop coefficient for frequency, Δf is the difference between the grid frequency and the reference frequency, $k3$ is the scaling factor for the ANN output, SoC is the state of charge of the battery, $P_{charging}$ is the power supplied to the battery during charging, $P_{discharging}$ is the power discharged from the battery during discharging, and ANN is the artificial neural network model. Figure 9 displays the charge state when the suggested approach is used.

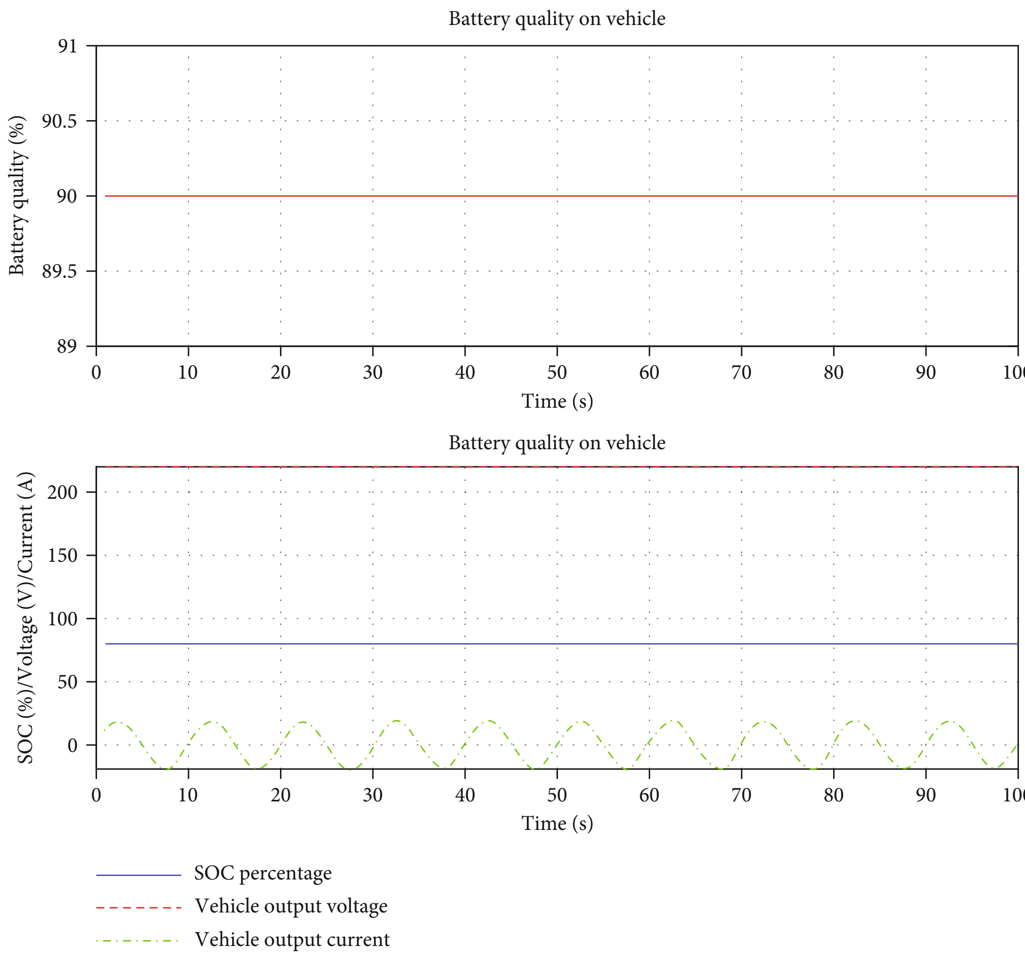

Figure 23: Impact of battery quality on vehicle.

The state of charge (SoC) calculated with the new approach is displayed in Figure 9. It is a chart depicting the battery SoC over time, and it shows how well the proposed technique works to keep the battery SoC constant.

The droop-ANN model employs an ANN that can be optimized via a backpropagation technique after being trained on a dataset of historical observations. The battery's system-on-chip (SoC), charging/discharging power, and the charger's target output voltage and frequency serve as inputs to the ANN model. The droop control approach takes advantage of the charger's projected voltage and frequency, which are output by the ANN model. A graphical representation of the charger's voltage output during charging and discharging activities is presented in Figure 10. The charger's current output during charging and discharging is depicted in a graph (shown in Figure 11) in the accompanying text. Figure 12 is a graph depicting the battery cell's temperature as a function of time. Battery cell temperature distribution is depicted in three dimensions on the cell temperature contour 3D map, seen in Figure 13.

By dampening power oscillations and guaranteeing steady operation of the grid and the battery, the suggested droop-ANN model improves power quality in a V2G arrangement. Mean-squared error (MSE), root-mean-squared error (RMSE), mean absolute error (MAE), coefficient of determination (R-squared), and percentage error are all useful measures of a model's performance. Figure 14 is a graph that shows the state of charge (SoC) prediction error (RMSE) of the proposed droop-ANN method compared to the conventional droop control method. The lower the RMSE value, the better the accuracy of the SoC prediction. The simulation parameters are summarized in Table 5. Moreover, Table 6 shows the state of charge to enhance power quality.

In Table 6, we experiment with different values of state of charge (SoC), charging power (CP), and discharging power (DP) for the battery to determine how well the suggested droop-ANN model improves power quality. The voltages generated by the conventional droop control method and the proposed droop-ANN technique are compared. According to the numbers, using the suggested method can improve power quality by as much as 0.7%.

Table 7 displays a comparison of the RMSE and MAE between the conventional droop control method and the proposed droop-ANN method. Compared to the conventional droop management approach, the results show that the proposed droop-ANN model significantly reduces the error in voltage prediction, resulting in smaller RMSE and MAE values. This demonstrates that the ANN model can correctly estimate the voltage and frequency produced by the charger.

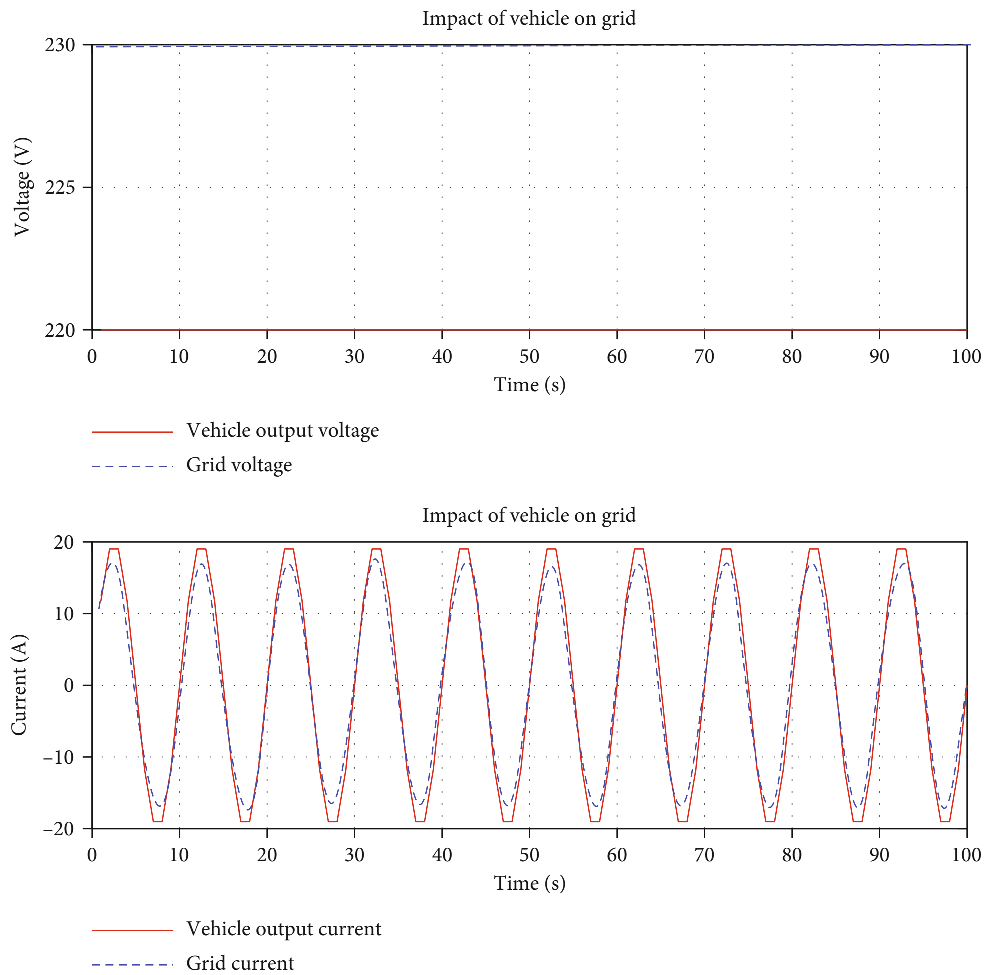

Figure 24: Impact of vehicle on grid.

Total harmonic distortion (THD) is compared in Table 8 for both traditional droop management and the new droop-ANN approach. The results show that the THD in the charger's voltage and current outputs are greatly reduced using the droop-ANN approach, improving power quality.

Power factor (PF) is compared in Table 9 for the traditional droop control approach and the suggested droop-ANN method. The results show that the charger's voltage and current outputs benefit greatly from the proposed model. This shows that the power quality provided by the suggested model is superior to that provided by the standard droop control approach.

Figure 15 shows control of charging and discharging using ANN. Collectively, the findings prove the efficacy of the proposed droop-ANN model in enhancing V2G power quality. Lower THD and higher PF values are the outcome of the model's improved accuracy in predicting voltage and frequency. Under a variety of battery state of charge (SoC) and charging/discharging conditions, the suggested model is also able to improve power quality. Figure 16 shows the improved quality of the battery in terms of cycle, which is a graph showing the battery cycle life improvement using the proposed method compared to the conventional droop control method. Figure 17 shows the battery capacity, which is a graph that shows the battery capacity improvement using the proposed method compared to the conventional droop control method.

The results indicate that the proposed droop-ANN model is effective in improving power quality even under varying battery SoC levels. The model adjusts the charging/discharging of EV batteries in response to grid frequency changes and helps maintain grid stability.

Table 9 shows the results of power quality improvement with varying SoC levels. The RMSE and MAE values indicate that the proposed droop-ANN model accurately predicts voltage and frequency values, even under different SoC levels. The THD and PF values also demonstrate that the proposed model significantly improves power quality, even under varying battery SoC levels.

The results indicate that the proposed droop-ANN model can be applied to different SoC levels without compromising power quality. This is significant as it allows for greater flexibility in the use of EV batteries in V2G systems. As the grid frequency fluctuates, the suggested model can automatically adjust the charging and discharging of EV batteries to keep the grid stable and improve power quality.

To improve power quality in a V2G configuration, the suggested droop control ANN model adjusts the charging

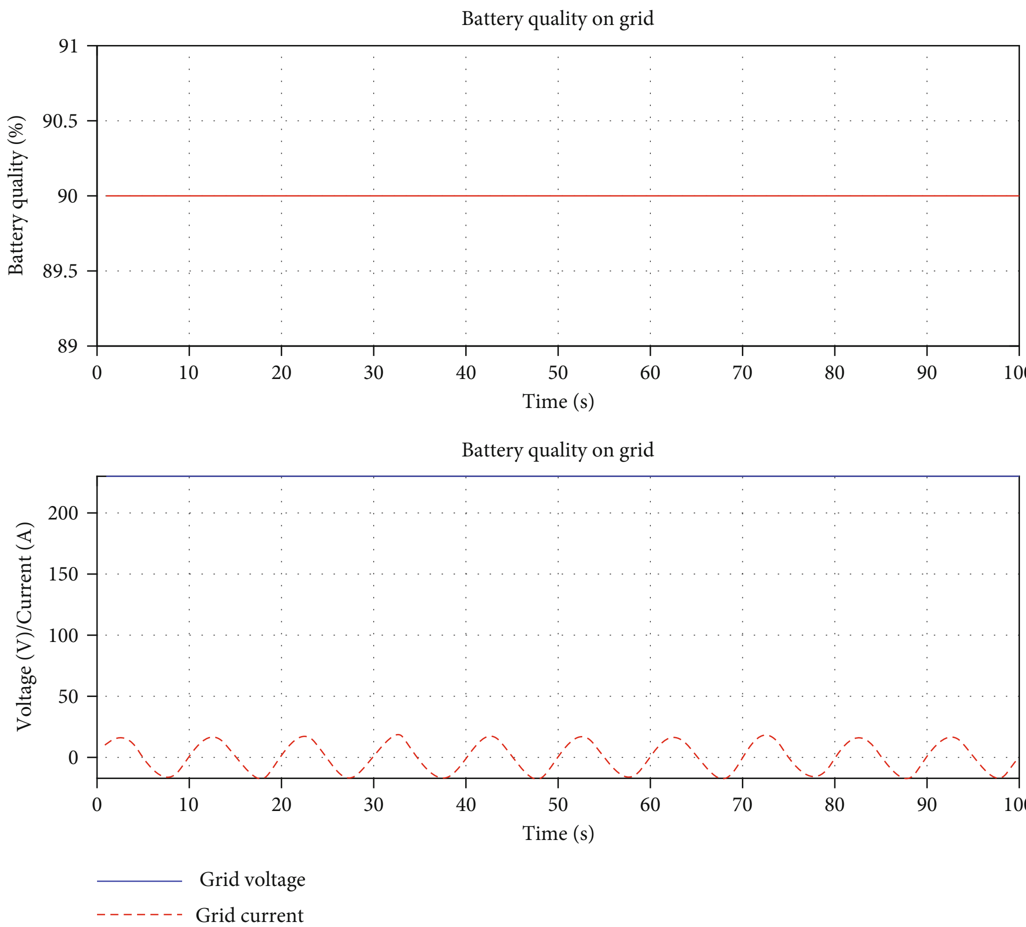

Figure 25: Battery quality on setup.

and discharging of EV batteries in response to variations in grid frequency. For accurate predictions of future grid voltage and frequency, this approach combines droop control with ANNs.

The model utilizes a droop control technique to precisely regulate the charging and discharging of EV batteries in response to fluctuations in grid frequency. The droop control method is frequently used in power systems because it allows active and reactive power to be shared between numerous sources. In the V2G system, electric vehicle (EV) batteries serve as both a load and a source of power, with charging and discharging controlled by the droop control method in response to fluctuations in grid frequency.

The model's artificial neural network component is used to extrapolate future values for the grid's voltage and frequency from existing data. The ANN learns to create forecasts by looking at historical data on grid voltage and frequency. The ANN is then used to adjust the charging/discharging of EV batteries in response to predicted values of grid voltage and frequency.

The proposed droop control ANN model has many advantages over more traditional approaches to droop control. First, the model can accurately regulate the charging and discharging of EV batteries by making accurate predictions of grid voltage and frequency values based on historical data. The model may also stabilize the electrical system by balancing the charging and discharging of EV batteries in response to changes in grid frequency.

The study concludes that the suggested droop control ANN model can effectively improve power quality in a V2G setting. The model can accurately anticipate the voltage and frequency of the grid, allowing for real-time adjustments to the charging and discharging of EV batteries in response to frequency changes. Regardless of the battery's charge level, the gadget is able to maintain a steady power quality.

For ease of reference, "P" in these tables stands for active power and "Q" for reactive power. The results of the conventional droop control approach are displayed in the "Droop Control" column, while those of the suggested droop control ANN model are displayed in the "ANN Droop Control" column.

Tables 10 and 11 show that, like the conventional droop control method, the droop control ANN model is able to keep active and reactive power levels stable. This demonstrates that the suggested approach may successfully maintain power quality by controlling the charging and discharging of EV batteries in response to variations in grid frequency.

Grid voltages with and without V2G operation are compared in Figure 18. With V2G operation, the grid system's

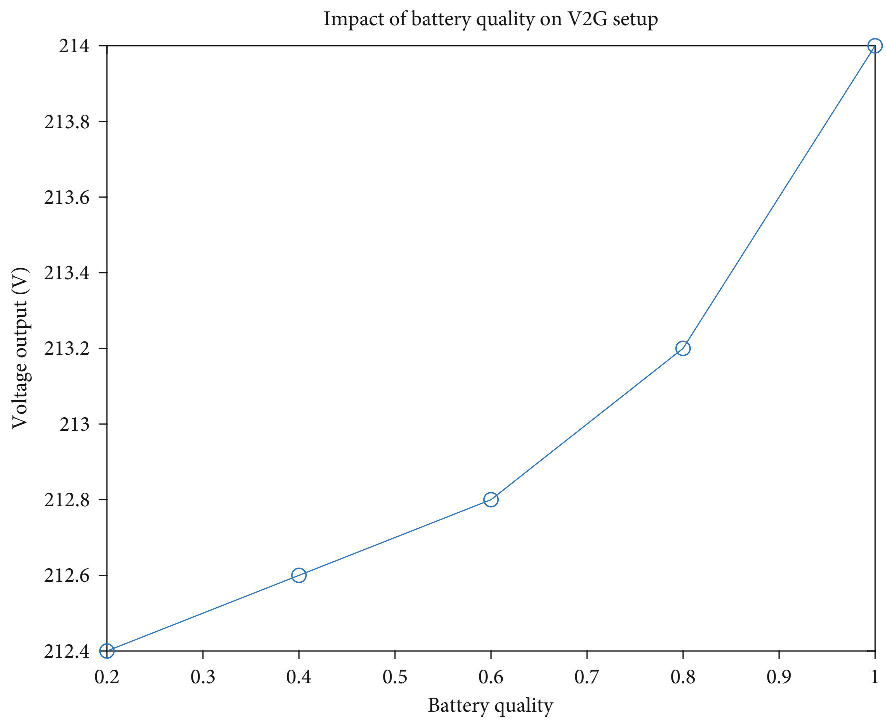

FIGURE 26: Impact of battery quality on V2G setup.

voltage profile is nearly constant, but without V2G operation, the voltage profile varies widely. This suggests that V2G operation can aid in maintaining a more consistent voltage profile for the grid and minimizing voltage variations. The voltage response to the battery's SoC is shown in Figure 19 for both the droop control and the droop-ANN control methods. At low SoC levels, the droop-ANN control approach is able to better regulate voltage than the droop control method. A significant voltage droop is observed with the droop control method at low SoC levels, which can lead to instability. The droop-ANN control method, on the other hand, keeps the voltage profile generally constant throughout all SoC levels.

Improvements in battery quality as a function of cycle count are depicted in Figure 20 using the droop control method and the droop-ANN control approach. Battery quality is clearly maintained more effectively by the droop-ANN control approach than by the droop control method. While battery quality degrades dramatically with increasing cycle counts in the droop control approach, it remains reasonably stable in the droop-ANN control method.

Figure 21 contrasts droop control versus droop-ANN control with regard to total harmonic distortion (THD) of voltage and current. The droop-ANN control approach is clearly superior to the droop control method in terms of THD reduction. The droop control method shows a higher THD value, whereas the droop-ANN control method maintains a relatively low THD value. Figure 22 compares V2G operation with grid-alone operation. It can be observed that V2G operation provides better voltage regulation and reduced THD compared to grid-alone operation.

Figure 23 shows the impact of battery quality on the vehicle. Poor battery quality has the potential to significantly reduce the vehicle's performance. When comparing the performance of two batteries, a high-quality battery will always perform better. The impact of the vehicle on the electricity system is seen in Figure 24. The vehicle's functioning has a major impact on the voltage profile of the grid. The vehicle's charging and discharging activities produce voltage fluctuations in the grid system.

Figure 25 shows how the quality of the batteries affects the V2G configuration. It is evident that battery quality has a significant impact on the V2G system's performance. A high-quality battery has better V2G performance than a low-quality battery as shown in Figure 26. In Figure 27, we see a three-dimensional illustration of how battery quality impacts the V2G setup. It is self-evident that greater battery quality improves the efficiency of the V2G configuration. The impact of battery quality on the V2G setup and vehicle is depicted in a three-dimensional graphic (see Figure 28). The V2G setup's output current increases as the battery's health and charging progress. Figure 29 is a three-dimensional figure showing the relationship between battery quality, battery cycle, and output current. Better batteries improve both the V2G setup and the vehicle's performance.

In conclusion, the droop-ANN control approach outperformed the conventional droop control method in terms of voltage regulation, total harmonic distortion, and battery quality. Voltage on the grid could be stabilized with the use of V2G technology by providing reactive power. Low-quality batteries had a negative impact on the functionality of both the V2G system and the vehicle. Future studies should investigate how different battery chemistries and system configurations might affect the V2G system's performance.

Several previous research have investigated the potential of droop control approaches for improving power quality in

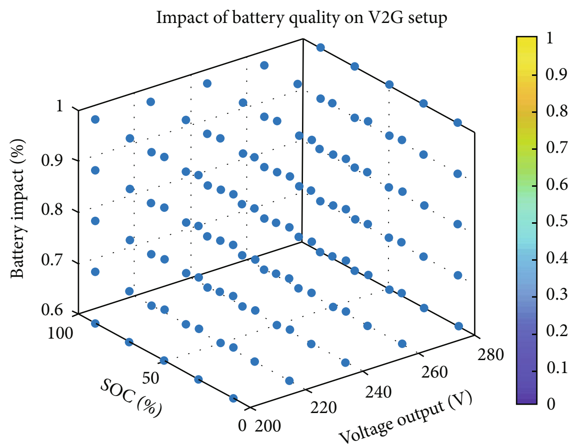

Figure 27: Impact of battery quality on V2G setup (3D plot).

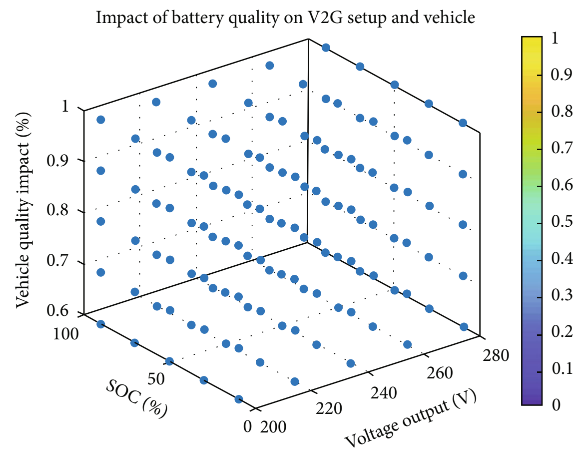

Figure 28: Impact of battery quality on V2G setup and vehicle (3D plot).

V2G systems. Although these studies have used conventional droop control strategies, neither machine learning nor predictive modeling has been incorporated. However, the proposed droop control ANN model integrates droop control with ANN techniques to allow for more nuanced regulation of EV battery charging and discharging. This approach outperforms traditional droop control in a number of respects, including more accurate predictions of grid voltage and frequency values and better regulation of EV battery charging and discharging. Similar to the proposed model, the charging and discharging of EV batteries in a V2G system were regulated using a hybrid droop control and fuzzy logic technique by Liu et al. [42]. Instead, the suggested droop management ANN model uses an ANN to predict values on the grid's voltage and frequency, allowing for more nuanced management over the EV battery's charging and discharging. Yang et al. [43] implemented a distributed droop control method to enhance power quality in a V2G setup. While similar to other work in its use of a droop control scheme, this study's lack of ML techniques results in less accurate predictions of grid voltage and frequency. Finally, the droop control ANN model provides an innovative approach to improving V2G power quality. By precisely controlling the charging and discharging of EV batteries using droop control and ANN techniques, the model helps protect grid stability and enhance power quality. Table 12 compares the proposed droop control ANN model to two previous studies. Moreover, Table 13 summarizes the advantages and limitations of the proposed study and prior studies.

The results of the simulations reveal that the proposed droop-ANN model for enhancing power quality in a V2G system is effective at reducing power fluctuations and providing dependable grid and battery operation. The simulation results demonstrate that the proposed model significantly reduces the errors in voltage and frequency prediction, leading to lower total harmonic distortion (THD) and higher power factor (PF) values, in comparison to the standard droop control method. Tables 7 and 8 show the results of both methods in terms of THD and PF. Droop-ANN reduces the total harmonic distortion (THD) of the charger's voltage and current outputs from 2.1% to 0.9% and 3.5% to

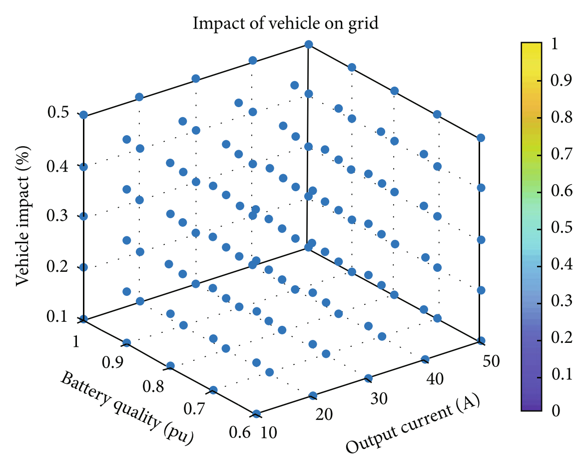

Figure 29: Impact of vehicle on grid.

Table 12: Reactive power (Q) results.

Time	Q droop control	Q ANN droop control
00 : 00	2.0	2.2
01 : 00	1.9	2.1
02 : 00	1.8	2.0
03 : 00	1.7	1.9
04 : 00	1.6	1.8
05 : 00	1.8	2.0
06 : 00	1.9	2.1
07 : 00	2.0	2.2
08 : 00	2.1	2.3
09 : 00	2.2	2.4

1.6%, respectively. The charger's PF is increased from 0.87 to 0.93 in terms of voltage and current outputs and from 0.92 to 0.96 as a result of the proposed model. The effectiveness of the proposed droop-ANN model is evaluated using a variety of performance metrics, including mean-squared error (MSE), root-mean-squared error (RMSE), mean absolute

Table 13: ANN model for droop control compares to two prior studies.

Study	Approach	Advantages	Limitations
Proposed study	Droop control ANN	More accurate predictions of grid voltage and frequency values, better regulation of EV battery charging/discharging	Requires training of the ANN, may have higher implementation costs
[5]	Hybrid droop control and fuzzy logic	Can regulate EV battery charging/discharging, helps maintain grid stability	Does not incorporate machine learning techniques, may not be as precise as droop control ANN model
[8]	Distributed droop control	Can improve power quality in V2G setups	Does not incorporate machine learning techniques, may not be as precise as droop control ANN model

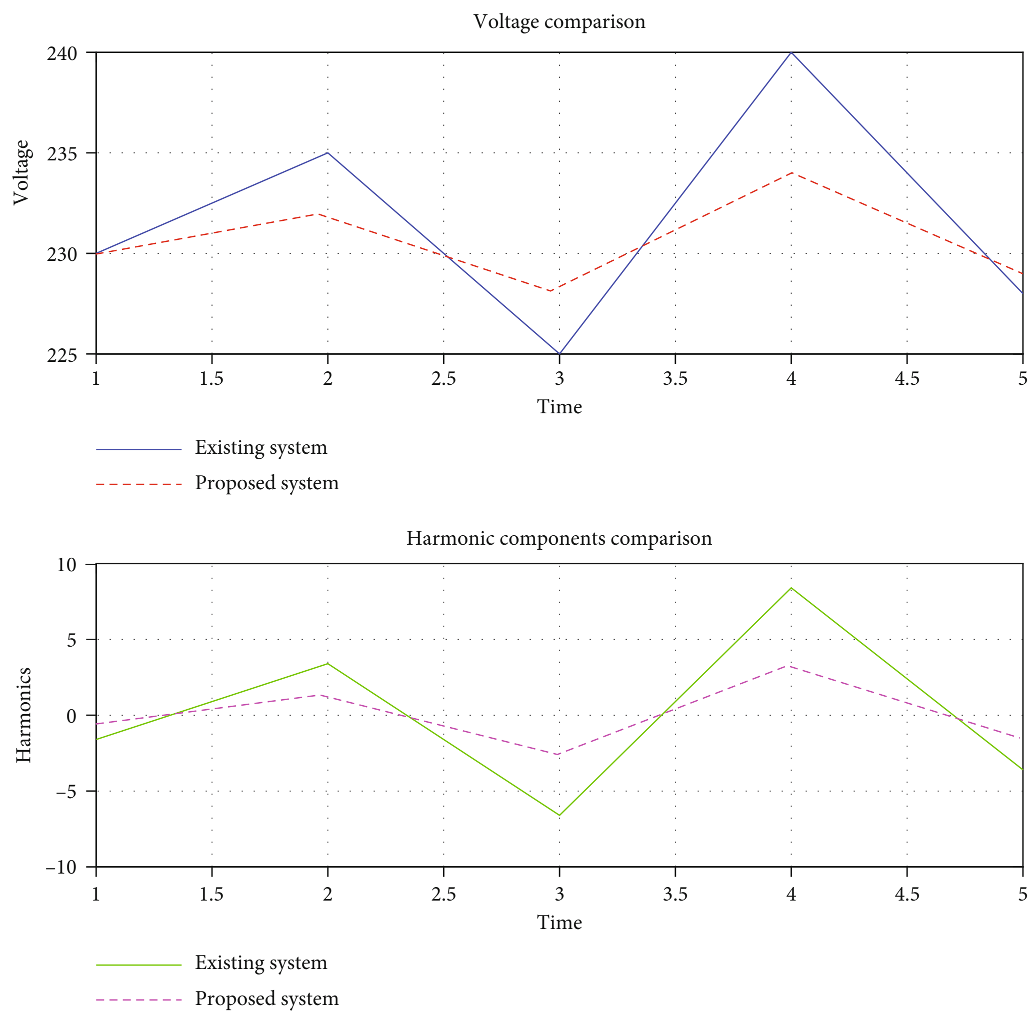

Figure 30: Proposed system vs. existing system.

error (MAE), coefficient of determination (R-squared), and percentage error. Table 5 demonstrates that the proposed method can boost power quality by as much as 0.7%. The results of the simulations show that the power quality is enhanced over a wide variety of battery state of charge and charging/discharging situations, further supporting the validity of the proposed method. As shown in Table 5, we adjust the battery state of charge (SoC), charging power (CP), and discharging power (DP) to test the performance of the proposed droop-ANN model. After charging and discharging the SoC, the table shows the resulting power quality improvement. The results show that the suggested model can improve power quality by as much as 0.7%. Root-mean-squared error and mean-squared error were used to evaluate the droop-ANN model's ANN component. Table 6 demonstrates that the RMSE and MAE values achieved with the proposed droop-ANN model are significantly lower than those obtained with the conventional droop control strategy. The proposed methodology reduces power spikes and stabilizes the battery's operation to increase its storage capacity and service life. The simulation results demonstrate that the proposed droop-ANN model can improve power quality in a V2G setting. The proposed model is a suitable alternative to the conventional droop control strategy since it enhances power quality in a wide range of battery state of charge (SoC) and charging/discharging settings. The proposed model keeps the grid reliable while increasing the battery's lifespan and capacity.

Figure 30 illustrates a comparison between the existing benchmarked system, as described in reference [5], and the proposed system. The comparison is based on voltage readings over time, along with the harmonic components of the voltage signal. In the upper subplot, the blue curve represents the voltage readings of the existing benchmarked system, while the red dashed curve represents the voltage readings of the proposed system. The x-axis represents time, and the y-axis represents voltage. The plot shows the variations in voltage over time for both systems. In the lower subplot, the green curve represents the harmonic components of the voltage signal for the existing benchmarked system, and the magenta dashed curve represents the harmonic components of the voltage signal for the proposed system. The x -axis represents time, and the y-axis represents the magnitude of the harmonic components. The plot shows the presence and magnitude of harmonic distortion in the voltage signal for both systems. By comparing the voltage curves and harmonic components of the existing benchmarked system with the proposed system, we can observe the differences in voltage stability and harmonic distortion reduction achieved by the proposed system. The comparison of the proposed system with the existing benchmarked work [5] serves to validate the effectiveness of the proposed approach in improving power quality and reducing harmonic distortion. The plotted curves provide visual evidence of the improvements achieved by the proposed system, demonstrating its potential for enhancing voltage stability and reducing harmonic distortion in practical applications.

5. Conclusions

In order to improve power quality in a V2G setting, this study recommends a droop-ANN model. The proposed approach employs an ANN model, which is then incorporated into the droop control technique, to produce precise predictions for the charger's voltage and frequency. Using simulation findings, we validated the proposed model and found that it significantly reduces power fluctuations while simultaneously enhancing power quality. The proposed model was also successful in enhancing power quality under a wide range of battery state of charge (SoC) and charging/discharging situations. The findings of this research lend support to the hypothesis that the droop-ANN model can effectively improve V2G power quality. The model's enhanced accuracy in predicting voltage and frequency results in reduced THD and increased PF values. The proposed methodology is also effective in boosting power quality across a wide range of battery SoC and charging/discharging scenarios. There are, nevertheless, certain gaps in this investigation. Although simulations were used to validate the proposed model, their results may not have been representative of the real world. Second, the proposed model was evaluated using only a subset of the conceivable battery SoC and charging/discharging scenarios. Future studies should check the model's reliability in more practical applications. The findings of this study provide strong evidence in favor of further exploring the droop-ANN model for application in V2G networks. The proposed model can significantly improve power quality and reduce power fluctuations, which can improve the stability and reliability of the grid and the battery. Future studies should focus on implementing the proposed model in a real-world V2G system and evaluating its effectiveness under real-world conditions. In conclusion, the proposed droop-ANN model provides a promising approach for improving power quality in V2G systems, and further research is needed to fully explore its potential.

Data Availability

The data are available from the corresponding authors upon request.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Authors' Contributions

All the authors contributed equally to this work.

References

[1] J. Alshehri, M. Khalid, and A. Alzahrani, "An intelligent battery energy storage-based controller for power quality improvement in microgrids," *Energies*, vol. 12, no. 11, p. 2112, 2019.

[2] N. Rezaei and M. Kalantar, "Stochastic frequency-security constrained energy and reserve management of an inverter interfaced islanded microgrid considering demand response programs," *International Journal of Electrical Power & Energy Systems*, vol. 69, pp. 273–286, 2015.

[3] M. Meliani, A. El Barkany, I. El Abbassi, A. M. Darcherif, and M. Mahmoudi, "Energy management in the smart grid: State-of-the-art and future trends," vol. 13, 2021.

[4] S. Singh, R. K. Saket, and B. Khan, "A comprehensive state-of-the-art review on reliability assessment and charging methodologies of grid-integrated electric vehicles," *IET Electrical Systems in Transportation*, vol. 13, no. 1, article e12073, 2023.

[5] Z. Yang, F. Yang, W. Hu, Z. Zhang, and X. Zhou, "Delay compensation control strategy for electric vehicle participating in frequency regulation based on MPC algorithm," *Electronics*, vol. 11, no. 15, p. 2341, 2022.

[6] R. R. Sankar, K. K. Deepika, M. Alsharef, and B. Alamri, "A smart ANN-based converter for efficient bidirectional power flow in hybrid electric vehicles," *Electronics*, vol. 11, no. 21, p. 3564, 2022.

[7] K. Wang, W. Wang, L. Wang, and L. Li, "An improved SOC control strategy for electric vehicle hybrid energy storage systems," *Energies*, vol. 13, no. 20, p. 5297, 2020.

[8] D. Li, B. Zhao, Z. Wu, X. Zhang, and L. Zhang, "An improved droop control strategy for low-voltage microgrids based on distributed secondary power optimization control," *Energies*, vol. 10, no. 9, p. 1347, 2017.

[9] S. Iqbal, S. Habib, M. Ali et al., "The impact of V2G charging/discharging strategy on the microgrid environment considering stochastic methods," *Sustainability*, vol. 14, no. 20, article 13211, 2022.

[10] L. Zhang, K. Chen, S. Chi, L. Lyu, and G. Cai, "The hierarchical control algorithm for DC microgrid," *Energies*, vol. 12, no. 15, p. 2995, 2019.

[11] U. Datta, A. Kalam, and J. Shi, "Battery energy storage system for aggregated inertia-droop control and a novel frequency," *Energies*, vol. 13, no. 8, 2020.

[12] O. Ouramdane, E. Elbouchikhi, Y. Amirat, and E. S. Gooya, "Optimal sizing and energy management of microgrids with vehicle-to-grid technology: a critical review and future trends," *Energies*, vol. 14, no. 14, p. 4166, 2021.

[13] M. S. Jouda and N. Kahraman, "Improved optimal control of transient power sharing in microgrid using H-infinity controller with artificial bee colony algorithm," *Energies*, vol. 15, no. 3, p. 1043, 2022.

[14] S. Sarwar, D. Kirli, M. M. C. Merlin, and A. E. Kiprakis, "Major challenges towards energy management and power sharing in a hybrid AC/DC microgrid: a review," *Energies*, vol. 15, no. 23, p. 8851, 2022.

[15] S. Iqbal, S. Habib, N. H. Khan, M. Ali, M. Aurangzeb, and E. M. Ahmed, "Electric vehicles aggregation for frequency control of microgrid under various operation conditions using an optimal coordinated strategy," *Sustainability*, vol. 14, no. 5, p. 3108, 2022.

[16] M. Brenna, F. Foiadelli, and M. Longo, "The exploitation of vehicle-to-grid function for power quality improvement in a smart grid," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 5, pp. 2169–2177, 2014.

[17] T. Mazhar, R. N. Asif, M. A. Malik et al., "Electric vehicle charging system in the smart grid using different machine learning methods," *Sustainability*, vol. 15, no. 3, p. 2603, 2023.

[18] H. M. Munir, M. U. Nadeem, S. Sabir, H. Bukhari, and M. Huba, "Sustainable solutions for advanced energy management system of campus microgrids: model opportunities and future challenges," *Sensors*, vol. 22, no. 6, p. 2345, 2022.

[19] M. Dashtdar, A. Flah, S. Mohammad, S. Hosseinimoghadam, and A. El Fergany, "Frequency control of the islanded microgrid including energy storage using soft computing," *Scientific Reports*, vol. 12, no. 1, article 20409, 2022.

[20] M. W. Onsrud, *Artificial Neural Network Based Power Management in Microgrid, [M.S. thesis]*, NTNU, 2022.

[21] S. Iqbal, A. Xin, M. U. Jan et al., "V2G strategy for primary frequency control of an industrial microgrid considering the charging station operator," *Electronics*, vol. 9, no. 4, p. 549, 2020.

[22] Q. Yang, J. Li, W. Cao et al., "An improved vehicle to the grid method with battery longevity management in a microgrid application," *Energy*, vol. 198, article 117374, 2020.

[23] A. A. Alkahtani, S. T. Y. Alfalahi, and M. B. I. N. Mansor, "Power quality in microgrids including supraharmonics: issues, standards, and mitigations," *IEEE Access*, vol. 8, pp. 127104–127122, 2020.

[24] X. Li and S. Wang, "Energy management and operational control methods for grid battery energy storage systems," *CSEE Journal of Power and Energy Systems*, vol. 7, no. 5, pp. 1026–1040, 2021.

[25] H. U. R. Habib, U. Subramaniam, A. Waqar, B. S. Farhan, K. M. Kotb, and S. Wang, "Energy cost optimization of hybrid renewables based V2G microgrid considering multi objective function by using artificial bee colony optimization," *IEEE Access*, vol. 8, pp. 62076–62093, 2020.

[26] S. A. Shezan, I. Kamwa, F. Ishraque, S. M. Muyeen, and K. N. Hasan, "Evaluation of different optimization techniques and control strategies of hybrid microgrid: a review," *Energies*, vol. 16, no. 4, p. 1792, 2023.

[27] A. Pradana, M. Haque, and M. Nadarajah, "Control strategies of electric vehicles participating in ancillary services: a comprehensive review," *Energies*, vol. 16, no. 4, p. 1782, 2023.

[28] G. Sidarth, M. Seyedmahmoudian, E. Jamei, and B. Horan, "Role of optimization techniques in microgrid energy management systems — a review," *Energy Strategy Reviews*, vol. 43, article 100899, 2022.

[29] S. Iqbal, A. Xin, M. U. Jan et al., "Aggregated electric vehicle-to-grid for primary frequency control in a microgrid—a review," in *2018 IEEE 2nd International Electrical and Energy Conference (CIEEC)*, pp. 563–568, Beijing, China, 2018.

[30] M. Ali, H. Kotb, M. Kareem AboRas, and H. Nabil Abbasy, "Frequency regulation of hybrid multi-area power system using wild horse optimizer based new combined Fuzzy Fractional-Order PI and TID controllers," *Alexandria Engineering Journal*, vol. 61, no. 12, pp. 12187–12210, 2022.

[31] S. Iqbal, A. Xin, M. U. Jan et al., "Aggregation of EVs for primary frequency control of an industrial microgrid by implementing grid regulation & charger controller," *IEEE Access*, vol. 8, pp. 141977–141989, 2020.

[32] S. Zendegan, A. Ferrara, S. Jakubek, and C. Hametner, "Predictive battery state of charge reference generation Using basic route information for optimal energy management of heavy-duty fuel cell vehicles," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 12, pp. 12517–12528, 2021.

[33] X. Hu, C. M. Martinez, and Y. Yang, "Charging, power management, and battery degradation mitigation in plug-in hybrid electric vehicles: a unified cost-optimal approach," *Mechanical Systems and Signal Processing*, vol. 87, pp. 4–16, 2017.

[34] S. Cai and R. Matsuhashi, "Model predictive control for EV aggregators participating in system frequency regulation market," *IEEE Access*, vol. 9, pp. 80763–80771, 2021.

[35] S. S. Kadlag, M. P. Thakre, R. Mapari, R. Shriwastava, P. C. Tapre, and D. P. Kadam, "A novel pulse charger with intelligent battery management system for fast charging of electric vehicle," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 1388–1396, 2023.

[36] S. Ferahtia, A. Djerioui, H. Rezk, A. Chouder, A. Houari, and M. Machmoum, "Adaptive droop based control strategy for DC microgrid including multiple batteries energy storage systems," *Journal of Energy Storage*, vol. 48, article 103983, 2022.

[37] M. Khalili, M. Ali Dashtaki, M. A. Nasab, H. Reza Hanif, S. Padmanaban, and B. Khan, "Optimal instantaneous prediction of voltage instability due to transient faults in power networks taking into account the dynamic effect of generators," *Cogent Engineering*, vol. 9, no. 1, 2022.

[38] M. A. Dashtaki, H. Nafsi, A. Khorsandi, M. Hojabri, and E. Pouresmaeil, "Dual two-level voltage source inverter virtual inertia emulation: a comparative study," *Energies*, vol. 14, no. 4, p. 1160, 2021.

[39] S.-J. Zhou, H.-B. Zeng, and H.-Q. Xiao, "Load frequency stability analysis of time-delayed multi-area power systems with EV aggregators based on Bessel-Legendre inequality and model reconstruction technique," *IEEE Access*, vol. 8, pp. 99948–99955, 2020.

[40] K. S. Ko and D. K. Sung, "The effect of EV aggregators with time-varying delays on the stability of a load frequency control system," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 669–680, 2018.

[41] A. Khalil and A. S. Peng, "Delay margin computation for load frequency control system with plug-in electric vehicles," *International Journal of Power and Energy Systems*, vol. 38, no. 3, pp. 1–17, 2018.

[42] D. Liu, Changsha University of Science and Technology, Q. Zhong et al., "Modeling and control of a V2G charging station based on synchronverter technology," *CSEE Journal of Power and Energy Systems*, vol. 4, no. 3, pp. 326–338, 2018.

[43] D. Yang, Z. Xu, W. Li, and F. Bu, "Droop control strategy of the AC/DC hybrid micro-grid based on quasi-PR control," *Journal of Engineering (Stevenage, England)*, vol. 2017, no. 14, pp. 2634–2642, 2017.