AN NOVEL MODEL AND DESIGN OF ANN CONTROLLED MULTIPORT CHARGER SIMULATION

[1]Mr. D. JOSEPH KUMAR, [2]Mr. K. SIVA SANKAR, [3]N. L. L. K. PAVAN, [4]CH. S. S. SUBRAHMANYAM, [5] V. RAJESH KUMAR, [6]L. SAI SIMHADRI
[12]ASSISTANT PROFESSOR, [3456]B.Tech Students,
Department of Electrical and Electronics Engineering,
D.N.R. College of Engineering and Technology, Andhra Pradesh, India

ABSTRACT

This paper presents a novel MATLAB/Simulink-based simulation model for a multiport charger designed for light electric vehicles (LEVs) with integrated capability to supply domestic loads. The proposed system employs an Artificial Neural Network (ANN) controller to replace the conventional Proportional–Integral (PI) controller, aiming to enhance system performance under dynamic and nonlinear operating conditions. The multiport converter supports three bidirectional operating modes, namely Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G), enabling flexible power exchange between electric vehicles, household appliances, and the grid. Unlike the PI controller, which exhibits limitations in handling system nonlinearities and disturbances, the ANN controller is trained to adaptively regulate voltage and current, ensuring optimal performance across all modes. Simulation results demonstrate that the ANN-based control significantly improves transient response, reduces steady-state error, and minimizes Total Harmonic Distortion (THD). Additionally, the controller maintains stable operation and high efficiency during rapid load variations and mode transitions. The comparative analysis confirms that the ANN controller outperforms the conventional PI approach in terms of power quality, robustness, and adaptability. Therefore, the proposed system offers a reliable and intelligent solution for advanced multiport charging applications in modern electric vehicle and smart grid environments.

Keywords: ANN controller, Multiport charger, Electric vehicles, V2G, V2H, Power quality, MATLAB Simulink

INTRODUCTION

The rapid growth of electric vehicles (EVs), particularly light electric vehicles (LEVs), has significantly transformed the modern transportation landscape and accelerated the transition toward sustainable energy systems [1]–[3]. With increasing environmental concerns, stringent emission regulations, and the global push toward electrification, efficient charging infrastructure has become a critical area of research [4], [5]. Conventional charging systems are primarily designed for unidirectional power flow, limiting their capability to support advanced applications such as energy sharing and grid support [6]. In contrast, multiport chargers have emerged as a promising solution, enabling bidirectional energy transfer among multiple sources and loads [7], [8]. These systems facilitate flexible energy management by supporting various operational modes, including Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G), thereby enhancing energy utilization and contributing to grid stability and resilience in smart grid environments [9], [10].

The design and control of multiport converters play a vital role in ensuring efficient and reliable operation under varying load and supply conditions [11]. Traditionally, Proportional–Integral (PI) controllers have been widely used due to their simplicity and ease of implementation [12]. However, PI controllers exhibit inherent limitations when dealing with nonlinear systems, parameter uncertainties, and dynamic disturbances, which are common in multiport charging applications [13]. These challenges often result in slower transient response, increased steady-state error, and higher Total Harmonic Distortion (THD). As the complexity of power electronic systems increases, there is a growing need for advanced control strategies that can adapt to changing operating conditions and maintain optimal performance across all modes of operation [14].

In recent years, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), have gained significant attention in power electronics and energy systems [15]. ANN-based controllers are capable of learning complex nonlinear relationships and adapting to dynamic environments through training processes. Unlike conventional controllers, ANNs can provide faster response, improved accuracy, and enhanced robustness without requiring precise mathematical models of the system. Their ability to generalize and handle uncertainties makes them highly suitable for controlling multiport converters operating under diverse conditions. Researchers have demonstrated that ANN controllers can effectively reduce harmonic distortion, improve voltage regulation, and ensure stable power flow, making them a viable alternative to traditional control methods in modern EV charging systems.

Motivated by these advancements, this work proposes a novel model and design of an ANN-controlled multiport charger simulated using MATLAB/Simulink. The proposed system replaces the conventional PI controller with an ANN-based control strategy to improve overall system performance. The multiport charger is designed to support V2V, V2H, and V2G modes, enabling seamless bidirectional power exchange between electric vehicles, domestic appliances, and the utility grid. The ANN controller is trained to optimize voltage and current regulation under different operating scenarios, ensuring efficient and stable performance. Through detailed simulation analysis, the proposed approach demonstrates superior transient response, reduced steady-state error, and lower THD compared to the conventional PI-controlled system. This study highlights the potential of intelligent control techniques in enhancing the functionality and reliability of next-generation EV charging infrastructure and smart grid applications.

LITERATURE SURVEY

The rapid development of electric vehicle (EV) charging technologies has led to extensive research on advanced converter topologies and intelligent control strategies aimed at improving efficiency, flexibility, and power quality. Early studies primarily focused on conventional unidirectional chargers using simple power electronic converters, which were limited in functionality and unable to support bidirectional energy flow [1], [2]. With the emergence of smart grid concepts, researchers began exploring bidirectional converters capable of enabling Vehicle-to-Grid (V2G) operations, allowing EVs to act as distributed energy storage units [3]. These systems demonstrated the potential to enhance grid stability, peak load management, and renewable energy integration. However, most initial designs were restricted to single-port or dual-port configurations, lacking the capability to handle multiple energy sources and loads simultaneously. To address these limitations, multiport converter architectures were introduced, enabling simultaneous power exchange between various ports such as the grid, EV batteries, and domestic loads [4], [5]. Researchers proposed different topologies, including isolated and non-isolated multiport converters, to achieve high efficiency and reduced component count. These systems supported multiple operational modes such as Vehicle-to-Home (V2H) and Vehicle-to-Vehicle (V2V), providing enhanced flexibility in energy management [6], [7]. Despite their advantages, controlling such converters posed significant challenges due to their nonlinear behavior and complex switching dynamics. Conventional control strategies, particularly Proportional–Integral (PI) controllers, were widely adopted to regulate voltage and current. While these controllers offered simplicity and ease of implementation, their performance was often compromised under varying load conditions and system uncertainties [8], [9].

In response to the limitations of traditional control techniques, advanced control methods such as fuzzy logic, sliding mode control, and model predictive control were investigated to improve system performance [10], [11]. These approaches demonstrated better robustness and dynamic response compared to PI controllers, particularly in handling nonlinearities and disturbances. However, they often required complex mathematical modeling and high computational resources, which limited their practical implementation in real-time applications. Moreover, tuning these controllers for multiport systems remained a challenging task due to the interaction between multiple ports and operating modes. Recently, Artificial Intelligence (AI)-based control strategies, particularly Artificial Neural Networks (ANNs), have gained considerable attention for power electronic applications [12], [13]. ANN controllers are capable of learning system dynamics from data and adapting to changing operating conditions without requiring an explicit mathematical model. Several studies have demonstrated the effectiveness of ANN-based controllers in improving voltage regulation, reducing Total Harmonic Distortion (THD), and enhancing transient response in DC–DC converters and EV charging systems [14]. Furthermore, hybrid approaches combining ANN with traditional controllers have also been explored to leverage the advantages of both techniques. Despite these advancements, limited research has been conducted on the application of ANN controllers in multiport charger systems that operate across multiple modes such as V2V, V2H, and V2G.

Therefore, there exists a research gap in developing an intelligent control framework that can effectively manage the complexity of multiport converters while ensuring high efficiency and stability. The integration of ANN-based control into multiport charger systems presents a promising solution to overcome the limitations of conventional and advanced controllers. By enabling adaptive and data-driven control, ANN can significantly enhance system performance under dynamic operating conditions. This study builds upon existing research by proposing an ANN-controlled multiport charger model and evaluating its performance through MATLAB/Simulink simulations, with a focus on improving power quality, reducing steady-state errors, and ensuring reliable operation across all supported modes [15].

METHODOLOGY

The methodology of the proposed system begins with the development of a comprehensive simulation model of the multiport charger in the MATLAB/Simulink environment. The system is designed to incorporate multiple ports, including the grid interface, electric vehicle (EV) battery port, and a domestic load port, enabling bidirectional power flow. Initially, the electrical parameters such as input voltage, switching frequency, inductance, capacitance, and load conditions are defined based on standard EV charging requirements. The multiport converter topology is then modeled using appropriate power electronic switches, diodes, and passive components to ensure efficient energy transfer among all ports. The converter is configured to operate under three distinct modes: Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G), with each mode representing a specific power flow condition.

In the next step, a conventional Proportional–Integral (PI) controller is designed and implemented as a baseline control strategy for the system. The PI controller is used to regulate output voltage and current by minimizing the error between the reference and measured signals. Proper tuning of proportional and integral gains is carried out using trial-and-error or standard tuning techniques to achieve acceptable performance. The system response under the PI controller is analyzed in terms of transient characteristics, steady-state error, and Total Harmonic Distortion (THD). This step serves as a reference framework to evaluate the effectiveness of the proposed Artificial Neural Network (ANN) controller.

Following this, an ANN-based control strategy is developed to replace the conventional PI controller. The ANN is structured as a feedforward neural network consisting of input, hidden, and output layers. The input layer receives system parameters such as voltage error, change in error, and current variations, while the output layer generates appropriate control signals for the converter switches. A dataset is generated from the simulation of the PI-controlled system under various operating conditions, including load variations and mode transitions. This dataset is used to train the ANN using supervised learning techniques, typically employing backpropagation algorithms. The training process aims to minimize the error between the predicted and desired control outputs, ensuring accurate mapping of system dynamics.

Once the ANN is trained, it is integrated into the Simulink model to replace the PI controller. The ANN controller continuously monitors system inputs and generates control signals in real time, adapting to changes in operating conditions. The switching pulses for the power electronic devices are derived from the ANN output through a pulse-width modulation (PWM) scheme. Special attention is given to ensure stable operation during transitions between V2V, V2H, and V2G modes, as these transitions involve significant variations in power flow direction and magnitude.

The controller's adaptability allows it to maintain voltage regulation and minimize disturbances during these transitions.

Subsequently, the performance of the ANN-controlled system is evaluated under different operating scenarios. These include sudden load changes, variations in input voltage, and switching between operational modes. Key performance metrics such as rise time, settling time, steady-state error, efficiency, and THD are measured and compared with those obtained from the PI-controlled system. The harmonic content of the output waveform is analyzed using Fast Fourier Transform (FFT) tools available in MATLAB/Simulink to quantify the reduction in THD. This step highlights the capability of the ANN controller to improve power quality and system stability.

Finally, a comparative analysis is conducted to validate the superiority of the ANN-based control strategy over the conventional PI controller. The results are systematically recorded and interpreted to demonstrate improvements in dynamic response, robustness, and efficiency. The methodology ensures a structured approach, starting from system modeling and baseline evaluation to intelligent controller design and performance validation. This step-by-step implementation provides a clear framework for developing advanced multiport charging systems capable of supporting next-generation EV and smart grid applications.

PROPOSED SYSTEM

The proposed system presents a novel design and simulation of an Artificial Neural Network (ANN) controlled multiport charger intended for light electric vehicles (LEVs) with integrated support for domestic energy applications. The system is developed in the MATLAB/Simulink environment and is structured to enable efficient bidirectional power flow among multiple ports, including the utility grid, EV battery, and household loads. The architecture is designed to operate seamlessly under three primary modes: Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G), thereby providing flexibility in energy utilization and supporting the concept of smart energy management. The central objective of the proposed system is to enhance performance, efficiency, and power quality by replacing the conventional Proportional–Integral (PI) controller with an intelligent ANN-based control mechanism. The core of the system is the multiport DC–DC converter, which acts as an interface for energy exchange between different sources and loads. The converter topology is designed to reduce the number of conversion stages while maintaining high efficiency and reliability. It consists of multiple switching devices, inductors, and capacitors arranged in such a way that power can flow in both directions depending on the operational requirement. The grid port is responsible for supplying or absorbing power from the utility, the EV port manages battery charging and discharging, and the load port supplies energy to domestic appliances. The converter operates using high-frequency switching techniques to ensure compact design and reduced losses. A pulse-width modulation (PWM) scheme is employed to control the switching actions of the semiconductor devices.

The control system plays a crucial role in maintaining stable operation of the multiport converter under varying conditions. In the proposed design, an ANN controller is implemented to replace the traditional PI controller, which often struggles with nonlinearities and parameter variations. The ANN is structured as a multilayer feedforward network comprising input, hidden, and output layers. The input parameters to the ANN include voltage error, rate of change of error, and current signals from different ports. These inputs allow the network to understand the dynamic behavior of the system. The ANN is trained using supervised learning techniques, where a dataset generated from various operating conditions is used to optimize the network weights. The training process ensures that the ANN can accurately predict control actions required to maintain desired voltage and current levels. Once trained, the ANN controller generates control signals that are fed into the PWM generator, which in turn produces switching pulses for the converter switches. This closed-loop control mechanism enables real-time adjustment of system parameters, ensuring rapid response to load variations and disturbances. The ANN controller exhibits strong adaptability, allowing it to maintain system stability even during sudden changes in operating modes. Unlike the PI controller, which requires manual tuning and may not perform well under all conditions, the ANN continuously adapts based on learned patterns, resulting in improved control accuracy and reduced steady-state error. The proposed system supports three operational modes that enhance its versatility. In V2V mode, energy is transferred between two electric vehicles, enabling one vehicle to charge another in the absence of grid support. In V2H mode, the EV battery supplies power to domestic appliances, which is particularly useful during power outages or peak demand periods. In V2G mode, excess energy stored in the EV battery is fed back into the grid, contributing to load balancing and grid stabilization. The ANN controller ensures smooth transitions between these modes by dynamically adjusting control signals to match the required power flow direction and magnitude.

Performance evaluation of the proposed system is carried out through detailed simulations in MATLAB/Simulink. The results demonstrate that the ANN-controlled multiport charger significantly outperforms the conventional PI-controlled system. Key improvements include faster transient response, reduced settling time, lower steady-state error, and significant reduction in Total Harmonic Distortion (THD). The system also exhibits higher efficiency and better voltage regulation under dynamic load conditions. The harmonic analysis confirms that the ANN controller effectively suppresses distortions, thereby improving overall power quality. In summary, the proposed ANN-controlled multiport charger provides an intelligent and efficient solution for modern EV charging and energy management systems. By integrating advanced control techniques with a flexible multiport converter design, the system addresses the limitations of conventional controllers and enhances overall performance. The ability to support multiple operational modes along with improved adaptability and robustness makes the proposed system highly suitable for next-generation smart grid and electric mobility applications.

RESULTS AND DISCUSSION

The performance of the proposed ANN-controlled multiport charger is evaluated through detailed simulations carried out in the MATLAB/Simulink environment under various operating conditions. The results are analyzed by comparing the performance of the ANN controller with that of the conventional Proportional–Integral (PI) controller. Key performance indicators such as transient response, steady-state error, Total Harmonic Distortion (THD), voltage regulation, and system efficiency are considered. The system is tested across all three operational modes—Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G)—to ensure comprehensive validation. The simulation results clearly demonstrate that the ANN-based control approach offers significant improvements in system performance and stability under dynamic conditions.

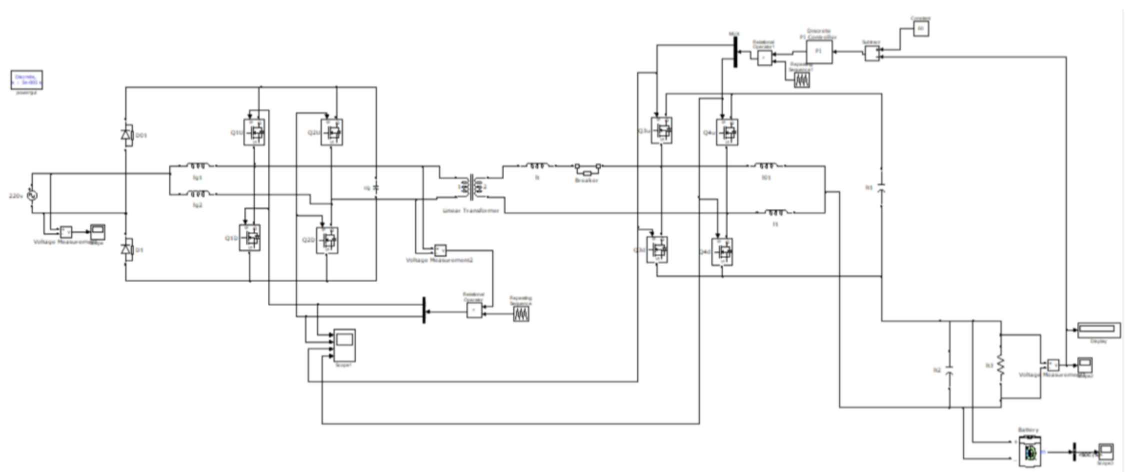

Fig 1: Proposed Simulation Circuit

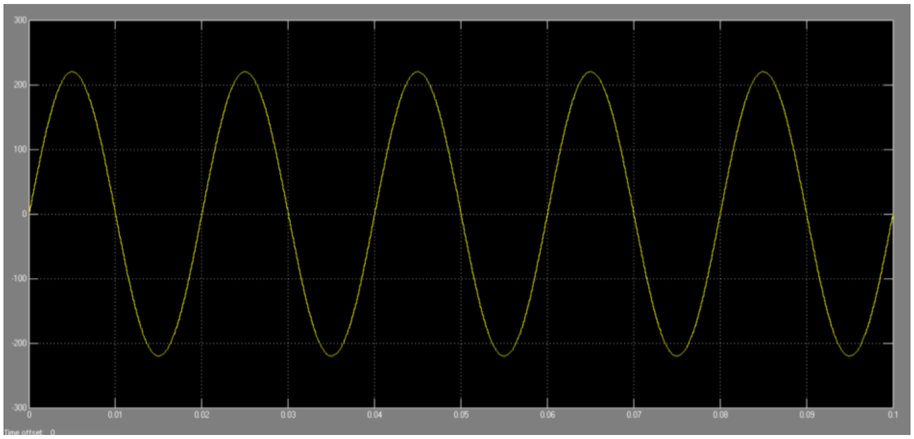

Fig 2: GRID VOLTAGE VS TIME

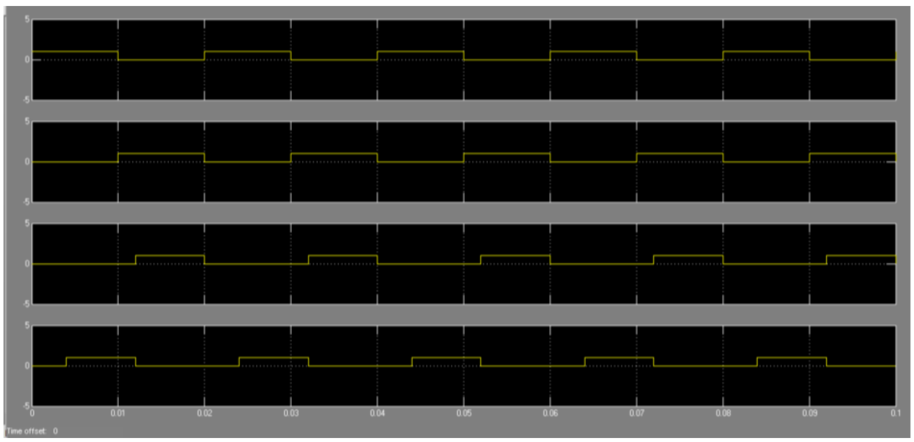

Fig 3: CONTROL SIGNALS

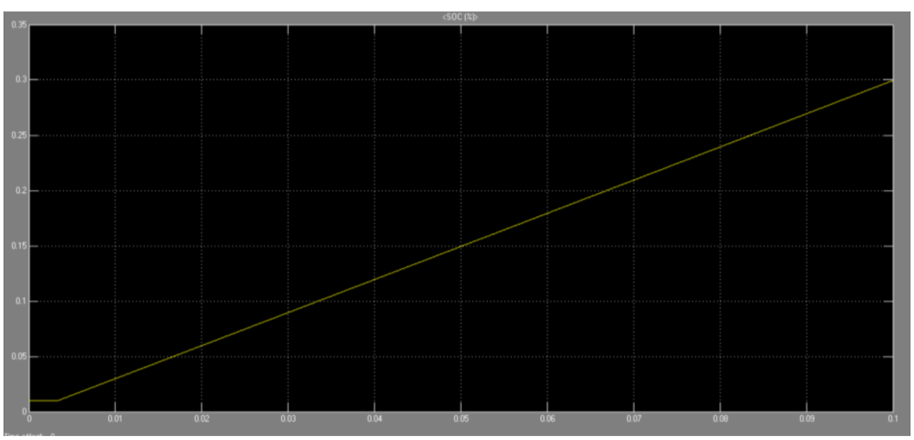

Fig 4: BATTERY VOLTAGE

In terms of transient response, the ANN controller exhibits a much faster rise time and reduced settling time compared to the PI controller. When sudden load variations are introduced, the PI-controlled system shows noticeable oscillations and longer stabilization periods, whereas the ANN-controlled system quickly adapts and restores the desired output conditions. This improvement can be attributed to the learning capability of the ANN, which enables it to predict system behavior and respond proactively rather than reactively. The reduced overshoot and smoother waveform transitions further highlight the effectiveness of the ANN in handling nonlinearities and disturbances within the multiport converter.

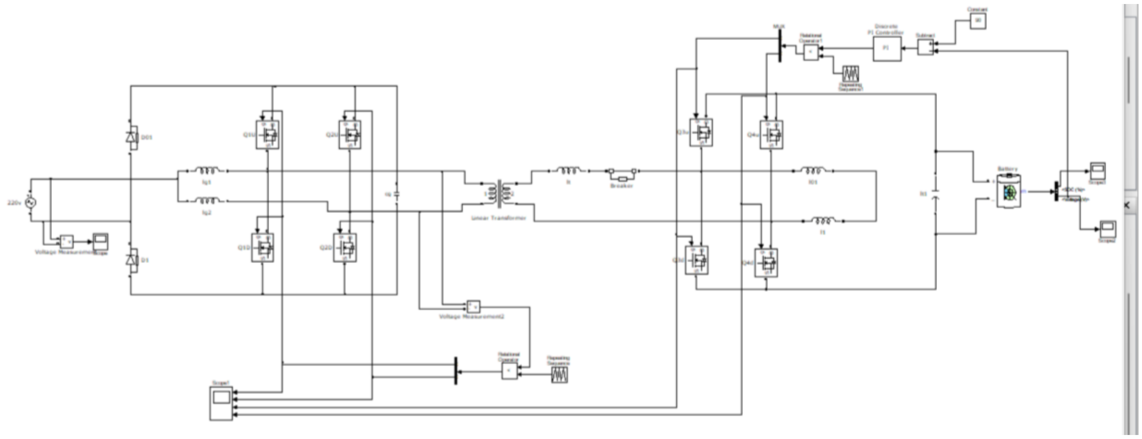

Fig 5: PROPOSED CIRCUIT CONFIGURATION IN V2G MODE

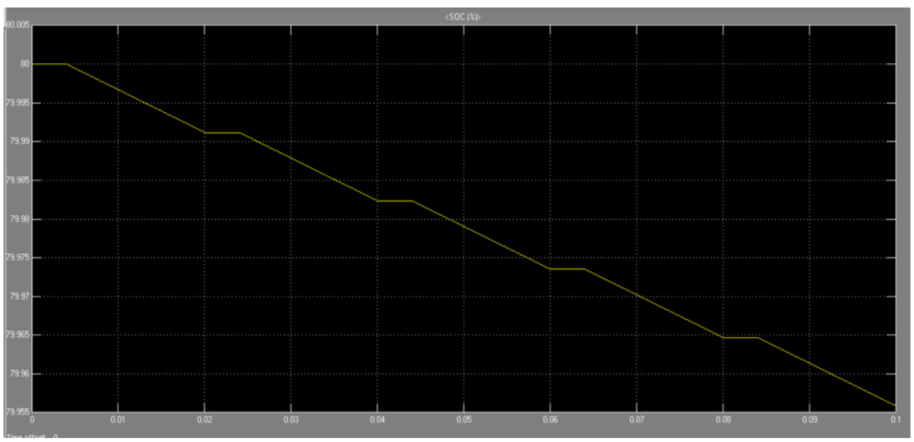

Fig 6: Battery SOC vs time

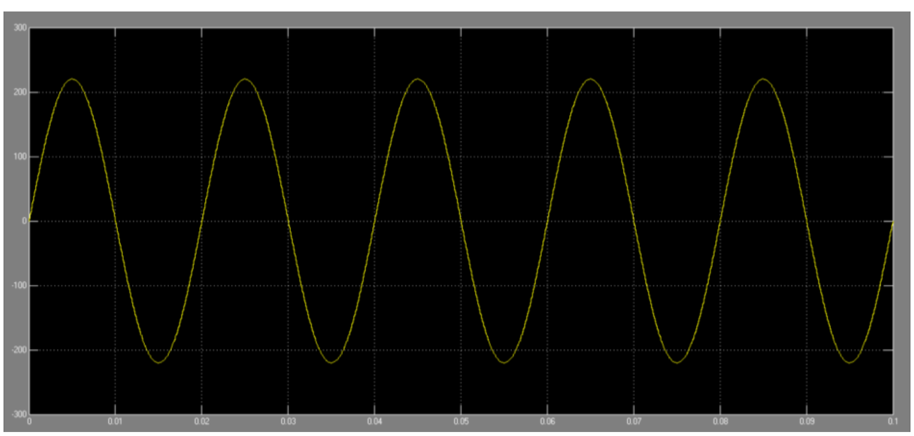

Fig 7: GRID VOLTAGE VS TIME

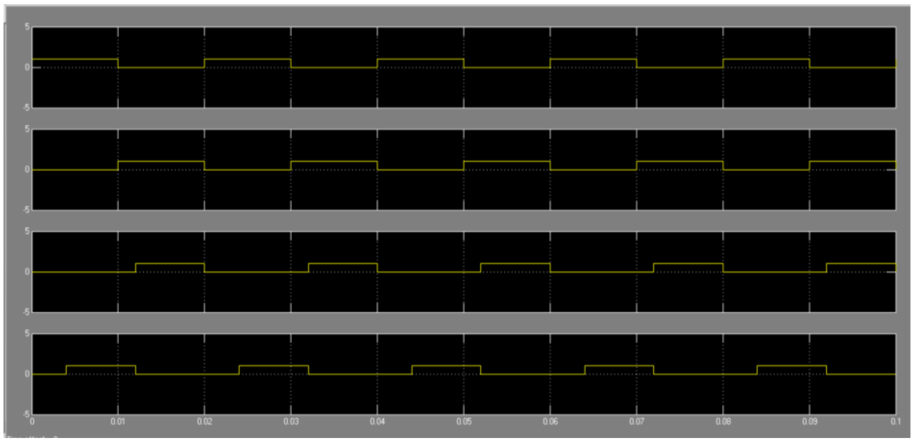

Fig 8: CONTROL SIGNALS

The steady-state performance of the system is also significantly enhanced with the ANN controller. The PI controller, although stable, exhibits small but persistent steady-state errors under varying load and input conditions. In contrast, the ANN controller minimizes these errors by continuously adjusting control signals based on real-time feedback. This results in more accurate voltage and current regulation across all ports. The improved steady-state accuracy ensures reliable operation of connected loads and prevents issues such as voltage fluctuations, which are critical in both EV charging and domestic power supply applications.

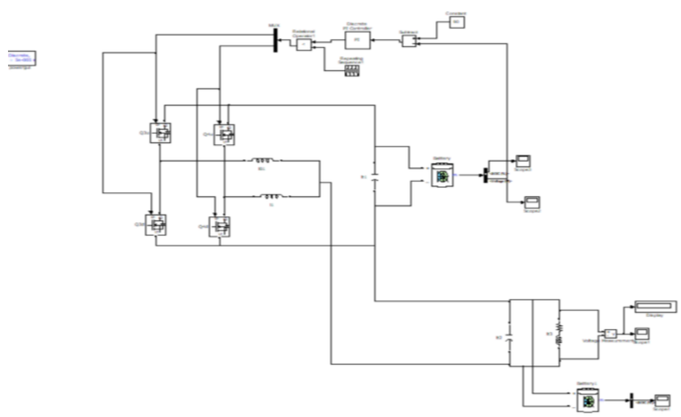

Fig 9: V2L mode circuit configuration

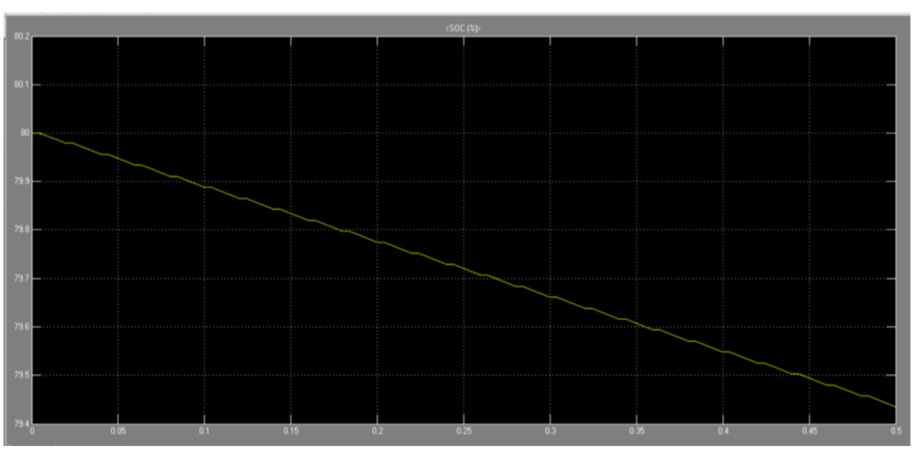

Fig 10: Dc input Battery Soc vs time

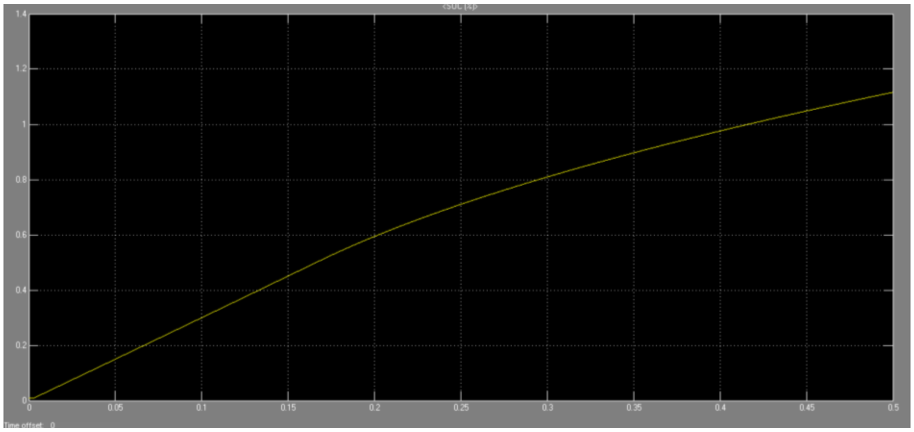

Fig 11: Load battery SOC

Harmonic analysis is performed using Fast Fourier Transform (FFT) tools to evaluate the quality of the output waveforms. The results indicate a substantial reduction in Total Harmonic Distortion (THD) when using the ANN controller. The PI-controlled system produces higher harmonic content due to its limited ability to handle rapid switching dynamics and nonlinear effects. On the other hand, the ANN controller effectively smoothens the output waveform by optimizing switching patterns, thereby reducing distortion. Lower THD not only improves power quality but also enhances the lifespan of electrical components and ensures compliance with grid standards.

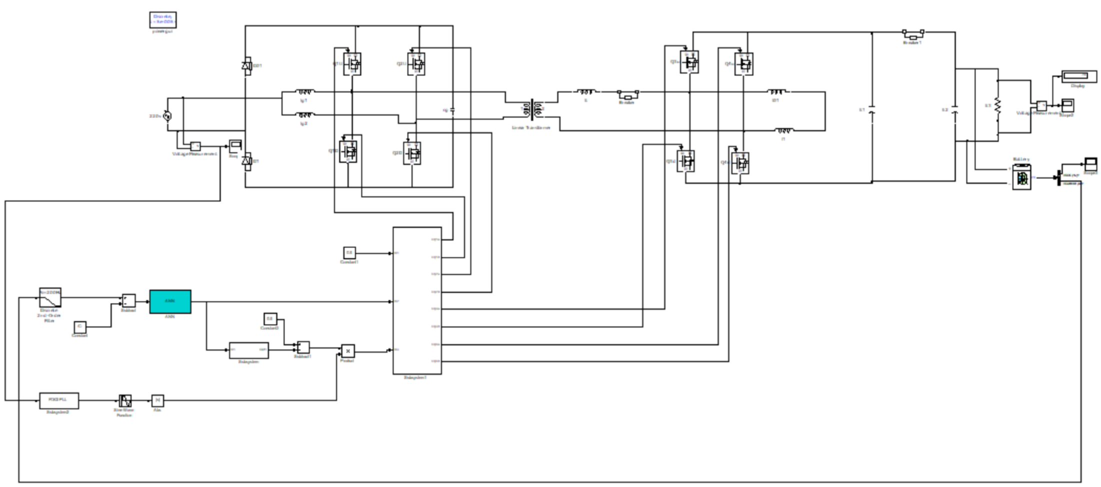

Fig 12: Proposed circuit with G2V Mode

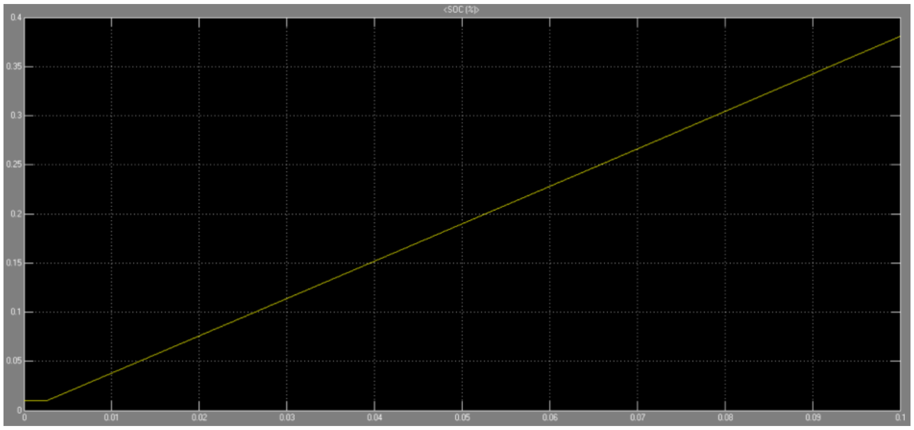

Fig 13: Battery SOC% In G2V Mode

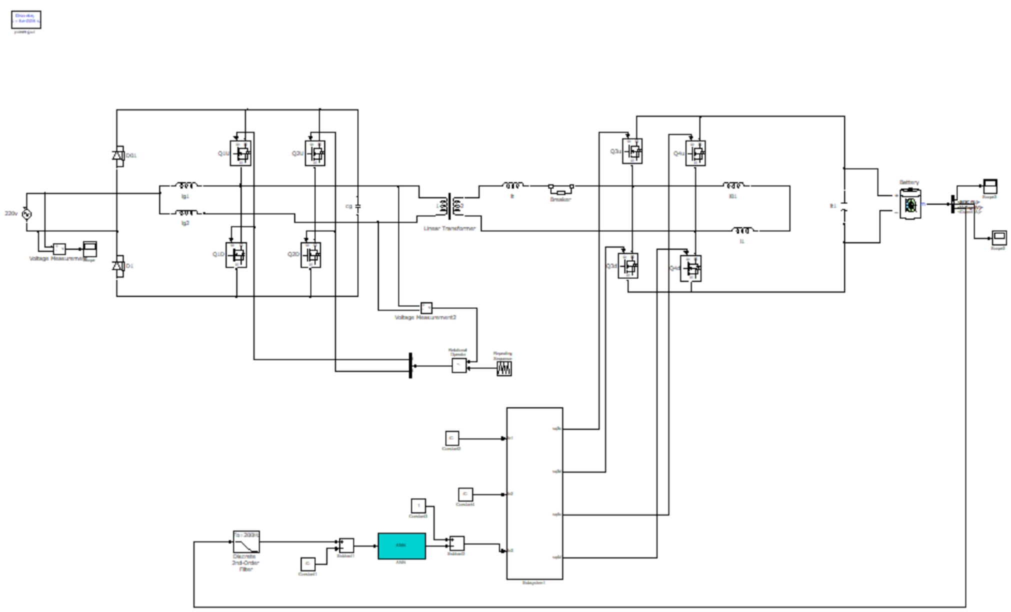

Fig 14: Proposed circuit with V2G Mode

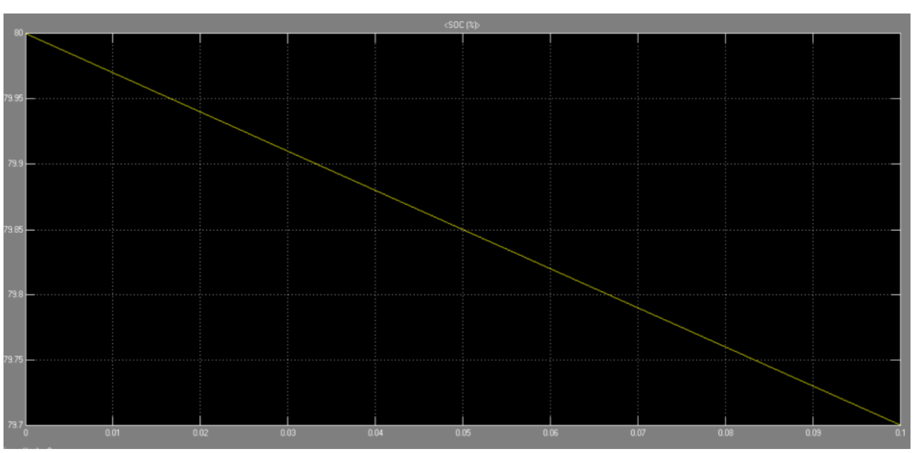

Fig 15: Battery SOC% in V2G Mode

The system performance across different operational modes further validates the robustness of the proposed approach. In V2V mode, the ANN controller ensures efficient and stable energy transfer between vehicles with minimal losses. During V2H operation, the system maintains a consistent power supply to domestic loads even under fluctuating demand conditions. In V2G mode, the ANN-controlled system demonstrates smooth and controlled power injection into the grid, contributing to grid stability. The transitions between these modes are seamless, with the ANN controller effectively managing changes in power flow direction without introducing significant disturbances or delays.

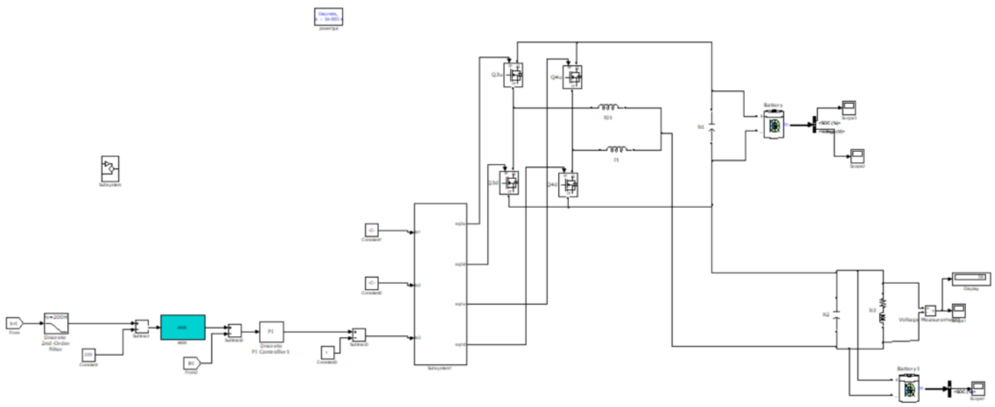

Fig 16: Proposed circuit with V2H Mode

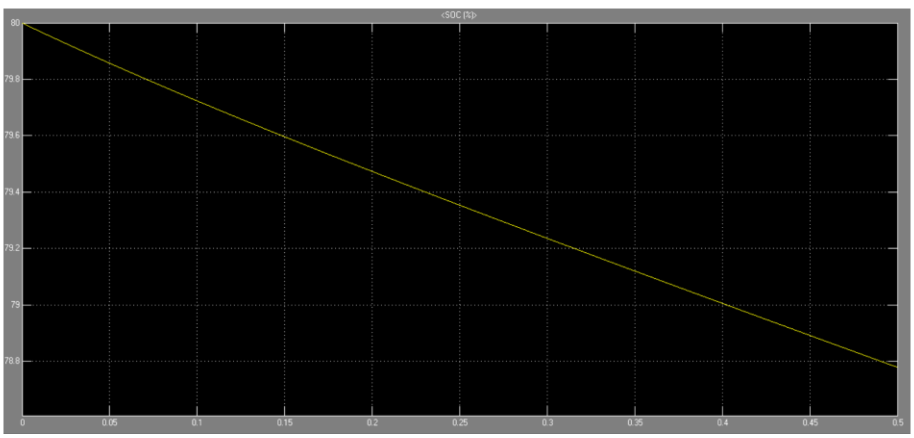

Fig 17: DC INPUT BATTRY SOC% WITH ANN

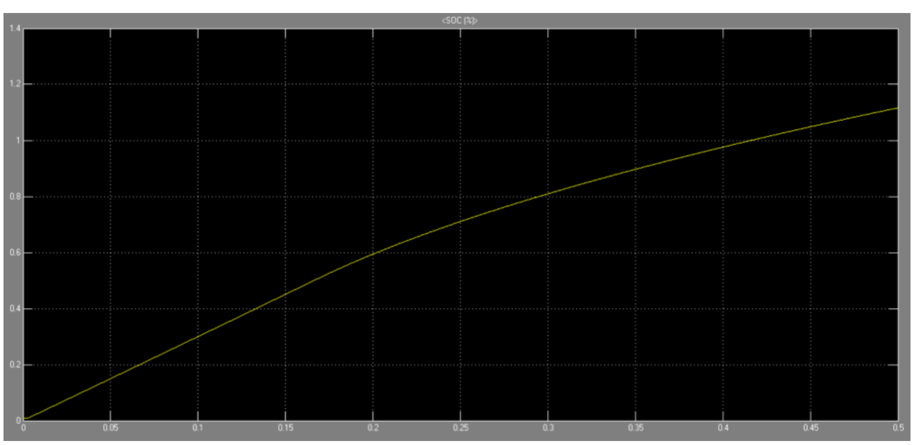

Fig 18: LOAD BATTRY SOC% WITH ANN

Overall, the comparative analysis confirms that the ANN-controlled multiport charger outperforms the conventional PI-controlled system in all key aspects. The improvements in transient response, steady-state accuracy, harmonic reduction, and operational flexibility highlight the superiority of the proposed control strategy. The system demonstrates high efficiency and reliability under diverse operating conditions, making it suitable for real-world applications. These results emphasize the potential of ANN-based control in advancing multiport charging technologies and supporting the development of intelligent, adaptive, and high-performance energy systems for electric vehicles and smart grids.

CONCLUSION

In conclusion, this study presented a novel design and simulation of an ANN-controlled multiport charger for light electric vehicles, developed using the MATLAB/Simulink platform. The proposed system effectively addressed the limitations of conventional PI controllers by introducing an intelligent control strategy capable of handling nonlinearities, dynamic disturbances, and varying operating conditions. By supporting multiple operational modes, including Vehicle-to-Vehicle (V2V), Vehicle-to-Home (V2H), and Vehicle-to-Grid (V2G), the system demonstrated enhanced flexibility and adaptability for modern energy applications. The ANN controller significantly improved system performance by reducing transient response time, minimizing steady-state error, and lowering Total Harmonic Distortion (THD), thereby ensuring superior power quality and stability. Furthermore, the system maintained efficient and reliable operation during mode transitions and load variations, highlighting its robustness. The comparative analysis confirmed that the ANN-based approach outperforms the traditional PI controller in all critical performance aspects. Overall, the proposed multiport charger offers a promising and intelligent solution for next-generation electric vehicle charging infrastructure and smart grid integration, contributing to efficient energy management and sustainable development.

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