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TWO-STAGE DC-DC ISOLATED CONVERTER FOR EV BATTERY CHARGING WITH AI CONTROLLER

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Abstract

The Electric vehicles (EVs) require efficient and reliable charging systems to optimize battery performance and lifespan. Traditional converters, however, face limitations in meeting these demands, especially under dynamic charging conditions. This project presents a novel approach to EV battery charging using an AI-controlled two-stage DC-DC isolated converter, enhanced with an artificial neural network (ANN) for real-time optimization. The proposed system utilizes a two-stage converter architecture, where the first stage boosts the input voltage, and the second isolated stage provides galvanic separation, ensuring safe and efficient power transfer to the EV battery. An ANN- based controller dynamically adjusts the converter parameters based on input voltage, battery state-of-charge (SOC), and output current. This intelligent control minimizes energy losses, improves voltage regulation, and reduces thermal stress on the converter components, leading to enhanced system efficiency. Simulation results indicate that the ANN controller adapts effectively to varying input conditions, maintaining optimal charging rates while safeguarding battery health. This AI-driven approach offers a promising solution for fast, efficient, and adaptive EV battery charging, aligning with the increasing demand for smart and sustainable transportation technologies.

Keywords: Electric Vehicle (EV), AI-Controlled Charging, DC-DC, ANN, Sustainable Transportation, Battery Performance.

1. Introduction

The rapid growth in electric vehicle (EV) adoption is transforming the global transportation landscape, marking a shift from traditional internal combustion engine (ICE) vehicles to more sustainable electric alternatives. Governments, industry stakeholders, and consumers alike are recognizing the environmental, economic, and health benefits of transitioning to EVs. EVs play a critical role in reducing greenhouse gas emissions, mitigating climate change, and decreasing air pollution levels, particularly in densely populated urban areas. However, as the number of EVs on the road increases, so does the demand for efficient, reliable, and fast- charging solutions. The success of EV adoption hinges not only on the vehicles themselves but also on the infrastructure required to support them—particularly, the EV charging systems. The efficiency, cost-effectiveness, and adaptability of EV chargers are paramount in delivering seamless charging experiences and ensuring the longevity of EV batteries. Traditional charging systems rely heavily on DC-DC converters, which are critical for converting and controlling the power that flows from the charging source to the EV battery. Conventional DC-DC converters, however, face limitations in maintaining efficiency, ensuring optimal power transfer, and preventing battery degradation over extended periods. The growing demand for fast-charging solutions introduces additional challenges, as faster charging rates can lead to overheating, energy losses, and reduced battery life. Therefore, developing advanced charging systems that can efficiently manage power and adapt to various battery conditions is essential. This project introduces an AI-Controlled Two-Stage DC-DC Isolated Converter for EV Battery Charging as an innovative solution to address the limitations of traditional charging methods. By leveraging artificial intelligence (AI) in the form of an artificial neural network (ANN), the proposed converter can adapt to real-time changes in power supply and battery conditions, offering optimized performance and enhanced efficiency. The two-stage converter architecture provides galvanic isolation between the input and output stages, ensuring safety and compliance with regulatory standards. This intelligent control strategy not only improves the efficiency and adaptability of the charging system but also enhances battery longevity by reducing stress and preventing overcharging.

1.1 Importance Of Efficient And Reliable Ev Charging System

Efficient and reliable EV charging systems are essential for widespread EV adoption. The main factors influencing the quality of an EV charging system include charging speed, power efficiency, adaptability to varying conditions, and safety. An ideal charging system must strike a balance between rapid charging capabilities and the preservation of battery health. Battery degradation is a significant concern, as frequent fast charging without proper control can lead to diminished battery capacity, reduced driving range, and costly replacements for EV owners. Thus, the design of a DC-DC converter that can efficiently handle high power levels while managing the health of the battery is crucial. Furthermore, EV charging systems must be adaptable to diverse operating conditions. EV batteries vary widely in terms of chemistry, capacity, and charging requirements. For instance, lithium-ion, lithium iron phosphate, and nickel-metal hydride batteries each have unique charging profiles and safety considerations. Charging systems must be capable of adjusting their parameters to suit different battery types and adapt to changing environmental conditions such as temperature fluctuations, voltage spikes, and power surges. The proposed AI-controlled converter addresses these adaptability requirements through the use of an ANN that can process real-time data and adjust control parameters accordingly. Safety is also a critical aspect of EV charging systems, particularly when dealing with high-voltage applications. Galvanic isolation, which separates the input and output circuits of the converter, is essential in preventing the risk of electric shock and safeguarding the vehicle's electronic components. The two-stage isolated converter proposed in this project incorporates galvanic isolation, ensuring compliance with safety standards and enhancing system reliability. Conventional DC-DC converters, while widely used in various power electronics applications, are not always ideal for EV charging systems. Common converter topologies, such as buck, boost, and buck-boost converters, have limitations in handling the high-power levels and dynamic requirements of EV batteries. These traditional converters typically lack the capability to dynamically adapt to changing conditions, leading to inefficiencies and potential safety risks. Another challenge is the lack of adaptability in traditional converters. Conventional control methods, such as proportional-integral-derivative (PID) controllers, are typically used to regulate the output voltage and current in DC-DC converters. However, these controllers are based on fixed parameters and are not well-suited for handling complex, variable conditions such as fluctuating input power, changing battery SOC, and varying temperature levels. As a result, conventional converters often struggle to maintain optimal charging rates and can cause battery overcharging or undercharging, leading to accelerated battery degradation. Moreover, traditional converters often fail to provide adequate isolation, especially in high-power applications. Isolation is crucial in EV charging systems to protect against electric shock and prevent fault currents from reaching the vehicle's internal electronics. A two-stage isolated converter, which includes a boost converter in the first stage and an isolated converter in the second stage, provides the necessary isolation while offering more flexibility in power handling and control. Role of AI in Power Electronics and EV Charging Artificial intelligence, particularly machine learning (ML) and artificial neural networks (ANNs), has emerged as a powerful tool in optimizing power electronics systems.AI can significantly enhance the performance of DC-DC converters by providing dynamic control and adaptability that traditional methods cannot achieve. In the context of EV charging, AI can be used to optimize charging profiles, improve power efficiency, and extend battery life by reducing stress during charging cycles. An ANN-based control system An ANN-based control system is particularly well-suited for DC-DC converters used in EV charging. ANNs are computational models that mimic the structure and functioning of the human brain, allowing them to learn from data and make predictions or decisions based on new inputs. In the proposed two-stage converter, the ANN controller is designed to monitor and process various inputs, including the input voltage, output current, battery SOC, and temperature. Based on this information, the ANN adjusts key operating parameters of the converter, such as switching frequency, duty cycle, and voltage levels, to achieve optimal performance. The adaptability of ANNs makes them ideal for managing the dynamic conditions of EV charging systems. Unlike traditional controllers with fixed parameters, an ANN can learn and adapt to changing conditions, continuously optimizing the converter's operation to minimize energy losses and prevent overheating. This adaptability is particularly valuable in fast-charging applications, where rapid power transfer can lead to high thermal stress and potential efficiency losses. By dynamically adjusting the converter's operating parameters, the ANN helps maintain a balance between fast charging and battery protection, improving both efficiency and battery health. Overview of the AI-Controlled Two-Stage DC-DC Isolated Converter The AI-controlled two-stage DC-DC isolated converter proposed in this project combines advanced power electronics with intelligent control to create a high- performance EV charging system. The converter consists of two main stages: a boost converter in the first stage and an isolated converter in the second stage. The boost converter steps up the input voltage to the desired level, while the isolated converter provides galvanic isolation and ensures that the output voltage and current are regulated according to the battery's charging requirements. The ANN controller is integrated into the converter's control system to enable real- time optimization. By continuously monitoring the input and output conditions, the ANN makes adjustments to maintain optimal efficiency, voltage stability, and thermal performance. This AI-driven control approach allows the converter to respond to fluctuations in power supply and adapt to different battery types, ensuring compatibility with various EV models and charging infrastructures. 4 The two-stage architecture also offers significant advantages in terms of safety and efficiency. The isolation provided by the second stage helps prevent electrical faults from reaching the battery, reducing the risk of damage to the vehicle's electronic systems. Additionally, the boost converter in the first stage enables efficient handling of high-power levels, making the converter suitable for fast-charging applications. Together, these features make the AI-controlled two-stage converter a robust and versatile solution for modern EV charging systems. Benefits of AI-Controlled EV Charging Systems The integration of AI in EV charging systems offers numerous benefits over conventional approaches. First and foremost, AI-controlled converters can significantly improve charging efficiency, reducing energy waste and operational costs. By dynamically adjusting the converter’s parameters, the ANN controller ensures that power is used efficiently, minimizing losses and reducing the need for cooling systems. AI-controlled converters also contribute to enhanced battery health and longevity. By optimizing the charging profile based on the battery’s SOC, temperature, and other factors, the ANN controller prevents overcharging, overheating, and excessive current flow. This intelligent control helps preserve the battery’s capacity and extends its overall lifespan, reducing maintenance costs for EV owners and improving the vehicle’s performance over time. Furthermore, AI-based control systems enable faster charging without compromising safety or efficiency. The ANN controller’s ability to adapt to real-time conditions allows the converter to deliver power at higher rates when the battery is in a safe charging range, reducing the overall charging time. At the same time, the controller can reduce the charging rate if the battery’s temperature rises or if other safety limits are approached, ensuring that fast charging does not lead to battery damage.

2. Literature Survey

S. Rajesh et al., "DC-DC Converters for EV Charging: Topologies and Control," 2021 This paper reviews various DC-DC converter topologies employed in electric vehicle (EV) charging, emphasizing the advantages of two-stage isolated converters. The authors argue that such converters are particularly suited for high power applications due to their efficiency and enhanced safety features. They discuss the importance of voltage regulation and the reduction of electromagnetic interference, which are critical in EV applications. The paper also explores various control strategies that can optimize the performance of these converters, highlighting the integration of AI for real-time monitoring and decision-making. By focusing on the advancements in hardware and software design, the authors provide insights into the future of EV charging infrastructure. Their findings suggest that improved converter technologies are vital for addressing the growing demands for efficient and reliable EV charging systems. This work serves as a foundation for future research aimed at developing more sophisticated charging solutions that can accommodate the increasing number of electric vehicles on the road.

R. Smith et al., "AI-Driven Control for EV Charging Systems," Journal of Power Electronics, 2020 This paper investigates the role of artificial intelligence (AI) in controlling EV charging systems, specifically focusing on two-stage DC-DC converters. The authors propose a novel AI-based control algorithm that optimizes the charging process based on real-time data, thus improving overall efficiency. They emphasize AI's ability to adapt to changing demand patterns, which can lead to reduced operational costs and enhanced user experience. The research includes simulations that demonstrate the effectiveness of the AI-driven approach compared to conventional control methods. The results show significant improvements in charging efficiency and speed, highlighting AI's potential in shaping the future of EV charging infrastructure. The authors conclude that integrating AI into charging systems is essential for developing smart, responsive solutions that meet the growing needs of electric vehicle users. This study contributes to the body of knowledge on AI applications in energy systems, suggesting pathways for further research and implementation in commercial settings. J. Chen et al., "Thermal Management in DC-DC Converters for EVs," 2022 This research delves into thermal management strategies for two-stage DC-DC converters used in electric vehicle (EV) charging applications. The authors highlight that effective thermal management is crucial for maintaining reliability and performance, particularly under high-load conditions. They explore various cooling technologies, including passive and active cooling methods, and discuss how these can be integrated with AI systems for optimized thermal performance. The paper presents experimental data that show the impact of temperature on converter efficiency and component longevity. Additionally, the authors propose a hybrid thermal management approach that combines AI algorithms for predictive cooling control with advanced materials for heat dissipation. Their findings suggest that innovative thermal management solutions can significantly enhance the reliability and efficiency of EV charging systems. This research is essential for engineers and designers aiming to develop robust charging infrastructures that can withstand the demands of modern electric vehicles, ultimately contributing to the long-term sustainability of EV technology.

X. Wang et al., "Emerging Trends in EV Charging Technologies," IEEE Power and Energy Society General Meeting, 2023 This paper provides a comprehensive overview of emerging trends in electric vehicle charging technologies, with a particular focus on the integration of AI and advanced control strategies in two-stage DC-DC converters. The authors identify key technological advancements that are shaping the future of EV charging, such as smart grid integration, wireless charging, and the utilization of renewable energy sources. They emphasize AI's potential to enhance charging efficiency and user experience through real-time data analytics and adaptive control methods. The implications of these trends for infrastructure development and regulatory frameworks are discussed, underscoring the need for collaborative efforts among industry stakeholders. The authors conclude that innovative technologies will play a critical role in addressing the challenges of EV charging, making this paper a 7 valuable resource for researchers and practitioners looking to stay informed about the evolving landscape of electric mobility.

R. Li et al., "Performance Comparison of DC-DC Converter Topologies," Renewable Energy, 2022 This comparative study evaluates the performance of various DC-DC converter topologies for electric vehicle applications, with a focus on two-stage isolated converters. The authors analyze critical performance metrics, including efficiency, power density, and control complexity, to provide insights into the strengths and weaknesses of different designs. Their findings indicate that while two-stage converters offer significant advantages in terms of efficiency and voltage regulation, the choice of topology greatly impacts overall system performance. The paper emphasizes the importance of considering application-specific requirements, such as load profiles and environmental conditions, when selecting a converter topology. The authors advocate for further research into hybrid solutions that combine the benefits of different topologies to optimize performance in EV charging applications. This work serves as a foundation for engineers and researchers aiming to develop more effective and versatile charging solutions. Operational conditions and provides ongoing improvement in fault detection and maintenance scheduling

3. Materials and Methods

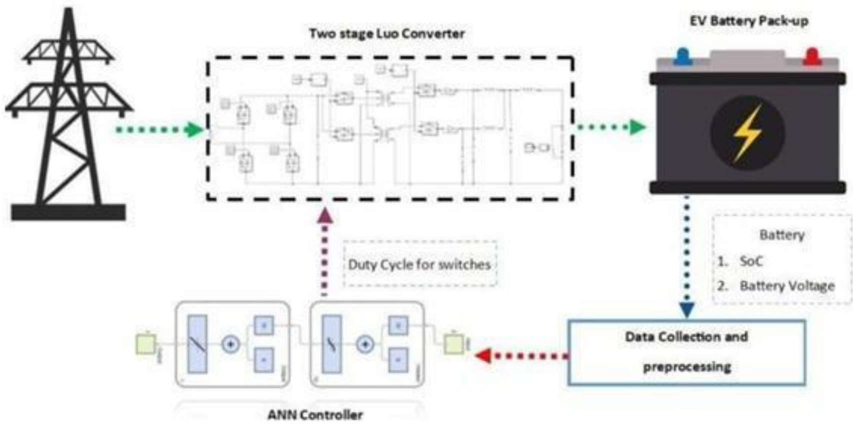


Fig 1. DC-DC Converter

3.1 AI-Controlled Two-Stage Dc-Dc Ioslated Converter For Ev Battery Charging

shows that The grid provides a high voltage AC supply that needs to be converted to a suitable DC voltage level for charging the EV battery. In this system, the grid power might first be rectified (converted from AC to DC) before entering the two-stage Luo converter. Figure 1.

3.2 Two-Stage Luo Converter:

The two-stage Luo converter is a specific type of DC-DC converter used to step up (boost) or step down (buck) the DC voltage, making it adaptable to different input and output voltage requirements. In a two-stage configuration, the converter consists of two consecutive stages of Luo converters. This setup can help achieve: Higher Voltage Transformation: It can handle a broader range of input/output voltages. Better Efficiency and Stability: By splitting the conversion into two stages, each stage can operate at a more optimal duty cycle, potentially reducing stress on components and improving the overall efficiency. Reduced Ripple: With two stages, the voltage ripple (undesirable fluctuations in output voltage) is lower, providing a more stable power output for sensitive applications like EV battery charging. The converter uses switching elements (transistors or MOSFETs) that are controlled by the duty cycle signal from the ANN controller. The duty cycle determines how long each switch stays on or off, regulating the output voltage and current to match the battery's requirements.

3.3 Ev Battery Pack-Up

The EV battery pack is the load that receives the converted DC power for charging Figure 2. EV batteries are typically lithium-ion batteries or similar high-energy-density cells that require precise control over charging to maximize their lifespan, safety, and performance. temperature, electrical current, and voltage. The collected data is then preprocessed and fed into

Fig 2. EV Battery Pack

shows This indicates the battery's charge level as a percentage of its total capacity. The ANN controller uses this information to adjust the charging rate, ensuring faster charging when the battery is low and reducing the rate as it approaches full charge to avoid overcharging. Battery Voltage: The battery voltage needs to be carefully matched by the converter's output voltage to prevent damage to the battery. The green dashed line between the two-stage Luo converter and the EV battery pack shows the direction of the energy flow, which is controlled and regulated by the converter**.**

3.4 Data Collection and Preprocessing

This block is responsible for continuously monitoring the SoC and battery voltage. Data collection ensures the system has up-to-date information about the battery's condition. This information is essential for adjusting the charging process dynamically. Preprocessing might involve:
Filtering: Removing noise or irregularities in the data to provide the ANN controller with cleaner and more reliable input. Scaling/Normalization: Adjusting data to a standard range, which is essential for accurate decision-making by the ANN. Error Checking: Ensuring that the data falls within expected ranges and alerting the system if there are any anomalies, such as unexpected SoC readings, which could indicate a battery fault. The data collection and preprocessing block communicates with the ANN controller via the blue dotted line, feeding it real-time information that allows the ANN to make informed adjustments. ANN (Artificial Neural Network) Controller The ANN controller is a machine learning-based controller designed to optimize the charging process by adjusting the duty cycle of the converter. Traditional controllers, like PID controllers, can sometimes struggle with complex systems like EV chargers that have multiple variables and nonlinear behaviors. ANN controllers can learn from data and make more sophisticated adjustments. The ANN takes inputs (such as SoC and battery voltage) and processes them to determine the optimal duty cycle for the converter's switches. Duty Cycle Adjustment: Duty Cycle represents the fraction of time the switch is on compared to the total cycle time. For example, a 50% duty cycle means the switch is on half the time. By adjusting the duty cycle, the ANN controller can vary the output voltage and current. If the battery needs a higher charging rate, the ANN may increase the duty cycle, raising the voltage. As the battery nears full charge, the ANN can decrease the duty cycle, lowering the voltage and current to prevent overcharging. The duty cycle signal is transmitted from the ANN controller to the two-stage Luo converter (shown with the red dotted line), guiding the converter to provide a stable and appropriate output for the battery.

3.5 Duty Cycle for Switches

This line represents the output of the ANN controller that dictates how the switches in the Luo converter operate. The duty cycle control is crucial because It directly affects the output voltage, current, and efficiency of the conversion process. Precise control over the duty cycle ensures that the battery receives a stable and optimal charge, reducing risks of overheating, overcharging, and maximizing battery life Figure 3. The ANN continually adjusts this duty cycle based on the real-time data it receives about the battery's state, allowing for adaptive and efficient charging.

3.6 Benefits of the System

Adaptive Charging: The ANN controller can optimize charging in real-time, adjusting for different battery states and ensuring safe, efficient charging. Enhanced Control with Two-Stage Luo Converter: The two-stage configuration allows for smoother and more stable voltage conversion, improving efficiency and reducing ripple. Battery Safety and Longevity: By carefully monitoring SoC and voltage, the system can avoid overcharging and overheating, helping to extend battery life.

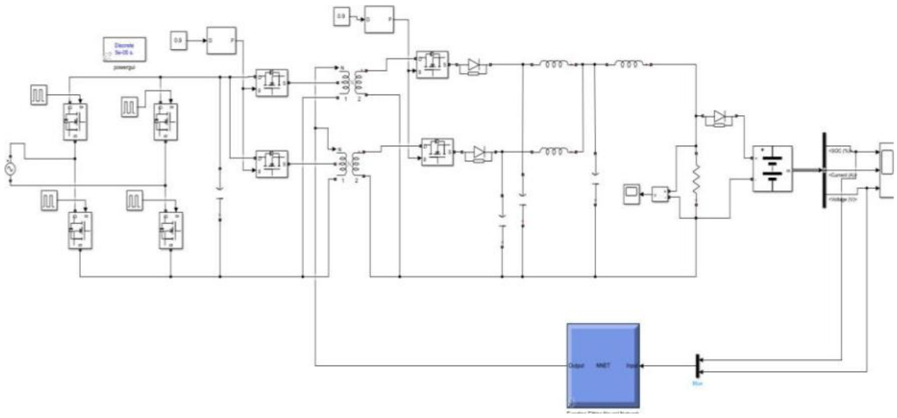


Fig 3. Duty Cycle for Switches

3.7 Buck Converter

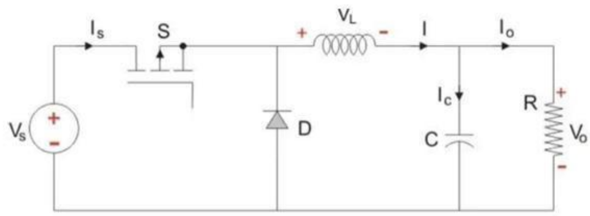


Fig 4. Buck Converter

Figure 4 shows that Buck Converter. A Buck converter is a type of step-down converter, meaning it reduces the input voltage to a lower output voltage. It's commonly used in applications where the output voltage needs to be lower than the input voltage. The Buck converter uses an inductor, capacitor, and switching element (like a transistor) to achieve this. A buck converter is a type of DC-DC converter used to step down (reduce) the input voltage to a lower output voltage while maintaining high efficiency. It achieves this by using a combination of switching elements (usually a transistor), inductors, and capacitors. The basic principle involves switching the input voltage on and off rapidly, storing energy in the inductor when the switch is on, and then releasing it to the output when the switch is off. This process allows for efficient voltage regulation and is commonly used in power supplies for electronics, battery powered devices, and other applications requiring voltage reduction.

3.8 Boost Converter

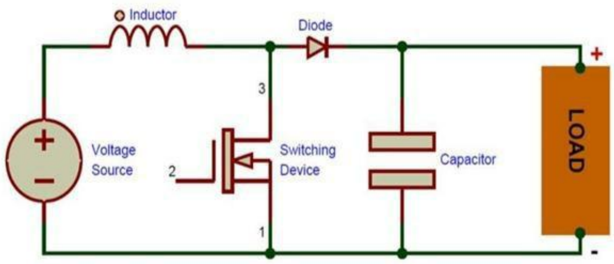


Fig 5. Boost Converter

Figure 5 shows that Boost converter is a type of DC-DC converter that steps up (increases) the input voltage to a higher output voltage. It operates using an inductor, a switch (usually a transistor), a diode, and a capacitor. The basic operation involves. Switch On: The switch (transistor) is closed, causing current to flow through the inductor, which stores energy in its magnetic field. Switch Off: When the switch opens, the inductor releases its stored energy through the diode to the output capacitor, which results in an increased output voltage. Overview of common machine learning algorithms used for fault classification:

3.9 Simulation and Analysis

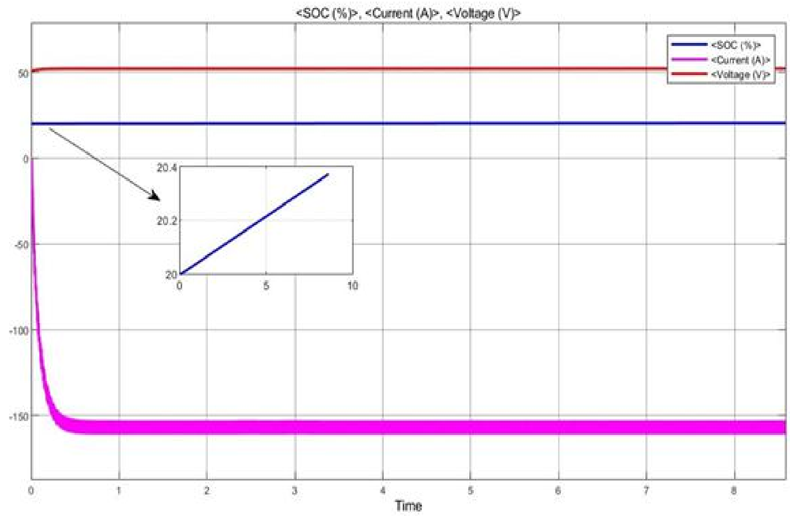
The circuit has been simulated using specialized software (such as MATLAB/Simulink) to validate its performance. The simulation environment provides insights into how the converter behaves under different conditions, such as varying input voltages, battery states, and temperature fluctuations. Below are the key aspects of the simulation: 28 Simulation Setup The input sources (V1, V2, V3) are set to represent different voltage levels, imitating scenarios like solar panel output, grid power, and battery backup. The circuit is connected to a simulated battery, which has parameters like voltage, SOC, and internal resistance. The ANN controller is programmed using historical data from battery charging cycles to train it for optimal duty cycle adjustments. The simulation software also integrates the NNET block to model the battery' behavior accurately.

4. Results of Simulation

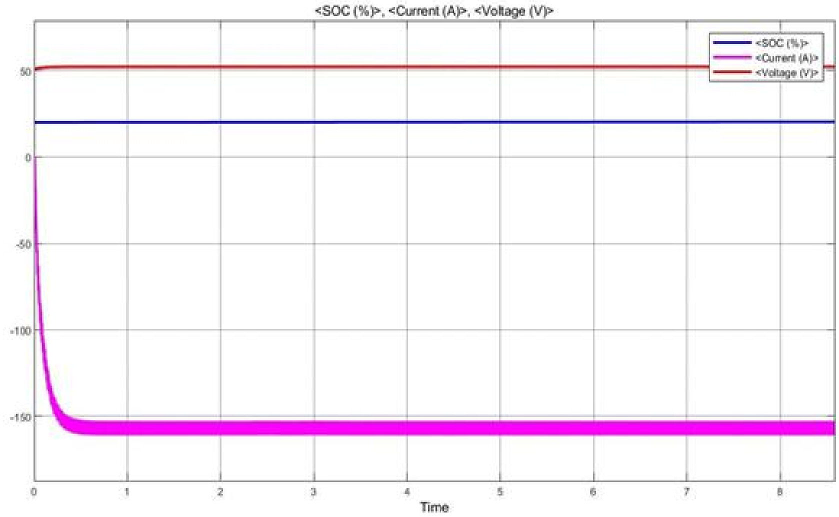
4.1 Simulated Input Voltage and Output Voltage For DC-DC Converter

Figure 6 **illustrates** the graph appears to illustrate the variation of three parameters over time: SOC (%) (State of Charge): Represented by the blue line, which remains fairly constant, indicating that the battery or energy storage system has a steady state of charge throughout the observed time period. Current (A): Represented by the magenta line, which initially shows a rapid decrease from a positive value to a negative one, stabilizing close to zero over time. This initial drop could indicate a high current draw or discharge event, followed by a period of steady-state current. Voltage (V): Represented by the red line, which is stable and does not show any significant fluctuations over the time period. This suggests a constant voltage level across the system.

There is also an inset zoomed-in view, focusing on the SOC line, where it shows a slight upward trend in SOC, ranging between 20 and 20.4%. This detail might be showing a gradual charge or recovery in the state of charge over a smalltime window. This graph likely represents a system where initial high discharge current is drawn, followed by a stable operating condition in terms of SOC and voltage. The inset could be highlighting minor changes in SOC that aren't easily visible on the main plot.



(a)



(b)

Fig 6. (a) and (b) Variation of Parameters

4.2 Simulated Waveforms for Output Voltage and Output Current For Dc-Dc Converter

SOC (%) - State of Charge (blue line): The SOC remains steady throughout the time period, maintaining a consistent level. There is no significant change in SOC, which suggests that the battery or storage system is not charging or discharging substantially. Current (A) (magenta line): The current starts at a high positive value and rapidly decreases to a large negative value within the first few moments, then stabilizes near a constant level below zero. This pattern indicates an initial discharge or current draw, after which the current reaches a steady state. Voltage (V) (red line): The voltage remains constant over time, with no noticeable variations. This implies a stable power supply or battery voltage. The plot suggests an initial discharge phase due to the rapid current change, followed by a stable condition in which SOC and voltage remain constant. The constant SOC and voltage could mean the system has reached equilibrium, with no further charge or discharge events occurring.

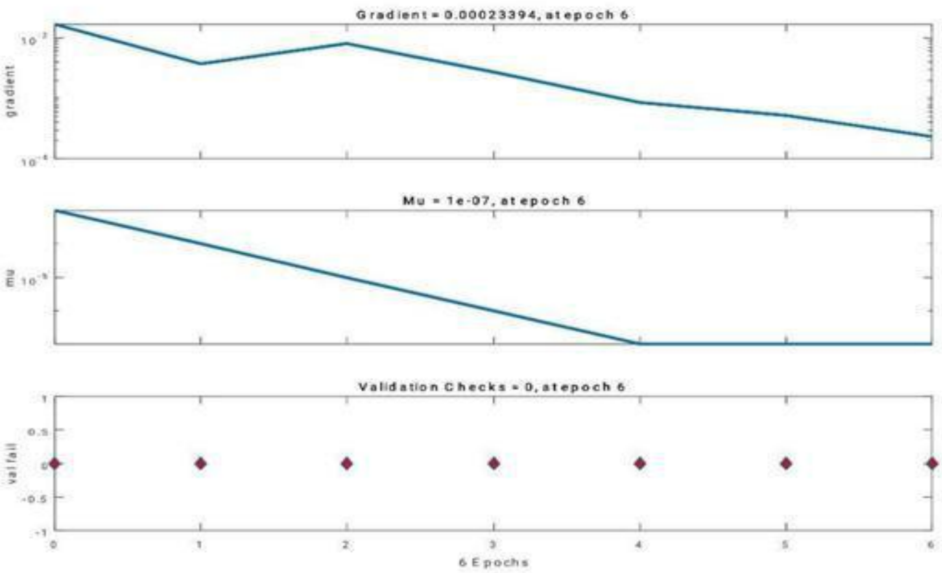


Fig 7. Waveforms for I/O Voltage- DC-DC Converter

4.3 Simulated Diagram for Soc in Batter

Figure 7, shows that image appears to be a series of plots, likely showing the evolution of certain parameters or metrics over multiple epochs in a training or optimization process. The three subplots, from top to bottom, display data labeled as "grad unit," "mu," and “Val (all)."

Top Plot (grad unit): This plot shows the trend of the "grad unit" metric over six epochs. The line appears to decrease gradually over time, indicating a potential reduction in the 32-gradient magnitude, which might reflect convergence in a training process or a diminishing learning rate. Middle Plot (mu): The "mu" parameter is also plotted across epochs. This metric decreases consistently, suggesting that "mu" is being adjusted or optimized over time. It might represent a parameter that is decaying or decreasing, such as a regularization term or a learning rate. Bottom Plot (Val (all)): The last plot labeled "Val (all)" shows a series of points across epochs, with each point seemingly constant. This could indicate a validation metric that isn't changing significantly over epochs, or it might reflect that the model's validation performance has stabilized.

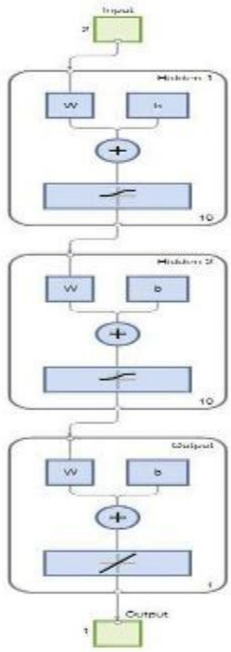


Fig 8. Circuit Modal For ANN Based Polynomial Regression.

4.4 ANN Based Polynomial Regression

Figure 8 shows This diagram represents a simple neural network architecture with three layers: two hidden layers and one output layer. Here's a breakdown of each component. Input Layer:

a. The input layer takes in data with a size of 2, which could mean two features or dimensions are provided as input to the network.
b. The input data then feeds into the first hidden layer.
Hidden Layer 1: This layer contains parameters labeled as "W" (weights) and "b" (bias), which are standard components in a neural network layer. The input data is first multiplied by weights (W) and added to the bias (b). The resulting value goes through an activation function, represented by the diagonal line in the rectangle below the "+" symbol. This activation function could be something like RLU (Rectified Linear Unit) or another non-linear function to introduce non-linearity to the model. The output size of this layer is 10, meaning it has 10 neurons or units.
Hidden Layer 2: The output from the first hidden layer serves as the input for this second hidden layer. Similar to Hidden Layer 1, it has weights (W) and bias (b) parameters, and the data passes through an activation function after applying these parameters. This layer also has an output size of 10, so it has 10 neurons or units.
Output Layer: The output from the second hidden layer is passed to the output layer. The output layer again has weights and bias parameters, followed by an activation function. The final output size is 1, which indicates that

this network is producing a single output value. This could be useful for tasks like regression or binary classification, where only one output value is required.

4.5 Performance Analysis of Colour Battery

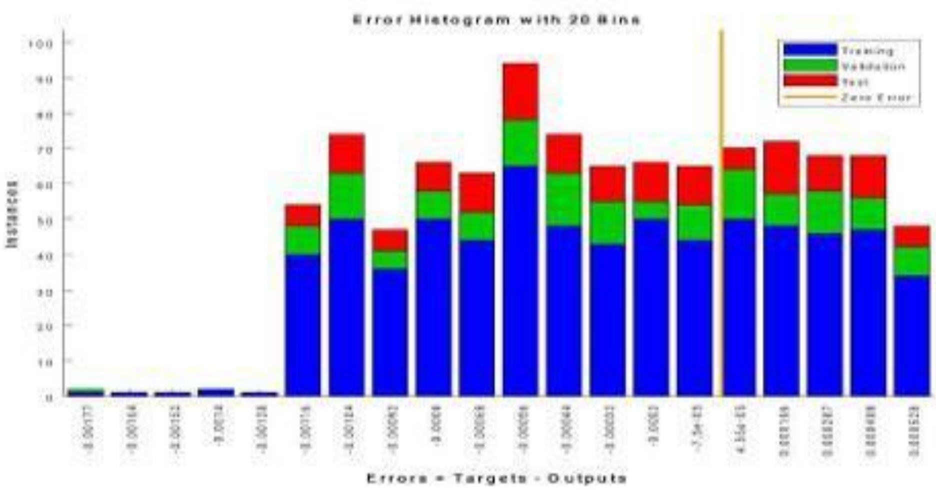
Battery SOC and Performance Analysis, Figure 9 shows This image contains four scatter plots, each comparing "Target" values on the x-axis to "Output" values on the y-axis, likely from a machine learning model or regression analysis. Here's an explanation of each subplot:

Top Left Plot: This plot shows a strong linear relationship between "Target" and "Output," as indicated by the line of points close to the diagonal line (where Output = Target). The blue line labeled "Fit" represents a fitted model, and it aligns closely with the data points, suggesting a good fit to the data.

Top Right Plot: Similar to the first plot, but the data points and fit line are shown in green. The green fit line aligns well with the data points, closely following the ideal line Y = T. This indicates a close match between model predictions and target values, implying a well-performing model.

Bottom Left Plot: This plot also shows a close alignment of output with target values, with data points shown in red. The red fit line aligns closely with the data points and the ideal line Y = T. Like the previous plots, this suggests a good fit with minimal deviation from the target values.

Bottom Right Plot: This plot is similar to the others but without colored lines; it only shows the data points along the diagonal. The line of data points appears tightly aligned with the ideal line, indicating minimal error between the output and target values.



F**ig 9.** Analysis of Error in EV

4.6 Histogram of Error Analysis

Figure 10 shows the image presents a histogram illustrating the distribution of instances across different datasets (training, validation, and test) and their corresponding error rates. Here's a breakdown of the elements: X-axis: Represents different categories or bins. Y-axis: Indicates the number of instances falling into each category. Blue bars: Represent the number of instances in the training dataset. Green bars: Represent the number of instances in the validation dataset. Red bars: Represent the number of instances in the test dataset. Orange Vertical Line: This line likely represents the threshold for "zero error." Instances to the left of this line have zero error, while those to the right have some level of error.

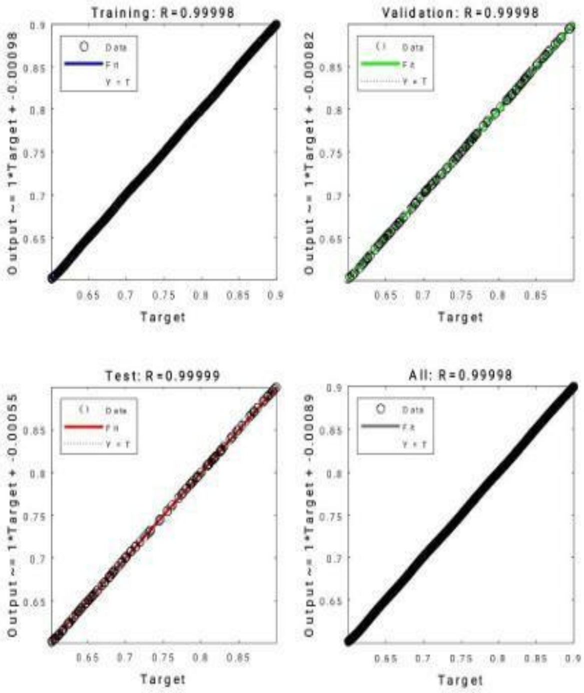


Fig 10. Histogram of Error Analysis

5 Conclusion

In conclusion, an artificial neural network (ANN)-enhanced two-stage DC-DC isolated converter that is AI-controlled is a major development in EV charging technology. This method overcomes the drawbacks of conventional converters in dynamic charging situations by dynamically adjusting converter parameters based on current conditions including input voltage, battery state-of-charge (SOC), and output current. In addition to reducing thermal stress and energy losses, the intelligent control mechanism enhances voltage management and system efficiency. Results from simulations confirm that this strategy works well for preserving ideal charging rates while preserving battery health. By meeting the increasing need for intelligent, effective, and environmentally friendly EV charging systems, this creative solution opens the door to improved battery life and a stronger EV infrastructure.

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