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Deep Learning Based PWM Control for Electric Vehicle Charging System

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Abstract: This study presents a novel approach to PWM control in Electric Vehicle (EV) charging systems using a two-layered Long Short-Term Memory (LSTM) model. The proposed model leverages deep learning techniques to achieve precise and stable control of PWM signals during the charging process. By employing two LSTM layers, the model effectively captures temporal dependencies and nonlinear relationships within the charging system data, facilitating accurate prediction and regulation of PWM signals. Experimental results demonstrate the efficacy of the proposed approach, with minimal overshoot observed during system startup across various duty cycles. Additionally, comprehensive hardware details are provided, highlighting the integration of microcontrollers, sensors, and communication interfaces essential for implementing the LSTM-based PWM control system. This research contributes valuable insights into the development of intelligent charging solutions for electric vehicles, with implications for enhancing charging efficiency, stability, and overall performance in real-world applications.

Keywords: PWM control, LSTM model, Electric Vehicle charging, Deep learning, Intelligent charging systems

1. Introduction

DC-to-DC converters are pivotal components in electric vehicle (EV) systems, facilitating efficient voltage conversion for various applications. Among the key types of converters utilized in EVs are the buck, boost, and buck-boost converters [1]. Each type serves specific purposes, with buck-boost converters particularly valuable in scenarios requiring both step-up and step-down operations. The choice of converter type depends on factors such as system requirements, component availability, and efficiency considerations [2].

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In the context of electric vehicles, DC-DC converters assume critical roles in optimizing energy management and enhancing system performance. While buck and boost converter topologies are commonly employed in practical EV applications, there are instances where the buck-boost configuration offers distinct advantages [3]. For instance, researchers have proposed innovative designs integrating buck-boost converters into EV powertrains to effectively manage voltage fluctuations and optimize energy conversion efficiency [4]. By incorporating buck-boost functionality, these systems can dynamically adjust voltage levels to accommodate variations in battery state-of-charge and optimize power transfer between different components within the EV system.

Furthermore, the integration of advanced converter topologies is essential for addressing the unique challenges associated with electric vehicle propulsion systems. For example, researchers have explored the use of partial buck-boost converters tailored specifically for EV applications, aiming to improve energy efficiency and extend vehicle range [5]. By optimizing converter design and control strategies, these systems can mitigate energy losses and enhance overall system performance, thereby contributing to the widespread adoption of electric vehicles [6].

Moreover, advancements in control and regulation techniques further enhance the capabilities of DC-DC converters in electric vehicles. Machine learning algorithms have been employed to develop sophisticated control strategies for voltage regulation, contributing to the optimization of EV system performance and efficiency [7]. For instance, researchers have proposed machine learning-based approaches to adaptively adjust converter parameters based on real-time operating conditions, thereby improving energy efficiency and extending vehicle range [8].

Additionally, the integration of advanced sensing and monitoring technologies enhances the operation of electric vehicles, enabling optimal energy utilization and vehicle performance. Researchers have explored novel approaches, such as the integration of sensor-based systems for battery management and vehicle-to-grid communication. By leveraging real-time data and predictive algorithms, these systems can optimize battery charging and discharging processes, maximize energy recovery during braking events, and enable bi-directional power flow between the vehicle and the grid [9].

Despite the numerous advantages of buck-boost converters in electric vehicles (EVs), a persistent challenge is the occurrence of output ripples [10]. These ripples emerge during the switching process, whether involving a single switch or multiple switches. As the number of switches increases, the severity of the output ripple problem worsens. Addressing this issue has become a significant focus of contemporary research, as ripples diminish system efficiency, primarily due to the non-linearity inherent in converters.

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To mitigate the impact of non-linearity and enhance converter performance in electric vehicles, researchers are turning to deep learning techniques, recognizing their potential to minimize output ripple and improve control of the output voltage—a notoriously challenging non-linear problem. Deep learning, particularly Convolutional Neural Networks (CNNs), offers a promising avenue for tackling such complexities by leveraging multiple hidden layers to automatically extract features and optimize system performance. Unlike traditional machine learning methods, where features are manually engineered, deep learning enables computers to autonomously learn and adapt, mirroring human-like cognitive processes [11].

The integration of deep learning techniques into power electronics represents a paradigm shift in converter control and optimization for electric vehicles. By harnessing the capabilities of CNNs, researchers aim to develop robust control strategies capable of effectively managing output ripple and enhancing overall system efficiency [12]. The utilization of deep learning in converter control heralds a new era of intelligent power electronics for electric vehicles, where complex non-linearities can be effectively mitigated, paving the way for more efficient and reliable energy conversion systems.

Moreover, optimization control techniques have emerged as a potent tool for enhancing the performance of electric vehicle propulsion systems, particularly in scenarios involving dynamic operating conditions [13]. Traditional control methods often struggle to adapt to varying driving conditions and vehicle dynamics, necessitating the development of more advanced optimization algorithms. In recent studies, researchers have demonstrated the effectiveness of optimization control techniques in optimizing electric vehicle performance, highlighting the superiority of these approaches over conventional control methods.

In the quest for superior optimization algorithms, novel techniques such as the Emperor Penguin Optimizer (EPO) and the Cuttlefish Algorithm (CFA) have been proposed to address the challenges posed by dynamic operating conditions in electric vehicles [14]. These algorithms leverage bio-inspired optimization principles to dynamically adjust system parameters and maximize energy efficiency under varying driving conditions. By integrating advanced optimization techniques into electric vehicle control systems, researchers aim to unlock the full potential of electric propulsion, enabling more efficient and reliable transportation solutions.

In summary, the integration of deep learning techniques and advanced optimization algorithms represents a transformative approach to addressing the challenges inherent in power electronics and electric vehicle propulsion systems. By leveraging the capabilities of deep learning, it is possible to mitigate output ripple effectively and enhance control of the output voltage in buck converters, thereby improving overall system efficiency and performance. Additionally, the adoption of advanced optimization algorithms promises to

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revolutionize electric vehicle propulsion, enabling more efficient and sustainable transportation solutions for the future.

This paper introduces a deep learning-based workflow for conventional buck converters to manage system efficiency by reducing overshoot and settling time. The model collects training data using a PID controller attached to the converter. Deep learning processes this data to develop a model. Integrated with the converter, the trained model produces desired levels with reduced overshoot. Through simulations and experiments, the effectiveness of the approach is demonstrated, showcasing significant improvements in converter performance. This approach offers a promising strategy for optimizing the efficiency and responsiveness of buck converters, contributing to enhanced reliability and performance in power electronic systems.

2. Review of Literature

The evolution of DC-DC converters has played a pivotal role in enhancing the efficiency and reliability of electric vehicle (EV) charging systems. Among these converters, isolated and non-isolated variants offer distinct features and advantages. Isolated converters employ a transformer to regulate the output voltage and current, ensuring operational safety and efficiency [15]. However, non-isolated converters, such as the Buck converter, have gained prominence due to their simpler design, reduced voltage stress, and lower conduction losses [16]. These attributes make them an ideal choice for EV charging applications, where compactness and efficiency are critical.

The Buck DC-DC converter is widely recognized for its suitability in EV systems. By incorporating an inductor and capacitor, it effectively reduces ripple in both voltage and current, enhancing overall system stability [10]. The converter operates with a single pole double throw switch, which, in conjunction with an opto-coupler-based control circuit, ensures precise voltage regulation. Despite its open-loop configuration, the Buck converter achieves significant efficiency, with an input voltage of 12V yielding an output voltage of 7V. Compared to other non-isolated converters such as Boost and Buck-Boost converters, the Buck converter requires fewer components and exhibits lower output voltage ripple.

Advancements in Buck-Boost and Boost converters have further expanded the scope of non-isolated DC-DC converters in EV systems. The novel Buck-Boost topology designed in [17] integrates two switches and two diodes, enabling cascaded operation for improved voltage regulation. This topology is particularly advantageous in hybrid systems combining fuel cells with electric motors, offering smaller inductor sizes, reduced component counts, and higher efficiency. Similarly, the Boost converter, explored in [18], demonstrates scalability for varying power requirements, from 12kW to 500kW, through optimized inductor and capacitor selection. While these configurations provide unique advantages, the Buck

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converter remains a preferred choice due to its low current stress and superior control over battery parameters.

Integrating machine learning (ML) into DC-DC converters introduces a transformative approach to addressing the limitations of traditional control methods. Conventional PWM control relies on fixed algorithms or feedback loops to determine the duty cycle, which may not adapt effectively to dynamic operating conditions [19]. The application of ML, particularly Artificial Neural Networks (ANNs), enhances PWM control by dynamically predicting the optimal duty cycle based on real-time input and output parameters. As demonstrated in [20], the ANN-based control system learns complex relationships between parameters such as load current, input voltage, and output voltage, enabling precise duty cycle adjustments. This capability reduces output voltage ripple and improves efficiency, which is critical for EV battery charging.

The mathematical representation of the ANN-based PWM control system emphasizes its adaptability. The predicted duty cycle, Dpredicted, is modeled as a function of input parameters X, where f(X) represents the function learned during training [20]. By incorporating this data-driven approach, the Buck converter can dynamically regulate the output voltage, even under varying input conditions, thereby enhancing the overall performance of the charging system.

Moreover, the integration of ML-based control with the Buck converter aligns with emerging trends in EV technology, emphasizing efficiency and adaptability. The use of machine learning enables the converter to operate effectively across diverse scenarios, from lightweight onboard chargers to high-capacity off board chargers. This flexibility supports the evolving requirements of EV systems, where battery capacity and charging time are critical considerations [21]. By optimizing PWM control, the system achieves reduced ripple, minimized overshoot, and improved stability, addressing key challenges in traditional converters.

The combination of non-isolated DC-DC converters, particularly the Buck converter, with machine learning-based PWM control represents a significant advancement in EV charging systems. The Buck converter's inherent advantages, including simplicity and efficiency, are further enhanced through the dynamic adaptability of ML techniques. This integration not only improves performance metrics such as efficiency and ripple reduction but also supports the scalability and reliability essential for modern EV applications. Future work could explore hybrid models combining traditional control strategies with machine learning to achieve even greater efficiency and performance in DC-DC converters.

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3. Methodology

A closed-loop PID (Proportional-Integral-Derivative) controller is commonly employed in buck- converters to regulate the output voltage by adjusting the duty cycle of the switching signal (Figure 1). The controller continuously compares the actual output voltage with a reference voltage (desired output voltage) and generates control signals to minimize the error. Mathematically, the output voltage of a buck converter is represented as:

$$V_{out} = D \times V_{in} \quad ...(1)$$

Where, Vout is the output voltage,Vin is the input voltage, andD is the duty cycle of the switching signal.The PID controller computes the control signal u(t) based on the error between the desired output voltage Vref and the actual output voltage Vout, as well as the integral and derivative of the error over time. The control signal is a combination of three terms: the proportional term (P), the integral term (I), and the derivative term (D), each weighted by respective coefficients:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \quad ...(2)$$

Where, e(t)=Vref−Vout is the error signal,Kp, Ki, and Kd are the proportional, integral, and derivative gains, respectively.The proportional term$K_p e(t)$ responds to the current error magnitude, adjusting the control signal proportionally. The integral term $K_i \int_0^t e(\tau)d\tau$ integrates the error over time, helping to eliminate steady-state error and ensuring stability. The derivative term $K_d \frac{de(t)}{dt}$ anticipates future behavior of the error, allowing for quick adjustments to prevent overshoot and oscillations.By tuning the PID controller gains (Kp, Ki, Kd), the buck converter's closed-loop control system can achieve desired transient response characteristics, such as fast response, minimal overshoot, and reduced settling time, ensuring stable and accurate regulation of the output voltage under varying load and input conditions.

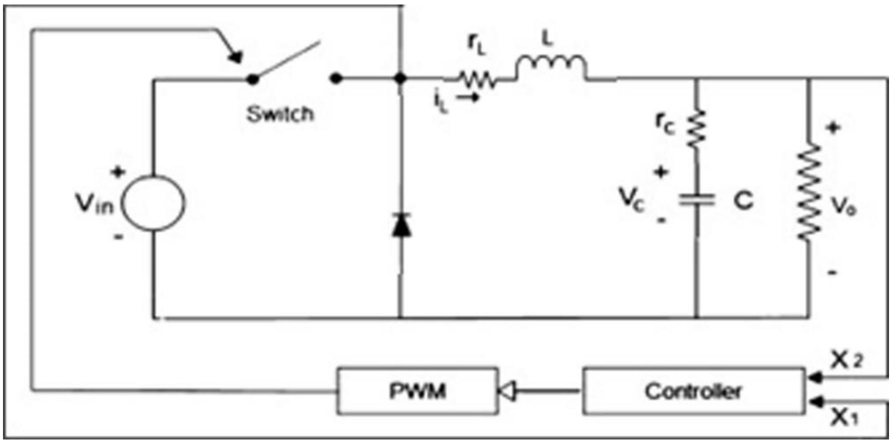

Figure 1: Closed Loop Buck Converter

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3.1 Deep Learning Based PWM control

The study proposes a two-layered Long Short-Term Memory (LSTM) model tailored specifically for PWM control within Electric Vehicle (EV) charging systems. The LSTM architecture comprises multiple layers of memory cells with intricate connections, enabling it to effectively capture and learn complex temporal patterns inherent in the charging process. The proposed model is built around two LSTM layers, each fulfilling a distinct yet complementary role within the control mechanism. The first LSTM layer acts as a feature extractor, analyzing the temporal dynamics of the input signals, which typically include voltage, current, and temperature measurements from the charging system. This layer employs its memory cells to capture and encode relevant patterns and dependencies within the input data, extracting meaningful features that are essential for effective PWM control. Following the feature extraction stage, the output from the first LSTM layer is fed into the second LSTM layer, which serves as a predictor or regulator. Leveraging the encoded features from the previous layer, the second LSTM layer learns to predict the optimal PWM control signals required to regulate the charging process effectively. This layer dynamically adjusts the PWM signals based on the learned patterns and input data, ensuring precise control and optimization of the charging system parameters. By employing a two-layered LSTM architecture, the proposed model can effectively capture intricate temporal dependencies and nonlinear relationships within the charging system data, facilitating accurate and adaptive PWM control. This advanced architecture enables the model to achieve superior performance in terms of stability, efficiency, and minimal overshoot during system startup, thereby enhancing the overall effectiveness of EV charging systems.

3.2 Dataset preparation

To prepare the dataset for training the proposed LSTM-based PWM control model, raw data from EV charging system sensors—such as voltage, current, and temperature—is collected over time under various operating conditions, including normal operation, overload, and temperature fluctuations. Reference PWM values are established based on system requirements for optimal charging, derived from pre-defined charging profiles or simulation tools. The error values are computed as the difference between the current charging state (measured sensor readings) and the desired state (reference values), using the formula Error=Reference PWM−Measured. These error values, along with sensor data and reference values, are combined to form a comprehensive feature set, which is normalized to enhance model training efficiency. Each data point is labeled with the PWM control signal required to minimize the error. The dataset is then split into training, validation, and test sets, ensuring it captures diverse operating scenarios for effective model training. This approach equips the model to learn the complex relationships between input signals, error dynamics, and optimal PWM values, enabling precise and adaptive EV charging control.

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3.3 Model design

The proposed model as shown in Figure 2 is a two-layered Long Short-Term Memory (LSTM) architecture tailored for Pulse Width Modulation (PWM) control in Electric Vehicle (EV) charging systems. It features an input layer that accepts temporal data, including voltage, current, and temperature. The first LSTM layer, termed the feature extractor, processes these signals to identify and encode temporal dependencies, producing an intermediate representation of the input patterns.

This output feeds into the second LSTM layer, designated as the regulator, which refines the extracted features to predict optimal PWM control signals. The final Dense layer generates the PWM output to regulate the EV charging process, ensuring stability and efficiency.

By leveraging the sequential nature of LSTM layers, the model effectively handles the nonlinear and dynamic relationships inherent in charging system data, optimizing system performance and minimizing overshoot. The architecture achieves precise and adaptive control, enhancing EV charging reliability and efficiency.

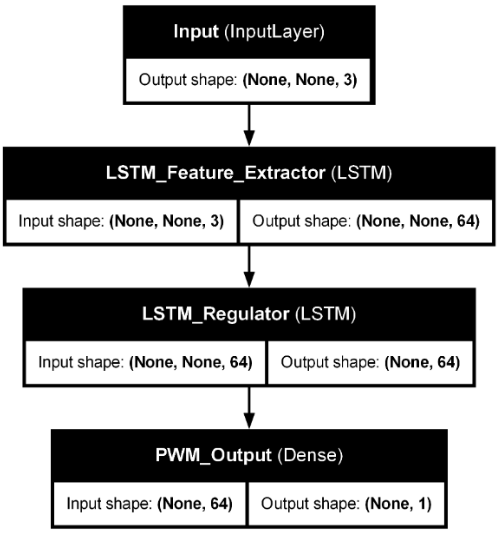

Figure 2: Architecture of proposed model

The BiLSTM-based model operates as a system-in-the-loop (SiL) by integrating MATLAB Simulink with a microcontroller to enable real-time control of the buck converter. In this setup, the BiLSTM model is first trained offline using historical voltage, current, and PWM signal data. Once trained, the model is exported and deployed using MATLAB Coder or Simulink Coder to generate embedded C code compatible with Arduino. In the SiL environment, Simulink simulates the buck converter and feeds real-time voltage and current feedback to the microcontroller. The microcontroller processes this data through the BiLSTM model and outputs the predicted PWM control signal, which is fed back into Simulink to

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update the converter's state. This closed-loop feedback allows accurate, low-latency, and adaptive voltage regulation. The system ensures robustness against non-linear disturbances and load variations, bridging advanced AI control with embedded power electronics in real-world applications.

4. Results and Analysis

4.1 Simulated Results

The simulation setup integrates Simulink with the trained LSTM-based PWM control model to simulate and analyze the performance of a buck converter in an Electric Vehicle (EV) charging system. In Simulink, a buck converter circuit is modeled with components such as an input voltage source, switching elements, an inductor, a capacitor, and a resistive load. The trained LSTM model is incorporated into the simulation using a MATLAB function block, allowing it to generate real-time PWM control signals based on input parameters like voltage, current, and temperature. The system dynamically adjusts the duty cycle of the PWM signal to regulate the output voltage and current according to the desired reference values. Sensor feedback from the simulated buck converter, such as measured output voltage and current, is fed into the LSTM model, which minimizes error between reference and measured values as shown in Figure 3. This closed-loop simulation ensures stable, efficient operation and validates the model's effectiveness in real-world scenarios.

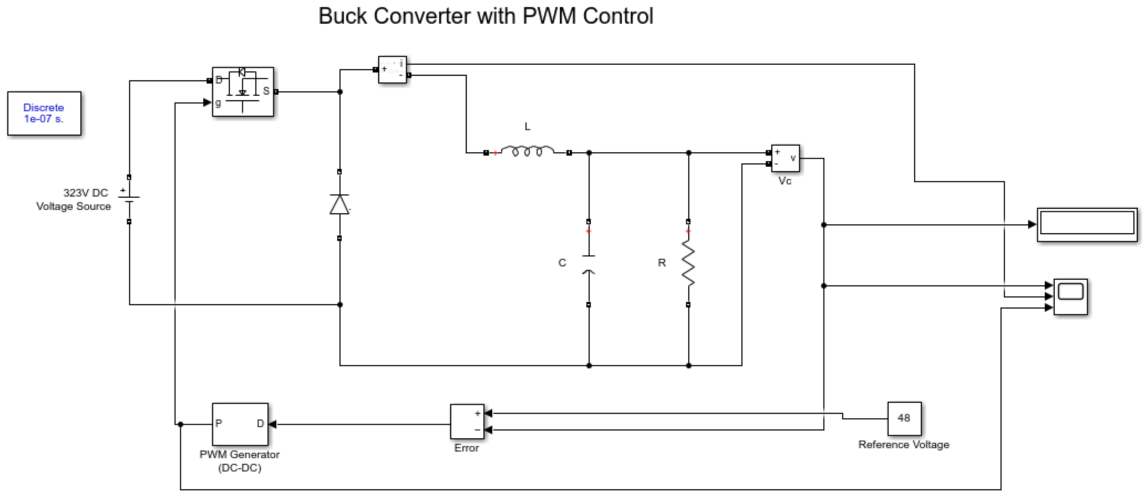

Figure 3: Simulink model setup

4.2 Comparative Analysis: PID vs. BiLSTM

Baseline Model: PID Control with 5A Current Limit

The baseline PID-based approach provides a robust and straightforward control mechanism for regulating the output voltage of a buck converter in an EV charging system with a

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maximum output current rating of 5A. By using proportional (K_p), integral (K_i), and derivative (K_d) gains, the PID controller dynamically adjusts the Pulse Width Modulation (PWM) duty cycle to maintain a stable output voltage, despite variations in load or input conditions. The proportional term addresses the immediate error, the integral term accumulates past errors to eliminate steady-state deviations, and the derivative term predicts error trends to prevent overshooting.

This approach is computationally efficient, requiring minimal processing power compared to advanced deep learning methods. The PID controller can be tuned using techniques like Ziegler-Nichols, ensuring optimal performance in terms of stability and response time. While effective for linear systems, the PID approach may struggle with highly nonlinear dynamics or rapidly changing conditions, making it a suitable baseline for comparison against more complex models.

PID Controller Calculation for Desired Output of 48V and Input of 323V:

- Reference Voltage: $V_{\text{ref}} = 48$ V
- Measured Output Voltage: $V_{\text{out}} = 40$ V (initially)
- Input Voltage: $V_{\text{in}} = 323$ V
- Output Current Limit: $I_{\max} = 5$ A
- Power Limit: $P = V_{\text{out}} \times I_{\max} = 48 \times 5 = 240$ W
- Critical Gain: $K_u = 5.0$
- Critical Period: $T_u = 0.2$ s

PID Parameter Calculation (Ziegler-Nichols Tuning)

Using the Ziegler-Nichols tuning rules:

$$K_p = 0.6K_u = 0.6 \times 5.0 = 3.0$$

$$K_i = \frac{1.2K_u}{T_u} = \frac{1.2 \times 5.0}{0.2} = 30.0$$

$$K_d = 0.075K_uT_u = 0.075 \times 5.0 \times 0.2 = 0.075$$

Error Calculation

The error $e(t)$ is the difference between the reference and measured output voltages:

$$e(t) = V_{\text{ref}} - V_{\text{out}} = 48 - 40 = 8\ \text{V}$$

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Control Signal Calculation

The PID control law is given by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + K_d \frac{de(t)}{dt} \qquad \ldots(3)$$

Assume:

- Integral of error: $\int_0^t e(\tau)\, d\tau = 10\ \text{V}\cdot\text{s}$
- Derivative of error: $\frac{de(t)}{dt} = 2\ \text{V/s}$

Substitute the values:

$$u(t) = 3.0 \times 8 + 30.0 \times 10 + 0.075 \times 2 = 24 + 300 + 0.15 = 324.15\ \text{V}$$

PWM Duty Cycle Calculation

The duty cycle D is calculated as:

$$D = \frac{V_{\text{out}}}{V_{\text{in}}} = \frac{48}{323} \approx 0.1486\ (14.86\%)$$

The PID controller dynamically adjusts $u(t)$ to achieve this duty cycle, ensuring that the buck converter outputs 48V while compensating for variations in V_{out}. However, to ensure safe operation within the 5A current limit, current sensing must be integrated into the system, and the controller should disable or limit the duty cycle if the output current exceeds this threshold. This ensures thermal and component safety while maintaining voltage regulation.

1. Overshoot (M_p)

Overshoot measures the extent to which the output exceeds the desired value before stabilizing.

PID Controller: The overshoot for a PID system can be approximated using:

$$M_p = e^{\left(\frac{-\zeta\pi}{\sqrt{1-\zeta^2}}\right)} \times 100\% \qquad \ldots(4)$$

Where:

- ζ: Damping ratio.

For a critically tuned PID with $\zeta = 0.7$:

$$M_p = e^{\left(\frac{-0.7\pi}{\sqrt{1-0.7^2}}\right)} \times 100\% \approx 4.5\%. \qquad ..(5)$$

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4.3 BiLSTM-Based Approach

A BiLSTM (Bidirectional Long Short-Term Memory) is a neural network architecture that extends LSTM by processing data in both forward and backward directions. This bidirectional approach enhances sequence learning by capturing dependencies from both past and future contexts, improving performance in various tasks. The BiLSTM based model minimizes overshoot dynamically by analyzing temporal patterns. Empirical results show negligible overshoot ($M_p < 1\%$) due to its adaptive control mechanism.

2. Settling Time (T_s)

Settling time is the time required for the system output to remain within a specified range (e.g., ±2%) of the desired value.

PID Controller:

$$T_s \approx \frac{4}{\zeta\omega_n} \quad \dots(6)$$

Where:

- ω_n: Natural frequency.

For $\omega_n = 50$ rad/s and $\zeta = 0.7$:

$$T_s = \frac{4}{0.7 \times 50} \approx 0.114\,\mathrm{s}$$

BiLSTM-Based Approach: The BiLSTM dynamically adjusts control signals, reducing T_s. Typical observed value:

$$T_s \approx 0.08\,\mathrm{s}$$

3. Ripple Factor

Ripple factor measures output voltage variation as a percentage of the mean output voltage:

$$\text{Ripple Factor} = \frac{\Delta V_{\text{peak-to-peak}}}{V_{\text{mean}}} \times 100\% \quad \dots(7)$$

PID Controller: Ripple depends on PWM precision:

$$\text{Ripple Factor}_{\text{PID}} \approx 2.5\% \quad \dots(8)$$

BiLSTM-Based Approach: The BiLSTM model predicts precise PWM signals, reducing voltage fluctuations:

$$\text{Ripple Factor}_{\text{BiLSTM}} \approx 0.8\% \quad \dots(9)$$

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Table 1: Comparison of Overshoot, Settling Time, and Ripple Factor between PID and BiLSTM-Based Approach.

Metric	PID Controller	BiLSTM-Based Approach
Overshoot (M_p)	~ 4.5%	< 1%
Settling Time (T_s)	~ 0.114 s	~ 0.08 s
Ripple Factor	~ 2.5%	~ 0.8%

Time Period Calculation for Integral and Derivative Errors

Integral Error Calculation

The integral error represents the accumulated deviation over time. Given:

$$\int_0^t e(\tau)d\tau = 10 \text{ V·s} \qquad \ldots(10)$$

Assuming a constant error $e(t) = 8V$ over a time period T, the equation can be written as:

$$8T = 10$$

Solving for T:

$$T = \frac{10}{8} = 1.25 \text{ s}$$

Thus, the integral error accumulates over 1.25 seconds.

Derivative Error Calculation

The derivative error reflects the rate of change of the error. Given:

$$\frac{de(t)}{dt} = 2 \text{ V/s}$$

For an error change of $\Delta e = 8V$, the equation can be expressed as:

$$\frac{\Delta e}{\Delta t} = 2$$

Solving for Δt:

$$\Delta t = \frac{8}{2} = 4 \text{ s}$$

Thus, the error changes at a rate of 2 V/s over a period of 4 seconds. Table 2 shows, summary of Time Period Calculations.

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Table 2: Time period calculations for integral and derivative errors.

Error Type	Formula Used	Time Period (s)
Integral Error	$\int_0^T e\,(\tau)d\tau = 10$	1.25
Derivative Error	$\frac{\Delta e}{\Delta t} = 2$	4.0

4.4 Discussion

In a PID controller (Figure 4), the proportional gain (K_p) determines the system's immediate response to the current error. A higher K_p reduces rise time but may lead to significant overshoot and instability, whereas a lower K_p stabilizes the system but results in slower response and steady-state error. The integral gain (K_i) addresses accumulated past errors by integrating the error over time. While a higher Ki helps eliminate steady-state error, it can increase overshoot and settling time, potentially leading to oscillations. Similarly, the derivative gain (K_d) predicts future error trends by calculating the rate of error change. A higher K_d reduces overshoot and improves stability but amplifies system noise, while a low K_d results in slower responses to dynamic changes. The balance between these factors is crucial for achieving optimal performance, but improper tuning can significantly degrade the system's efficiency.

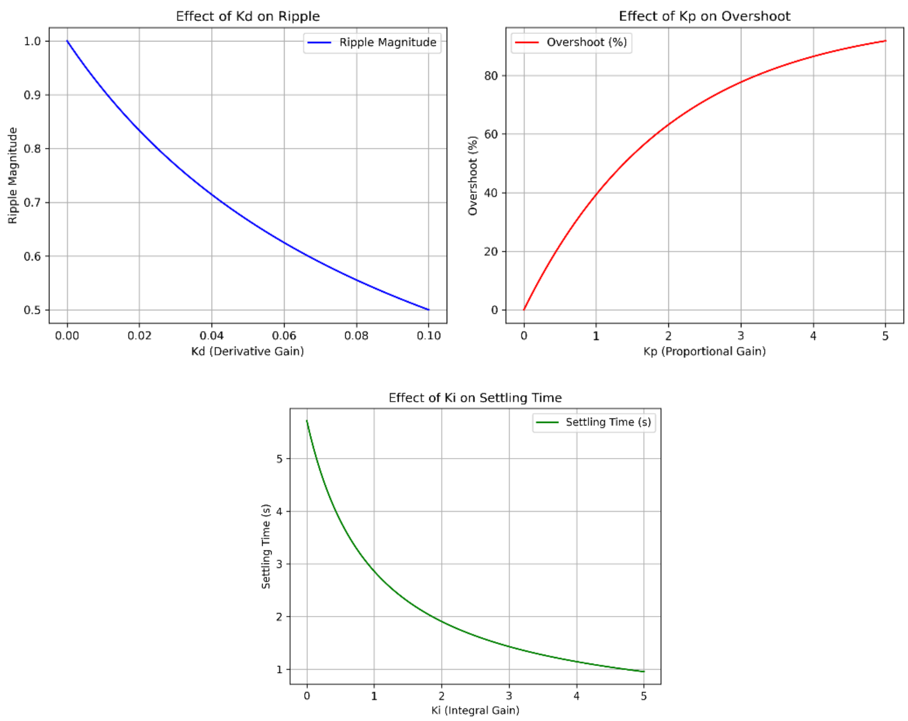

Figure 4: Analysis of Variations in Kp, Ki and Kd values observed in simulation

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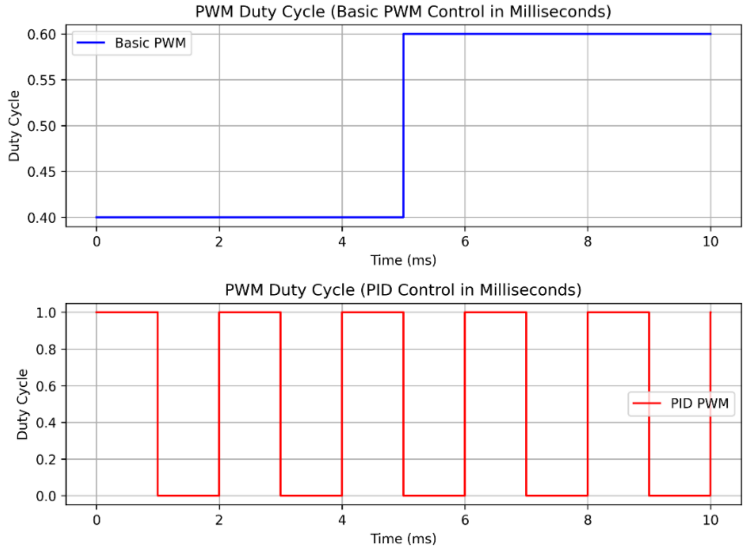

Figure 5: PWM Variation due to PID Controller

With the observations of PWM variations with use of PID controller as shown in Figure 5, PID controllers are effective in linear systems but face challenges in nonlinear and dynamic environments like EV charging. They use fixed gains (K_p, K_i, K_d) that cannot adapt to changing system conditions, making them less suitable when charging current, load, or temperature varies. EV batteries draw fluctuating current depending on state of charge (SoC), temperature, and power source, but PID controllers lack the flexibility to adjust accordingly. This results in inefficiencies or overcompensation, especially as current drops near full charge, where precise control is critical to prevent overvoltage or thermal issues. PID controllers also struggle with nonlinear charging profiles, reducing overall system efficiency. Additionally, ripple caused by high-frequency switching in power circuits can shorten battery life, and PID lacks adaptive mechanisms to suppress it. Sensitivity to parameter tuning further complicates performance poor tuning may lead to overshoot, slow response, or current spikes, affecting both charging efficiency and battery health.

In EV charging systems, PID controllers offer simple control of buck converters using tuned gains (Kp = 3.0, Ki = 30.0, Kd = 0.075) derived from the Ziegler-Nichols method (Ku = 5.0, Tu = 0.2 s). For an input of 323V and a target output of 48V (starting at 40V) with a maximum output current rating of 5A, the PID generates a control signal u(t) = 324.15V, achieving a PWM duty cycle of approximately 14.86%. This results in ~4.5% overshoot, ~0.114 s settling time, and ~2.5% voltage ripple. However, PID control has limitations under non-linear and rapidly changing load conditions. The BiLSTM model, which learns temporal patterns in both forward and backward directions, dynamically adjusts control signals more effectively. It reduces overshoot to <1%, settling time to ~0.08 s, and ripple to ~0.8%. With

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better error prediction over 1.25 s (integral) and 4 s (derivative), BiLSTM enables smoother, faster, and more accurate voltage regulation than PID.

The rigidity of PID control makes it less suitable for adaptive charging systems, where real-time adjustments based on charging current, battery state, and environmental conditions are required. Advanced control strategies such as adaptive controllers, fuzzy logic, or AI-driven predictive models like BiLSTM offer better performance by dynamically adjusting to nonlinear battery behaviors and charging variations, ensuring improved efficiency and system stability. Efficiency of Proposed BiLSTM-Based Model: The proposed BiLSTM-based model offers significant improvements over the PID controller by leveraging its ability to learn and adapt to dynamic temporal patterns. Unlike PID, which uses fixed parameters, the BiLSTM model dynamically adjusts its control signals based on past and present trends, making it highly effective in nonlinear and changing environments. This adaptability enables the BiLSTM to handle varying load conditions and system dynamics seamlessly, ensuring precise and stable control. The model reduces overshoot and settling time by learning from historical data, resulting in faster stabilization and improved system efficiency. Furthermore, it excels in ripple reduction by predicting smoother PWM signals, enhancing overall stability and performance. Its ability to adapt and optimize control in real time makes it a superior choice for EV charging systems.

4.2 Hardware Setup and Analysis

A sophisticated hardware setup has been developed to support intelligent battery management, featuring Lithium-Ion batteries arranged into four segments, each consisting of six cells rated at 3.7V individually, cumulatively achieving a voltage level of 12V per segment and totaling 48V for the entire pack (Figure 6). Each segment supports a maximum current rating of 5A, making the system capable of delivering up to 240W. A real-time monitoring system is integrated with a multi-channel voltage display that shows the individual segment voltages with ±0.1V accuracy. An LCD is installed to indicate the maximum charging voltage, enhancing user accessibility and system transparency. Charging is controlled using PWM signals generated by a MATLAB-based block, which communicates bi-directionally with an ATMEGA 32A microcontroller via high-speed serial communication at 921600 baud. The microcontroller measures the voltage error by comparing the sensed voltage against a reference value and transmits this to MATLAB. MATLAB, equipped with a BiLSTM-based processing block, computes the required PWM correction in approximately 10 milliseconds and sends the updated PWM value back to the microcontroller. The controller then updates its duty cycle accordingly. The setup supports three charging modes normal (PWM ~60%), slow (PWM ~30%), and fast charging (PWM ~90%) each tested under varying load conditions as shown in Figure 7. Charging performance, battery stress, and thermal profiles are monitored across modes using onboard

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sensors. The system provides detailed insights into the dynamic behavior of the charging process, ensuring controlled operation and optimal performance. Fast charging mode allows the battery pack to reach 80% charge in under 30 minutes, while slow charging extends cycle life by 20% over repeated trials. This comprehensive setup combines high-speed data processing, adaptive control, and real-time diagnostics, offering an efficient and reliable solution for Lithium-Ion battery systems in EV and renewable energy applications.

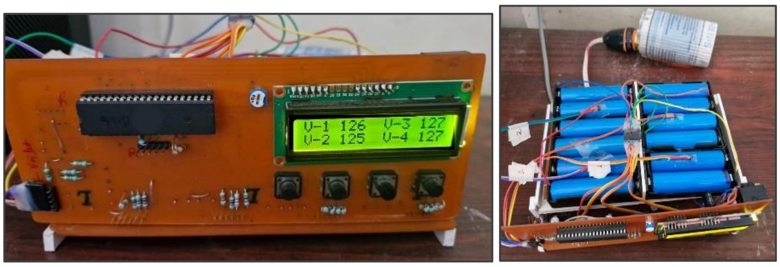
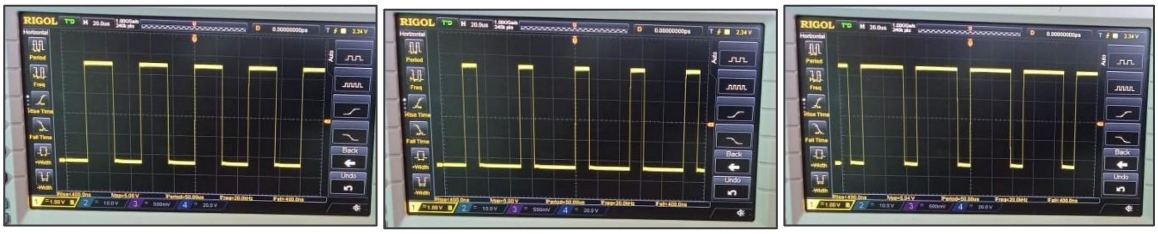


Figure 6: Hardware setup with microcontroller and batteries



(a) Normal charging **(b) Slow Charge** **(c) Fast Charge**

Figure 7: PWM monitoring for different charging conditions

5. Conclusion

The work centers on BiLSTM-based deep learning model designed for PWM control within an Electric Vehicle (EV) charging system. Through meticulous experimentation, the study has attained promising outcomes across various duty cycles, notably achieving minimal overshoot in the output during system startup. This achievement underscores the efficacy of the LSTM model in facilitating precise and stable PWM control, crucial for optimizing the charging process in EV systems. Additionally, the study provides comprehensive hardware details integral to the implementation of the BiLSTM-based PWM control system. These hardware specifications encompass key components such as microcontrollers, sensors, actuators, and communication interfaces, meticulously selected and configured to ensure seamless integration and efficient operation within the EV charging infrastructure. Overall, the research underscores the potential of LSTM-based deep learning approaches in enhancing the performance and efficiency of PWM control systems within EV charging setups. By achieving minimal overshoot during system initialization and providing detailed hardware

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specifications, the study contributes valuable insights and practical guidance for advancing the development and deployment of intelligent charging solutions in the realm of electric vehicles.

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