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Original Article

Design and Performance Analysis of Bi-Directional DC-DC Buck/Boost Converter for Energy Storage Systems Using Advanced Control Strategies

E. Kalaiyarasan[1], S. Singaravelu[2]

[1,2]*Electrical Engineering, Annamalai University, Tamilnadu, India.*

[1]*Corresponding Author : kalaiyarasan.a.m@gmail.com*

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Abstract *- The growing demand for efficient and reliable energy storage systems has led to increased research and development in the field of advanced control strategies. This research evaluates and compares the effectiveness of advanced control strategies such as Proportional and Integral controller (PI), Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for energy storage systems employing a DC-DC bi-directional converter. ANFIS control combines the strengths of fuzzy logic and neural networks to provide a hybrid approach, particularly appealing for its adaptability and capacity to handle complex and uncertain operational environments. Energy storage systems have emerged as vital components in modern energy management, and they play a pivotal role in addressing renewable energy intermittency, enhancing grid stability, and efficiently managing energy demands. At the heart of these systems lies the DC-DC bi-directional buck/boost converter, which plays a critical component in enabling bidirectional energy transfer between the storage system (lead acid battery) and the DC source. This research employs a simulation-based methodology for a comprehensive evaluation and comparison of these control strategies. The aim is to provide valuable insights into the accuracy, stability, control complexity and suitability of various control approaches in optimizing the operation of such systems.*

Keywords *- Energy Storage Systems, PI, DC-DC Bi-directional converter, Control strategies, Efficiency, Stability, Robustness, Simulation, Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System.*

1. Introduction

The growing demand for efficient and reliable energy storage systems has led to increased research and development in the field of advanced control strategies. These systems often rely on DC-DC bi-directional converters to manage energy flow and make the choice of control strategy critical for their optimal operation. This study compares different advanced control strategies to assess their performance in energy storage systems with DC-DC bi-directional converters. Energy Storage Systems play a pivotal role in modern energy management which presents the capability to store surplus energy in intermediate forms such as thermal, compressed air, electro-mechanical and other mediums.

The Battery Energy Storage Systems (BESS) stand out as a technologically advanced means of storing energy in the form of electric charge. One of the key advantages of BESS is its versatility, as it is not constrained by geographical limitations, making it a highly adaptable solution for various applications [1]. Within the range of BESS technologies, lithium-ion batteries have garnered substantial attention and preference due to their favorable characteristics, including high energy density and relatively low self-discharge rates. This paper focuses on applying lithium-ion battery technology for simulation purposes by exploring the advanced control strategies for energy storage systems using DC-DC bi-directional converters.

The integration of renewable energy sources and the efficient utilization of electrical power have become increasingly critical in the contemporary scenery of energy management. The ever-growing demand for clean, reliable and sustainable energy solutions has led to a surge in research and development efforts aimed at advancing the control strategies employed in energy storage systems [2].

The central to these endeavors is the utilization of DC-DC bi-directional buck/boost converters, which is pivotal in enabling bidirectional energy transfer between the energy storage system and its associated DC source. The converter's ability to efficiently convert voltage levels and facilitate bidirectional power transfer is crucial for energy storage systems' overall performance and effectiveness [3]. Conventional buck converters step down voltage levels, and boost converters increase them. In PV applications, the input and output voltage levels will not neatly align with these traditional modes.

Bidirectional buck/boost converters are engineered to handle situations where input and output voltage ranges overlap, accommodating diverse power sources and loads with varying voltage requirements [4]. Bidirectional buck/boost converters can able to maintain high efficiency during power conversion. They employ advanced control algorithms such as ANN and ANFIS aided by higher frequency switching techniques to regulate the output voltage accurately, even when the input and output voltages fluctuate or overlap [5].

PI control is a widely used and well-established control strategy in the realm of energy storage systems that employ DC-DC bi-directional converters [6]. PI control is well-known for its ability to maintain voltage regulation [7] and system stability. It continuously adjusts the converter's operation based on the error signal, which is the difference between the desired and actual voltage, to ensure that the output voltage remains within the desired range [8].

Meanwhile, PI control may not always be the optimal choice in scenarios with highly nonlinear dynamics or rapidly changing operating conditions. In such cases, more advanced AI-based control strategies like sliding mode control, Fuzzy logic control [9], ANN and ANFIS can potentially outperform the PI controller by adapting to these complexities more effectively [10]. One of the primary applications of ANN in BESS is the estimation and control of the State-of-Charge (SoC). Accurate SoC estimation is crucial for optimizing the battery's performance and extending lifespan [11].

Based on historical data, ANN control is employed in BESS to perform real-time energy management, making decisions about when to charge and discharge the battery. ANN is known for its ability to adapt and learn from data, making it suitable for BESS control in dynamic and uncertain environments. They can adjust control strategies based on changing input voltage, load profiles and battery health [12].

ANFIS is a hybrid control system that combines fuzzy logic and neural networks. It utilizes fuzzy inference rules to model complex, non-linear systems and the learning capabilities of neural networks to adapt to changing conditions. This unique combination makes ANFIS well-suited for the dynamics in input voltage, loads and the uncertain nature of BESS operations [13]. ANFIS controllers can optimize battery charging and discharging strategies, which helps extend the lifespan of batteries and maintain their performance over time [14].

The existing literature lacks a comprehensive assessment and comparison of advanced control strategies, specifically PI, ANN and ANFIS, applied to bi-directional DC-DC buck/boost converters in energy storage systems. While the importance of energy storage systems is recognized in managing renewable energy intermittency and enhancing grid stability, there is a gap in understanding the suitability, adaptability and effectiveness of these control strategies in optimizing the operation of such converters.

The increasing demand for efficient and reliable energy storage systems necessitates a deeper exploration of advanced control strategies for bi-directional DC-DC buck/boost converters. The lack of a comprehensive evaluation and direct comparison of PI, ANN and ANFIS controllers in the context of these converters poses a challenge in selecting the most suitable control approach. Addressing this gap is crucial for ensuring optimal bidirectional energy transfer between storage systems, like lead-acid batteries and DC sources. This research aims to bridge this gap by providing valuable insights into the accuracy, stability, and control complexity of different control strategies, contributing to energy storage systems' effective design and performance analysis.

The scope of this research encompasses a comprehensive analysis and comparison of advanced control strategies for energy storage systems that utilize DC-DC bi-directional converters. Specifically, it focuses on evaluating the performance and effectiveness of three main control strategies: PI, ANN, and ANFIS controllers. The research aims to provide valuable insights into converter efficiency, stability, robustness, suitability, and control complexity.

This research tries to find a comprehensive understanding of how PI, ANN and ANFIS control strategies perform in the context of energy storage systems using DC-DC bi-directional converters. The findings will contribute to the knowledge base in the field of energy management, which can assist researchers, engineers and practitioners in making informed decisions regarding the selection of control strategies for their specific energy storage system applications. The graphical outline of the proposed work is shown in Figure 1.

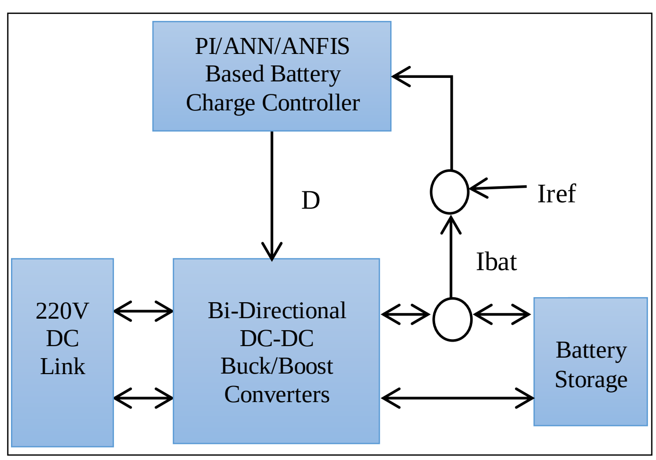

Fig. 1 Graphical outline of projected work

2. Methodology

Integrating battery storage systems with bidirectional DC-DC converters has gained significant prominence in pursuing sustainable energy solutions and efficient power management. This research undertakes a comprehensive investigation into such systems' intricate design and control. The primary objective of this study is to develop an optimized energy management system capable of efficiently regulating the charge and discharge of a battery system within a 220V DC link environment.

The methodology follows a step-by-step approach, with each stage playing a vital role in determining the project's ultimate success. These stages are disparate components and likely interconnected facets of a holistic strategy that combines theoretical analysis and practical implementation for a robust battery storage system. The following stages are the step-by-step approach of this research.

2.1. Selection of Battery Rating

The suitability of a battery for a renewable energy system depends on various factors, including the system's specific requirements, the available technology and budget considerations. The most commonly used battery storage technologies are lead-acid and lithium-ion batteries. Lead-acid batteries are one of the most established and cost-effective options for renewable energy systems. They are suitable for off-grid backup power applications but have limitations in cycle life and energy density.

Lithium batteries come in various chemistries like lithium-ion (Li-ion) and lithium polymer (LiPo) batteries, with a nominal voltage of 3.7 volts per cell [15]. Lithium-ion batteries have gained popularity in recent years due to their high energy density, longer cycle life and faster charge and discharge capabilities.

The nominal current discharge characteristics curve of a lithium-ion battery covers more nominal area than that of a lead-acid battery, implying that the lithium-ion battery offers a higher energy density and potentially better performance in terms of capacity and power output, as shown in Figure 2.

A 24V, 150AH Li-ion battery has been implemented in this work in view of its advantages and suitability. The battery current (I_{bat}) for a 24V, 150Ah battery can be calculated using Ohm's law, which states that current is equal to voltage divided by resistance. The relationship in the context of a battery (very low battery resistance) is shown in Equation 1,

$$I_{bat} = \frac{Q}{t} \tag{1}$$

Where, Q is the charge (AH), and t is the time (hours).

In this case, the battery current is 150A (t = 1hour).

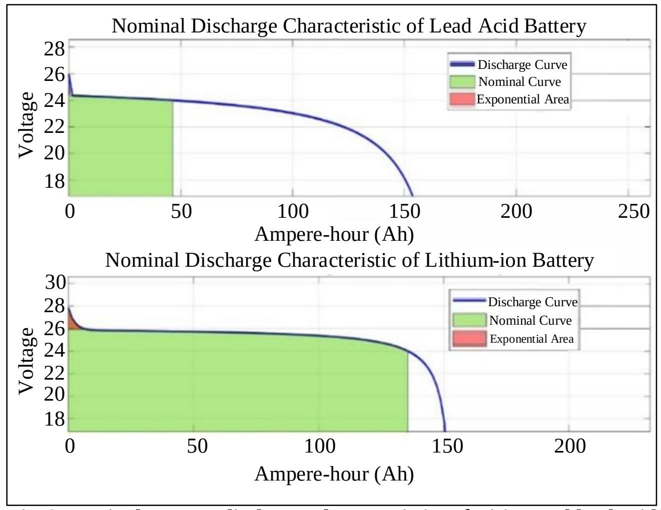

Fig. 2 Nominal current discharge characteristics of Li-ion and lead acid batteries

2.2. Design of Proposed Bidirectional DC-DC Buck/Boost Converter

The bidirectional DC-DC buck/boost converter is at the heart of energy transfer within the projected system. The most critical step is designing the converter elements, such as switches, inductors, and capacitors. The converter is designed by considering efficiency, voltage regulation and response to fluctuations. The functional circuit diagram of the bi-directional DC-DC buck/boost converter is shown in Figure 3.

The duty cycle (D) is key for controlling the output voltage of the converter. The duty cycle less than 1 is for a buck converter (step-down), while it is greater than 1 for a boost converter (step-up). The duty cycle of the DC-DC converter is calculated as given in Equation 2,

$$D = \frac{V_{bat}}{V_{in}} \tag{2}$$

The desired peak-to-peak inductor current ripple current is calculated by considering 20% of ripples in battery current, which is given in Equation 3,

$$\Delta I_L = 0.2 * I_{bat} \tag{3}$$

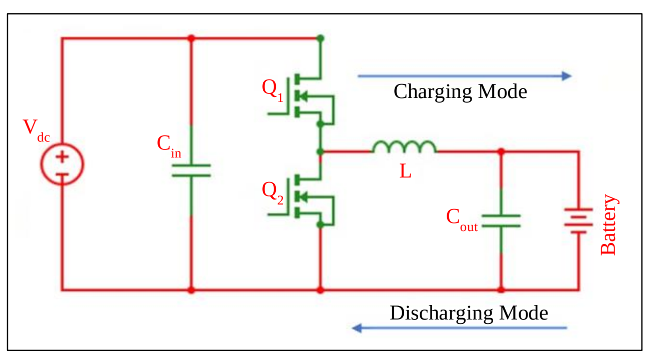

Fig. 3 Operating circuit of bidirectional DC-DC buck/boost converter

The value of inductor (L) is calculated by using the Equation 4,

$$L = \frac{V_{in\_min} * (1-D)}{(f * \Delta I_L)} \quad (4)$$

Where, V_{in_min} is V_{in} and f = 100KHZ. The desired input voltage ripple is calculated using Equation 5,

$$\Delta V_{L1} = 0.01 * V_{in} \quad (5)$$

The input filter capacitance and output capacitance are calculated by using Equations 6 and 8, respectively,

$$C_{IN} = \frac{(I_{bat} * D)}{(\Delta V_{L1} * f)} \quad (6)$$

The desired output voltage ripple is calculated using Equation 7,

$$\Delta V_{L2} = 0.01 * V_{bat} \quad (7)$$

$$C_{OUT} = \frac{(I_{bat} * (1-D))}{(\Delta V_{L2} * f)} \quad (8)$$

2.2.1. Switching Component Selection

The switching components are selected based on the following criteria. The forward voltage drops across the diode (V_{f_diode} = 0.5). The maximum input voltage during boost mode is calculated as given in Equation 9 by assuming the voltage stress (V_{ds_max}) on the switch is equal to V_{in_max},

$$V_{in\_max} = \frac{V_{in}}{(1-D)} \quad (9)$$

The safety margin for voltage stress on the switch ($V_{ds\_safe\_margin}$) = 0.1 * V_{in_max}. The actual voltage stress on the switch is given in Equation 10,

$$V_{ds\_switch} = V_{in\_max} + V_{f\_diode} + V_{ds\_safe\_margin} \quad (10)$$

$$\text{Converter efficiency} = P_{out}/P_{in} \quad (11)$$

The calculations of the proposed bidirectional DC-DC buck/boost converter were done using the above-mentioned equations listed in Table 1.

Table 1. Bidirectional DC-DC buck/boost converter specifications

S. No.	Parameters	Values
1	I_{bat}	150AH
2	Switching Frequency	100KHZ
3	L	6.53333e-05 H
4	C_{IN}	7.43802e-05 F
5	C_{OUT}	5.56818e-03 F
6	V_{ds_switch}	272.13 V

2.3. PI Control

PI control is a classic control algorithm. It will be implemented to regulate the bidirectional DC-DC converter’s operation and ensure the battery current and voltage align with the desired reference values. The PI controller begins by measuring the battery current. It then compares this measured current to the desired output current. Finally, it adjusts its settings to generate a control signal that maintains a consistent output current for the input voltage of the converter changes [16].

2.4. ANN Model

Closed-loop control of 24V, 150AH battery storage system using Artificial Neural Networks (ANNs) is an innovative approach that leverages the power of machine learning to optimize the performance of battery systems. In this setup, the battery current and SOC are utilized as inputs to the ANN, with the target or output as the duty cycle, which determines the charging or discharging rate of the battery.

Gathering historical data on battery current, SOC, and corresponding duty cycles is crucial for training the ANN model. The obtained historical data is used to train the ANN. The objective is to enable the network to learn the relationships between battery current, SOC and the optimal duty cycle. The training process involves adjusting the weights and biases of the network to minimize the difference between the predicted duty cycle and the actual duty cycle from the training data. The ANN model of this particular work is created using the SIMULINK platform, as shown in Figure 4.

The difference between the predicted and actual duty cycles is calculated using a loss function. The loss function quantifies the error between the predicted and actual values. The weights and biases were adjusted based on the gradient of the loss function with respect to these parameters. This step is performed using the Levenberg-Marquardt optimization method.

The Levenberg-Marquardt algorithm is an optimization algorithm commonly used for solving nonlinear least squares problems. It’s named after the mathematicians Kenneth Levenberg and Donald Marquardt, who independently proposed the method. The goal is to adjust the model’s parameters to minimize the difference between the observed data and the model predictions.

The Levenberg-Marquardt algorithm iteratively adjusts the model parameters to minimize the sum of the squares for the differences between the observed and predicted values. A well-behaved error histogram with errors centered around zero indicates that the model has predicted accurate predictions, as shown in Figure 5. The training, validation and testing data for the ANN model are shown in Figure 6. When R=1, it indicates the predicted data is closer to or the same as the actual data.

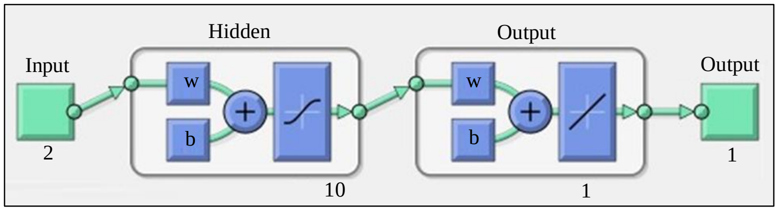

Fig. 4 Structure of ANN

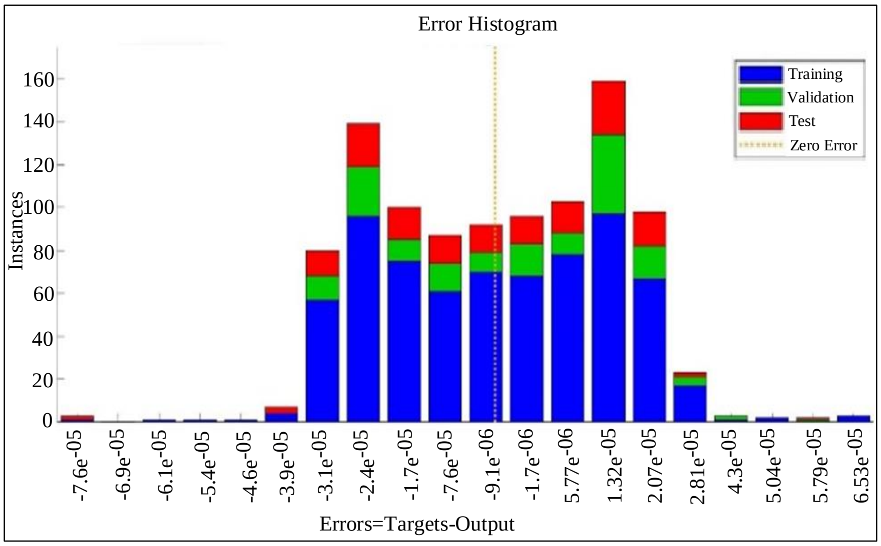

Fig. 5 Error histogram

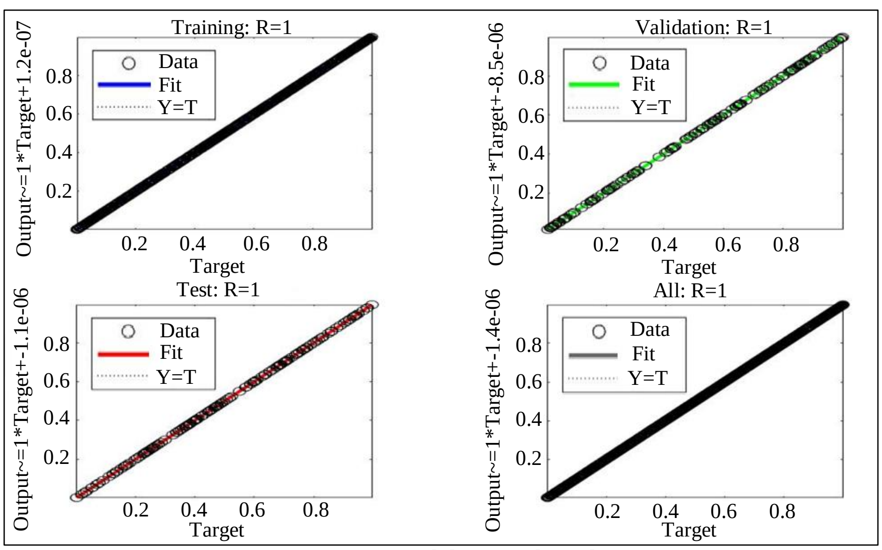

Fig. 6 Training, validation and test data

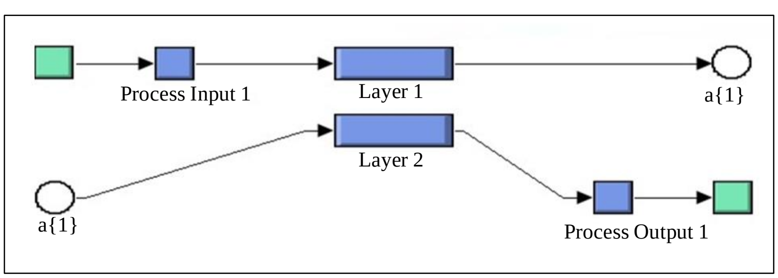

Fig. 7 SIMULINK model of ANN

The mean squared error is obtained as 1.6450e-10 with a minimum gradient of 9.99e-8. This proves that the developed ANN model behaves well in the desired application. Implement the trained ANN in the closed-loop control system where the battery current and SOC are continuously monitored and fed into the ANN. The ANN then predicts the optimal duty cycle for the current operating conditions. The SIMULINK model of the developed ANN for this particular work is shown in Figure 7.

2.5. ANFIS Model

ANFIS model is employed to predict the dynamic behavior of the 24V, 150AH battery storage system, which involves training the ANFIS model using input-output data from the system. Input parameters include battery current and SOC. The duty cycle is an output parameter of the ANFIS model that controls the on/off duration of the converter switches, which effectively regulates the energy flow between the battery and the DC link. The ANFIS controller continuously monitors the battery state and adjusts the duty cycle based on its learned knowledge, ensuring that the battery operates within desired voltage and current limits.

This ANFIS model is developed using 9 fuzzy sets for both battery current (I_{bat}) and SOC, which is described as follows:

Layer 1 - Fuzzification Layer: Fuzzify the battery current and SOC using Gaussian or other membership functions. Let $f_{i,j}$ represent the membership grade for the i^{th} fuzzy set of the j^{th} input variable.

$$f_{i,j} = \mu A_j(x_i)$$

Where x_1 indicates battery current and x_2 indicates SOC.

Layer 2 - Rule Layer: Determine the rule strengths ($w_{i,j}$) connecting fuzzy sets of battery current and SOC since we use 9 fuzzy sets for each input (9 rules for each combination of battery current and SOC fuzzy sets).

$$w_{i,j} = Rule\ strength\ for\ rule\ i$$

Layer 3 - Normalization Layer: Normalize the rule strengths to ensure they sum up to 1.

$$\alpha_{i,j} = \frac{w_{i,j}}{\sum_{i=1}^{81} w_{i,j}}$$

Layer 4 - Consequent Layer: Determine the consequent parameters (p and q) based on the input variables and rules.

$$p_{i,j} = centroid\ of\ A_i\ for\ rule\ j$$

$$q_{i,j} = varience\ of\ A_i\ for\ rule\ j$$

Layer 5 - Output Layer: The final output (y) represents the duty cycle of the bidirectional DC-DC converter.

$$y = \sum_{i=1}^{81} (\alpha_{i,j} \frac{1}{1 + (\frac{x_i - p_{i,j}}{q_{i,j}})^2})$$

The structure of the ANFIS model, including the above-explained five stages, is shown in Figure 8.

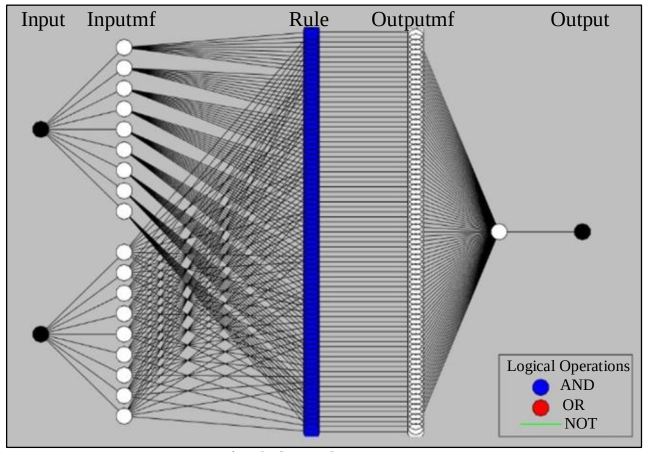

Fig. 8 ANFIS structure

2.5.1. Training

The ANFIS model is trained using a dataset with known input-output pairs in this stage. Adjust the parameters ($w_{i,j}$, $p_{i,j}$, $q_{i,j}$) through a learning algorithm to minimize the difference between the predicted duty cycle and the actual duty cycle. The training data set of the specific ANFIS model trained in this work is simulated, as shown in Figure 9. The ANFIS Surface Viewer in MATLAB provides several advantages for understanding and analyzing the behavior of an Adaptive Neuro-Fuzzy Inference System (ANFIS) model, as shown in Figure 10.

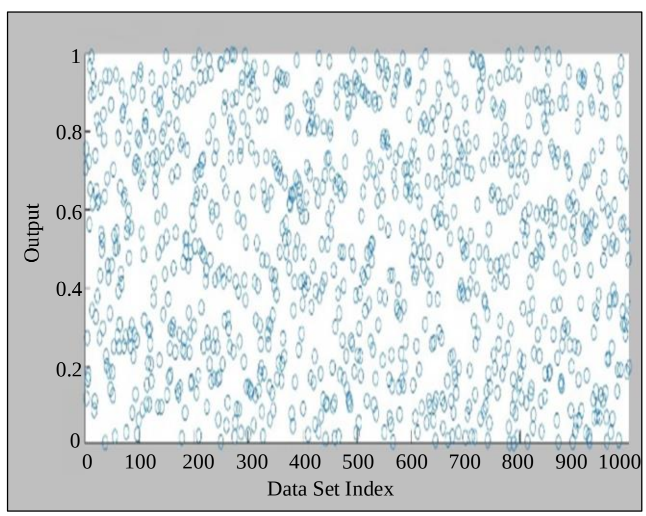

Fig. 9 Training data set for the specific ANFIS model

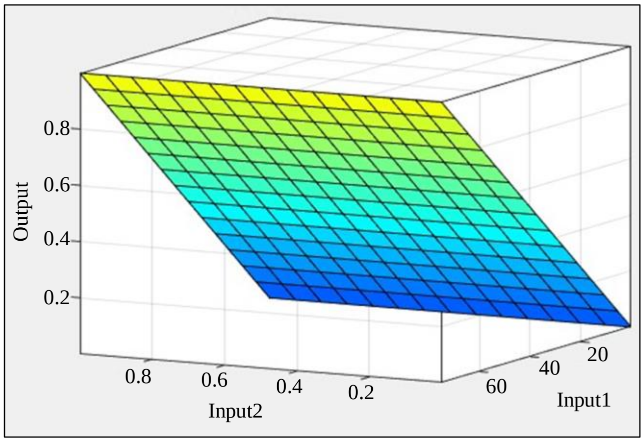

Fig. 10 Surface view of simulated ANFIS model

The Surface Viewer offers a visual representation of the response surface of the ANFIS model. This visualization helps users intuitively understand how the system's output changes with variations in input variables. The ANFIS Surface Viewer is a valuable tool for exploring, validating, and fine-tuning ANFIS models.

The minimal training Root Mean Square Error (RMSE) is too low (5.92434e-08), as observed from the training of the ANFIS model. The minimum RMSE is 3.18539e-06, and the maximum RMSE of 5.92434e-08 was observed during the AFIS training process, as shown in Figure 11. The value of RMSE of training error shows the accuracy of ANFIS when compared with other control techniques.

Test data of the fuzzy inference system is shown in Figure 12. It shows the instantaneous values of output (D) for different instantaneous values of input parameters. Convergence occurs when the duty cycle values stabilize and reach a relatively constant level. This indicates that the fuzzy inference system has learned the underlying patterns in the training data. It shows how well the fuzzy inference system generalizes to unseen data and patterns in the duty cycle over iterations during testing.

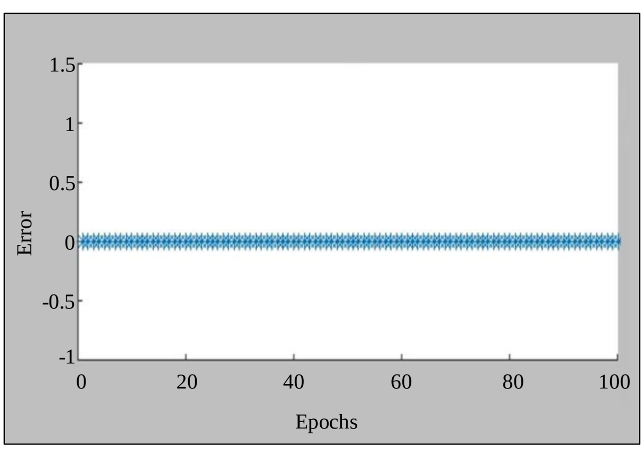

Fig. 11 Training error

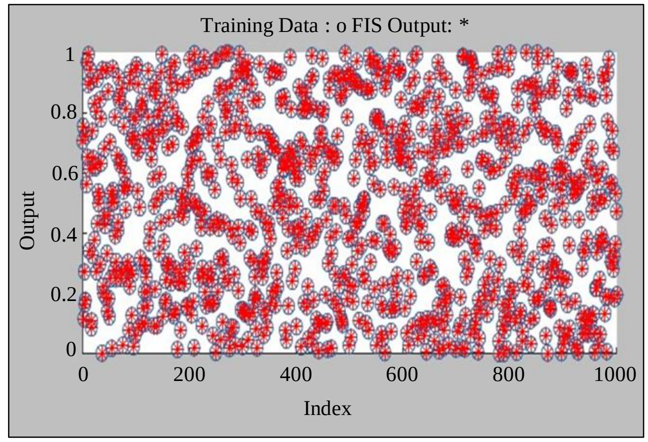

Fig. 12 Test data

2.6. 220V DC Link

The final stage of the research involves the establishment of a 220V DC link. This 220V DC link serves as the backbone for efficient power distribution, interconnecting the bidirectional converter, battery system, and load, forming the complete power management system.

The combined efforts within these stages aim to deliver a robust and adaptable battery storage system with the capability of efficiently managing energy flow and ensuring reliable power supply. As the research progresses through each stage, it will focus on integration, performance optimization, and the successful realization of a sustainable and versatile energy management solution. The SIMULINK model of PI/ANN/ANFIS enabled closed-loop control of bi-directional dc-dc buck/boost converter for 24V, 150AH Lithium-ion battery is shown in Figure 13.

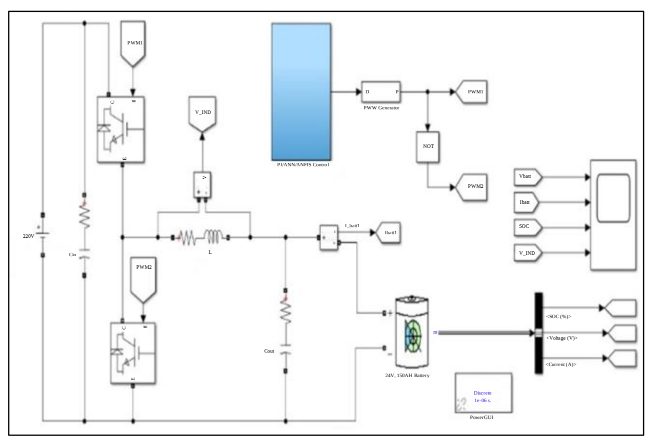

Fig. 13 Overall, the SIMULINK model of PI/ANN/ANFIS enabled closed-loop control

3. Results and Discussions

The simulation-based performance analysis of the bi-directional DC-DC buck/boost converter employing different advanced control strategies such as Proportional and Integral Controllers, Artificial Neural Networks, and Adaptive Neuro-

Fuzzy Inference Systems yields valuable insight into their performance in energy storage systems. The following results and discussions provide a comprehensive understanding of the stability, accuracy, robustness and control complexity of each control strategy. Results of the observed parameters, such as battery charging/discharging current, battery voltage, State of Charge (SOC) and voltage stress across the inductor for both buck and boost modes, provide a critical insight into the performance of the bi-directional DC-DC converter.

The analysis of these parameters is essential for understanding the behavior of the converter under different operating conditions. The analysis is made with ANFIS control strategy because of its higher accuracy and stability, which is then compared with PI and ANN control strategies. During charging/buck mode, the battery reference voltage is set for 75, 45, 30 and 15 amperes at the time intervals of 0.2, 0.5 and 0.8 seconds, respectively, as shown in Figure 14. The battery voltage is almost constant during charging with a limited rise in magnitude, as shown in Figure 14.

The SOC of the battery during charging is the rising manner, as shown in Figure 15. The voltage stress across the inductor is a crucial consideration for the converter's design and operation. In both buck and boost modes, the voltage stress across the inductor should be within acceptable limits to ensure the reliability and longevity of the components. The observed stress across the Inductor is 195V, as shown in Figure 16, which is higher in the other two methods.

In the buck mode, the converter steps down the voltage and the battery charging current is observed to be within the expected range. The buck mode is characterized by efficient charging as the converter adjusts the voltage to match the battery requirements.

SOC is a critical parameter directly influencing the battery's performance and lifespan. Observing SOC in both buck and boost modes provides insights into how well the converter manages energy transfer between the battery and the DC source.

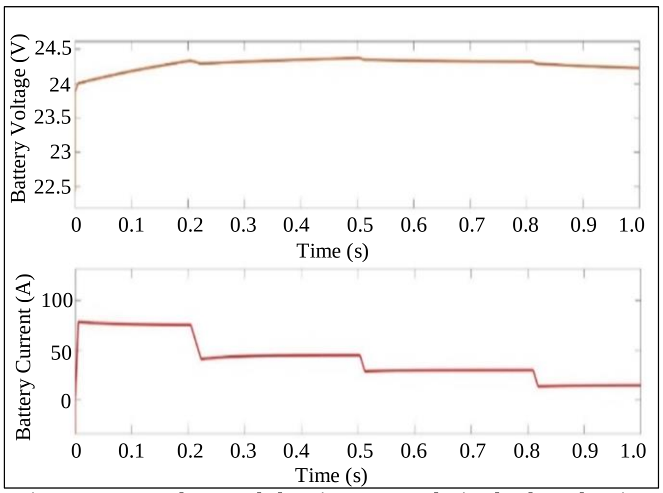

Fig. 14 Battery voltage and charging current during buck mode using ANFIS control

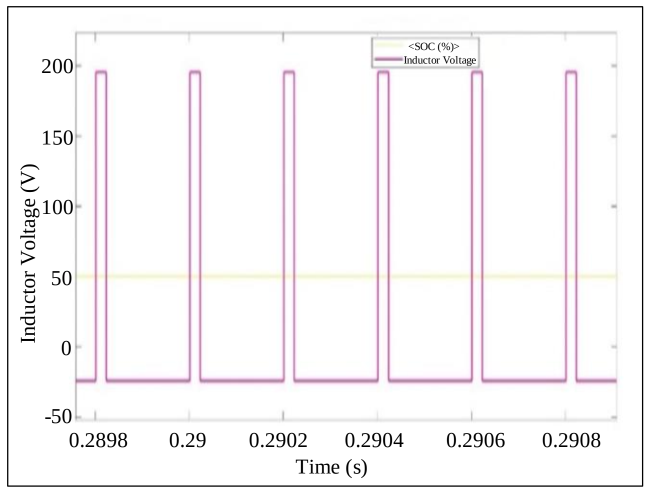

Fig. 16 Voltage stress across inductor using ANFIS control

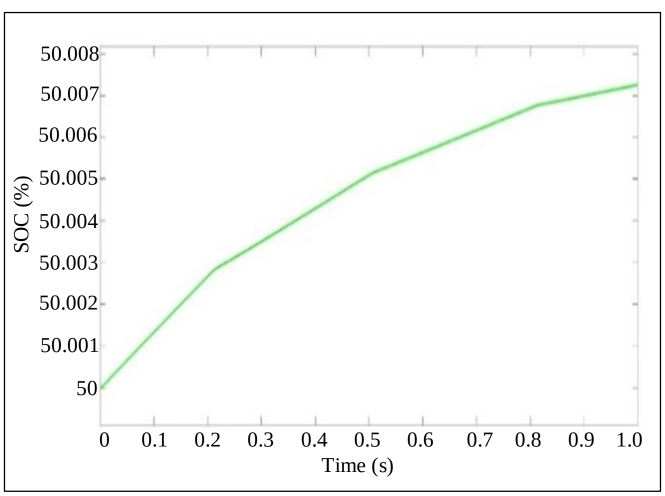

Fig. 15 State of charge during buck mode using ANFIS control

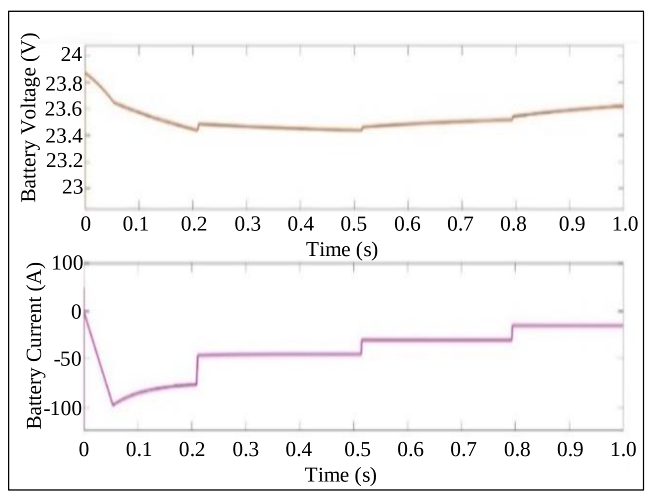

Fig. 17 Battery voltage and discharging current during boost mode using ANFIS control

Maintaining SOC within the desired range is essential for optimizing battery performance and ensuring longevity. The analysis of SOC helps assess the effectiveness of the control strategies in regulating the charging and discharging processes. During dis-charging mode, the battery current is negative; the reference currents are -75, -45, -30 and -15 amperes at the time intervals of 0.2, 0.5 and 0.8 seconds, respectively, as shown in Figure 17.

The SOC of the battery is observed in a reducing manner, as shown in Figure 18. The observation and analysis of battery charging/discharging current, battery voltage, SOC and voltage stress across the inductor provide a comprehensive understanding of the modified bi-directional DC-DC converter's performance in both buck and boost modes.

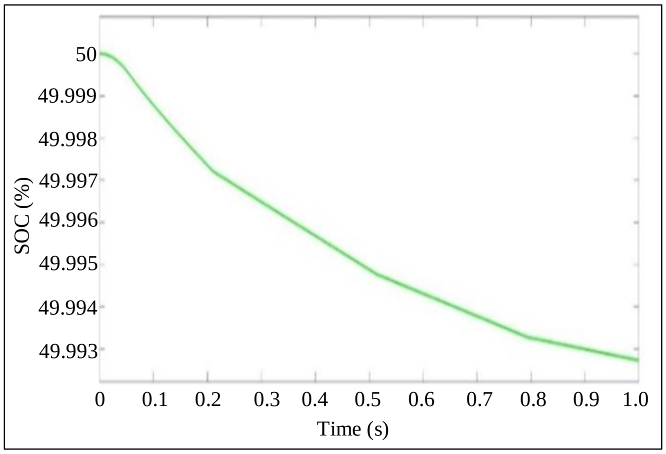

Fig. 18 State of charge during boost mode using ANFIS control

Table 2. Comparison of battery voltage and current during buck/boost modes

Control Strategy	V_{bat} (Buck)	I_{bat} (Buck)	V_{bat} (Boost)	I_{bat} (Boost)
PI	22.6V	73.7A	22.8V	-72.3A
ANN	23.7V	74.6A	23.2V	-74.1A
ANFIS	24V	74.9A	23.4V	-74.4A

The comparison of battery voltage and current during buck/boost modes using PI, ANN and ANFIS control strategies is shown in Table 2. All control strategies (PI, ANN, ANFIS) maintain relatively close battery voltage levels with ANFIS slightly higher at 24V in the buck mode. In the boost mode, ANFIS yields the highest voltage at 23.4V, followed closely by PI and ANN. In the buck mode, ANFIS achieves the highest charging current at 74.9A. In the boost mode, it demonstrates the highest discharging current at -74.4A. These results suggest that the ANFIS control strategy performs favorably in both charging and discharging modes by achieving higher battery voltage and current compared to PI and ANN. The study focused on parameters such as battery charging/discharging current battery voltage, State of Charge (SOC), and voltage stress across the inductor in both buck and boost modes. The analysis is conducted using the ANFIS control strategy for its higher accuracy and stability, comparing results with PI and ANN control strategies. During charging/buck mode, the converter efficiently adjusted the voltage, resulting in a nearly constant battery voltage and a rising SOC.

4. Conclusion

This research has comprehensively analysed advanced control strategies for energy storage systems employing DC-DC bi-directional converters. The growing demand for efficient and reliable energy storage solutions necessitates a thorough understanding of control strategies to optimize the operation of these systems. The study compared three main control strategies Proportional and Integral Controller, Artificial Neural Network, and Adaptive Neuro-Fuzzy Inference System. The evaluation revealed that PI control is a well-established strategy that effectively maintains voltage regulation and system stability. However, its limitations in handling highly nonlinear dynamics or rapidly changing operating conditions underscore the need for more advanced control strategies. ANN is known for its adaptability and learning capabilities particularly excels in State-of-Charge estimation.

On the other hand, ANFIS is a hybrid control system which combines the strengths of fuzzy logic and neural networks to handle complex, non-linear systems and adapt to changing conditions, making it well-suited for the dynamic and uncertain nature of energy storage system operations, which is proved in this study. The research emphasizes the importance of choosing the appropriate control strategy based on the specific requirements and characteristics of the energy storage system. Advanced strategies like ANN and ANFIS offer enhanced adaptability and performance in dynamic and uncertain environments.

The findings of this study contribute valuable insights into the accuracy, stability, control complexity and suitability of these control approaches. Furthermore, the research highlights the significance of DC-DC bi-directional converters in energy storage systems, specifically focusing on their role in enabling bidirectional energy transfer between the storage system and the DC source. The outcomes of this study are expected to guide researchers, engineers and practitioners in making informed decisions regarding the selection of control strategies for their specific energy storage system applications.

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