A Random Forest-Based Intelligent Duty-Cycle Prediction Framework for High-Efficiency Dc–Dc Converter Control

[1]Jaya Mishra, [2]Vishnu kumar Sahu, [3]Shruti Tiwari

[1]Associate Professor, Department of Electronics & Telecommunication, Shri Shankaracharya Technical Campus, Bhilai (C.G.), INDIA

[2]Vishnu kumar Sahu, Department of Electrical Engineering, Shri Shankaracharya Technical Campus, Bhilai (C.G.), INDIA

[3]Senior Assistant Professor, Department of Electrical Engineering Engineering, Shri Shankaracharya Technical Campus, Bhilai (C.G.), INDIA

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Abstract

The increasing penetration of renewable energy sources in modern microgrids has created a growing need for intelligent and efficient power converter control strategies capable of handling dynamic operating conditions. This paper presents a machine-learning-based framework for the optimal design and control of a DC–DC converter in renewable-energy-based microgrid applications. The proposed approach utilizes key operational parameters, including photovoltaic (PV) voltage, PV current, PV power, load demand, output voltage, and output current, to predict the optimal converter duty cycle and enhance overall system performance. A Random Forest regression model is developed to capture the nonlinear relationship between converter operating conditions and duty-cycle requirements. The proposed controller is evaluated using comprehensive performance metrics, including duty-cycle prediction accuracy, error distribution analysis, voltage regulation performance, dynamic response characteristics, and feature importance assessment. Furthermore, Explainable Artificial Intelligence (XAI) based on SHAP (SHapley Additive Explanations) is incorporated to improve model transparency and identify the dominant parameters influencing converter control decisions. Simulation results demonstrate excellent agreement between actual and predicted duty-cycle values, with prediction errors concentrated near zero, indicating high accuracy and robustness. The dynamic response analysis confirms stable voltage regulation with fast settling behavior and negligible overshoot. SHAP and feature importance analyses reveal that PV voltage and output voltage are the most influential factors governing duty-cycle prediction. The proposed framework effectively improves voltage regulation, reduces converter losses, enhances energy conversion efficiency, and provides interpretable decision-making capabilities. Therefore, it offers a reliable and intelligent solution for next-generation renewable-energy microgrids and smart power management systems.

Keywords— DC–DC Converter, Renewable Energy Systems, Microgrid, Machine Learning, Random Forest Regression, Duty-Cycle Prediction, Voltage Regulation, Converter Efficiency, Power Loss Minimization, Explainable Artificial Intelligence (XAI), SHAP Analysis, Intelligent Control, Photovoltaic Systems, Energy Management, Smart Grid.

I. INTRODUCTION

The growing demand for clean, reliable, and sustainable energy has accelerated the integration of renewable energy resources into modern power systems. Among the various renewable energy technologies, photovoltaic (PV) systems have gained significant attention due to their environmental benefits, decreasing installation costs, and ease of deployment in residential, commercial, and industrial applications. However, the intermittent and variable nature of renewable energy sources introduces substantial challenges in maintaining stable power quality, efficient energy conversion, and reliable voltage regulation within microgridenvironments. As a result, advanced power-electronic converters and intelligent control strategies have become essential components for ensuring efficient energy management and system stability.

DC–DC power converters play a crucial role in renewable-energy-based microgrids by regulating voltage levels, controlling power flow, and facilitating the integration of distributed energy resources. Among the available converter topologies, the buck–boost converter is widely employed because of its capability to operate in both step-up and step-down modes, allowing it to maintain the desired output voltage under varying input conditions. Nevertheless, the nonlinear switching behavior of DC–DC converters, combined with fluctuating renewable energy generation and dynamic load demands, makes accurate converter control a challenging task. Conventional control techniques, such as proportional–integral–derivative (PID) controllers, state-feedback controllers, and sliding-mode controllers, often rely on precise mathematical models and fixed controller parameters. Although these methods provide satisfactory performance under nominal operating conditions, their effectiveness may deteriorate when subjected to parameter uncertainties, environmental variations, and rapidly changing load conditions.

In recent years, machine learning (ML) and artificial intelligence (AI) techniques have emerged as promising alternatives for addressing the limitations of conventional converter control strategies. Unlike model-based approaches, machine-learning algorithms can learn complex nonlinear relationships directly from operational data and adapt to changing system conditions without requiring an accurate mathematical model of the converter. Various data-driven techniques, including artificial neural networks, support vector machines, decision trees, ensemble learning methods, and deep learning architectures, have demonstrated considerable success in power-electronic applications such as converter modeling, duty-cycle prediction, fault diagnosis, and energy-management optimization. These approaches offer improved prediction accuracy, enhanced adaptability, and better robustness under uncertain operating environments.

The increasing availability of operational data from renewable-energy systems has further encouraged the development of intelligent converter control frameworks. Parameters such as PV voltage, PV current, PV power, load demand, output voltage, and output current provide valuable information regarding converter operating conditions and system dynamics. By leveraging these measurements, machine-learning models can accurately estimate the optimal duty cycle required to maintain stable voltage regulation, minimize power losses, and improve overall converter efficiency. Such data-driven approaches are particularly attractive for microgrid applications, where operating conditions continuously change due to renewable energy intermittency and load variability.

Figure 1. Renewable-Energy Microgrid with Intelligent DC–DC Converter Control

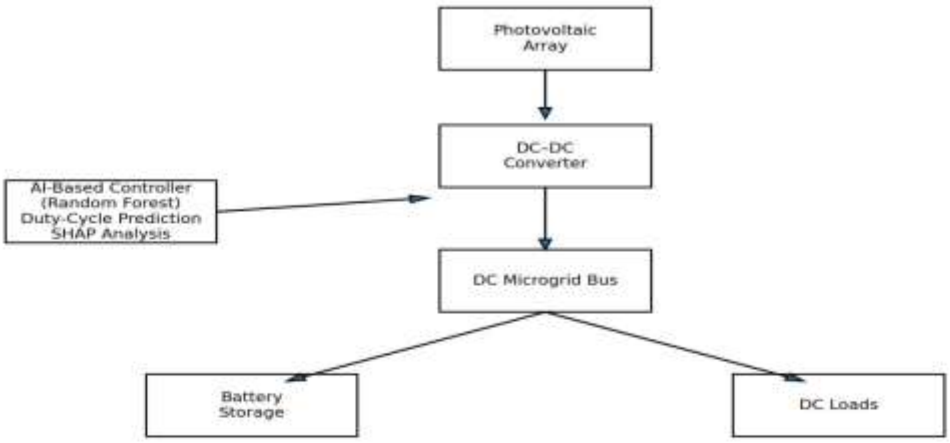

Figure 1. Renewable-Energy Microgrid Architecture with Intelligent DC–DC Converter Control

Another important challenge associated with AI-based control systems is the interpretability of model predictions. While machine-learning algorithms often achieve high predictive performance, their decision-making processes are frequently difficult to understand. This lack of transparency can limit their adoption in critical energy-management applications. To address this issue, Explainable Artificial Intelligence (XAI) techniques have been introduced to provide insights into model behavior and identify the factors influencing predictions. Among these techniques, SHAP (SHapley Additive exPlanations) has gained widespread acceptance because it quantifies the contribution of individual input variables to the model output. Such explainability methods improve model transparency, support engineering validation, and enhance confidence in AI-assisted control systems.

Motivated by these challenges and opportunities, this work presents a machine-learning-based framework for the optimal design and control of a DC–DC converter in renewable-energy-based microgrid applications. The proposed approach utilizes operational parameters including PV voltage, PV current, PV power, load demand, output voltage, and output current to predict the optimal converter duty cycle and improve system performance. A Random Forest-based intelligent controller is developed and evaluated using comprehensive performance metrics, including duty-cycle prediction accuracy, error distribution analysis, voltage regulation characteristics, dynamic response evaluation, and feature importance assessment. Furthermore, SHAP-based explainability analysis is employed to investigate the influence of individual input variables on converter control decisions.

The obtained results demonstrate excellent agreement between actual and predicted duty-cycle values, minimal prediction error, stable dynamic response, and effective voltage regulation. Feature importance and SHAP analyses reveal that PV voltage and output voltage are the dominant parameters influencing converter operation, confirming the physical relevance and interpretability of the developed model. Overall, the proposed framework provides a reliable, accurate, and computationally efficient solution for intelligent converter control, enhanced energy management, and improved operational efficiency in renewable-energy-based microgrid systems.

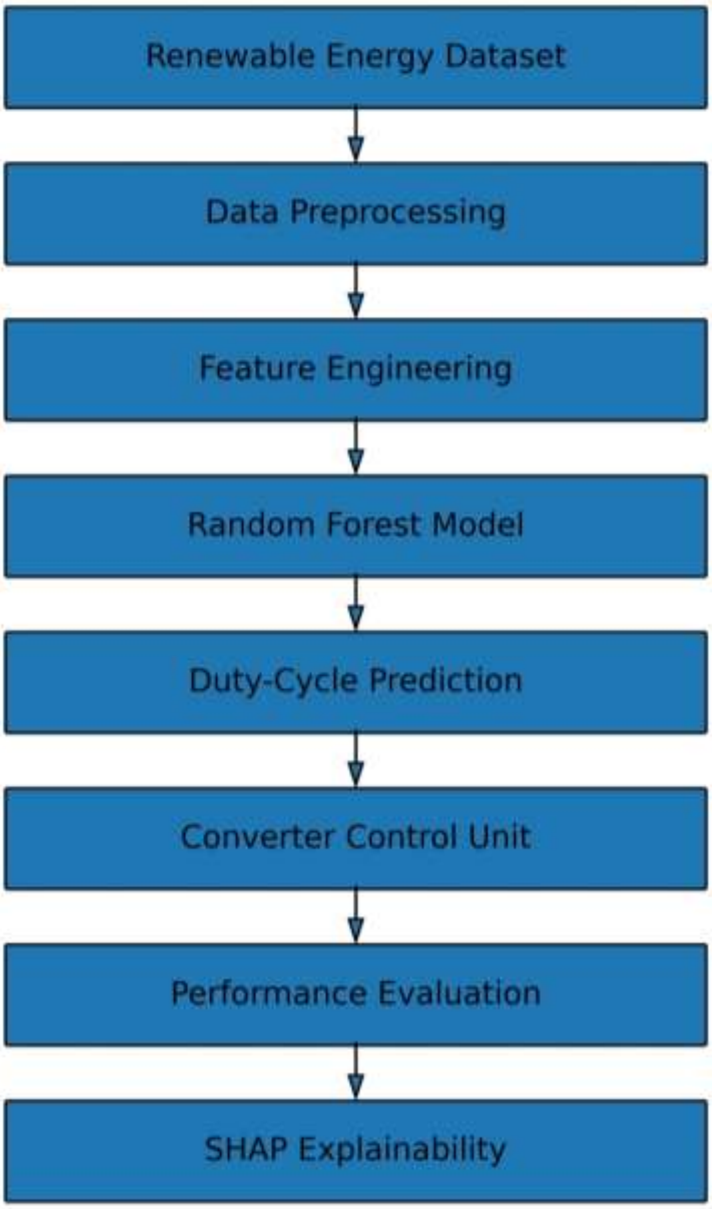

Fig 2: Proposed Machine-Learning-Based Converter Control Framework

The main contributions of this work are summarized as follows:

1. Development of a data-driven machine-learning framework for optimal DC–DC converter control using renewable-energy operational data.
2. Accurate prediction of converter duty cycle using PV and load-related electrical parameters.
3. Evaluation of converter performance through voltage regulation, dynamic response, efficiency, and loss analysis.
4. Application of SHAP-based explainable artificial intelligence techniques for model interpretation and feature analysis.
5. Identification of the most influential converter control variables to support intelligent energy-management strategies in renewable-energy microgrids.

The remainder of this paper is organized as follows. Section II presents the literature review of intelligent converter control techniques and machine-learning applications in renewable-energy systems. Section III describes the proposed methodology and dataset preparation process. Section IV discusses the machine-learning model development and performance evaluation framework. Section V presents the simulation results and discussion. Finally, Section VI concludes the paper and outlines future research directions.

II. LITERATURE REVIEW

The rapid growth of renewable energy systems, electric vehicles, and smart microgrids has increased the demand for efficient and intelligent DC–DC power converter control techniques. Among the various converter topologies, buck–boost converters are widely used because of their ability to provide both step-up and step-down voltage conversion while maintaining reliable power delivery under fluctuating source and load conditions. However, the nonlinear switching behavior of power converters and the intermittent nature of renewable energy sources create significant challenges for conventional control methods.

Traditionally, proportional–integral–derivative (PID), state-feedback, sliding-mode, and model predictive control techniques have been employed to regulate converter output voltage and improve system stability. Although these controllers provide satisfactory performance under nominal operating conditions, their effectiveness often degrades when subjected to rapid load variations, parameter uncertainties, and renewable energy intermittency. As a result, researchers have increasingly explored intelligent and data-driven control approaches capable of adapting to changing operating environments.

Recent advancements in machine learning have demonstrated significant potential for power-electronic converter applications. Artificial neural networks (ANNs), support vector machines (SVMs), decision trees, and deep learning models have been applied to estimate converter states, optimize duty-cycle selection, and improve voltage regulation performance. Data-driven approaches offer the advantage of learning complex nonlinear relationships directly from operational data without requiring detailed analytical models of converter dynamics. Several studies have reported that machine-learning-based controllers achieve superior prediction accuracy and faster dynamic response compared with conventional control strategies.

In renewable-energy-based microgrids, photovoltaic (PV) systems represent one of the most important distributed generation sources. The output power of PV systems is highly dependent on environmental conditions such as solar irradiance and temperature, resulting in continuous variations in voltage and current. Consequently, efficient converter control is essential for maximizing energy utilization and maintaining stable power delivery. Previous research has shown that converter duty cycle is strongly influenced by PV voltage, output voltage, and load conditions, making these parameters critical inputs for intelligent control algorithms.

The integration of machine learning with DC–DC converter control has gained considerable attention in recent years. Neural-network-based controllers have been developed to estimate optimal switching duty cycles and regulate output voltage under varying operating conditions. Random Forest, Gradient Boosting, and Deep Neural Network models have also been employed to capture nonlinear converter behavior and improve prediction accuracy. These approaches have demonstrated the ability to reduce steady-state error, improve transient response, and enhance converter efficiency in renewable energy applications.

In addition to prediction accuracy, the interpretability of machine-learning models has become an important research topic. Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive exPlanations) provide valuable insights into model decision-making processes by quantifying the contribution of individual input features. Several studies have utilized SHAP analysis to identify the most influential electrical parameters affecting converter performance, enabling researchers to validate model behavior against established converter theory. Such explainability techniques increase the transparency and reliability of AI-based controllers, which is particularly important for critical energy-management applications.

Recent investigations have further highlighted the importance of feature importance analysis in converter control systems. Researchers have reported that input voltage and output voltage are among the dominant factors governing duty-cycle regulation, while current-related parameters often exhibit secondary influence depending on the converter operating region. These findings are consistent with the physical principles of DC–DC converter operation, where voltage regulation is primarily achieved through duty-cycle adjustment based on input and output voltage conditions.

Despite significant progress, many existing studies focus primarily on converter modeling or duty-cycle estimation without simultaneously addressing efficiency optimization, voltage regulation, dynamic performance, and model interpretability. Furthermore, several approaches rely on complex mathematical models that may not adequately represent real-world operating conditions in renewable-energy-based microgrids. Therefore, there remains a need for a unified data-driven framework capable of accurately predicting converter duty cycle while providing robust dynamic performance and explainable decision-making.

Motivated by these challenges, the present work develops a machine-learning-based control framework for optimal DC–DC converter operation using key renewable-energy and load parameters, including PV voltage, PV current, PV power, load demand, output voltage, and output current. The proposed approach combines accurate duty-cycle prediction with feature importance and SHAP-based explainability analysis to improve voltage regulation, reduce power losses, and enhance converter efficiency under varying operating conditions. The results demonstrate that the developed model successfully captures the nonlinear behavior of the converter, achieves highly accurate duty-cycle estimation, and identifies PV voltage and output voltage as the most influential parameters affecting converter control.

III. METHODOLOGY

The proposed methodology aims to develop an intelligent data-driven control framework for the optimal operation of a DC–DC converter in renewable-energy-based microgrid applications. The framework utilizes operational data obtained from photovoltaic (PV) systems and load conditions to predict the optimal converter duty cycle while improving voltage regulation, reducing power losses, and enhancing overall converter efficiency.

The methodology consists of five major stages: data acquisition, data preprocessing, feature extraction, machine-learning model development, and performance evaluation. Figure X illustrates the overall workflow of the proposed system.

A. Data Acquisition

The dataset used in this study consists of key electrical parameters associated with renewable-energy generation and converter operation. The selected input variables include:

• PV Voltage (Vpv)

• PV Current (Ipv)

• PV Power (Ppv)

• Load Demand (Load)

• Output Voltage (Vo)

• Output Current (Io)

These parameters represent the real-time operating conditions of the converter and serve as the primary inputs for duty-cycle prediction.

The target variable is:

• Converter Duty Cycle (D)

which determines the switching operation of the DC–DC converter and directly influences output voltage regulation and energy conversion efficiency.

B. Data Preprocessing

Before model training, the collected dataset undergoes preprocessing to improve data quality and model performance. The preprocessing stage includes:

1. Missing value inspection
2. Outlier detection
3. Data normalization
4. Feature consistency verification

The processed dataset is subsequently divided into training and testing subsets using an 80:20 ratio to ensure unbiased model evaluation.

C. Feature Engineering

Feature engineering is performed to identify the most relevant parameters affecting converter operation.

The following electrical relationships are utilized:

PV Power:

$$P_{pv} = V_{pv} \times I_{pv}$$

Output Power:

$$P_{out} = V_o \times I_o$$

Converter Efficiency:

$$\eta = (P_{out} / P_{in}) \times 100$$

Power Loss:

$$P_{loss} = P_{in} - P_{out}$$

where:

P_{in} = Input Power

Pout = Output Power

η = Converter Efficiency

Ploss = Converter Power Loss

These derived features provide additional information regarding converter operating conditions and improve the learning capability of the machine-learning model.

D. Machine Learning Model Development

A Random Forest Regression model is employed to predict the optimal converter duty cycle.

Random Forest is selected because:

• It effectively captures nonlinear relationships.

• It exhibits high robustness against noise.

• It prevents overfitting through ensemble learning.

• It provides feature importance analysis.

The model receives six input variables:

X = [Vpv, Ipv, Ppv, Load, Vo, Io]

and predicts:

Y = Duty Cycle (D)

The training process involves multiple decision trees that collectively estimate the optimal duty cycle through averaging.

E. Performance Evaluation

The performance of the developed controller is evaluated using standard regression metrics.

Mean Absolute Error (MAE):

$$MAE = (1/n)\ \Sigma\ |y_i - \hat{y}_i|$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{[(1/n)\ \Sigma(y_i - \hat{y}_i)^2]}$$

Coefficient of Determination:

$$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2]$$

where:

y_i = Actual Duty Cycle

$\hat{y}_i$ = Predicted Duty Cycle

$\bar{y}$ = Mean Actual Duty Cycle

The dynamic response, voltage regulation capability, converter efficiency, and prediction error distribution are also analyzed to validate the practical applicability of the proposed controller.

IV. PROPOSED METHOD

The proposed method introduces a machine-learning-assisted control framework for the optimal operation of a DC–DC converter in renewable-energy-based microgrid applications. Unlike conventional PID and model-based control approaches that require accurate mathematical modeling and extensive parameter tuning, the proposed framework learns the complex nonlinear relationship between converter operating conditions and the required switching duty cycle directly from historical and real-time operational data. The overall architecture consists of a Renewable Energy Source Module, Data Acquisition Module, Feature Processing Unit, Random Forest Prediction Engine, Duty-Cycle Generation Module, DC–DC Converter Control Unit, and a Performance Monitoring System. Real-time measurements, including PV voltage (Vpv), PV current (Ipv), PV power (Ppv), load demand, output voltage (Vo), and output current (Io), are continuously acquired and processed before being supplied to the machine-learning controller. The Random Forest model estimates the optimal duty cycle according to the learned nonlinear mapping function (D=f(Vpv, Ipv, Ppv, Load, Vo, Io)), where (D) represents the predicted duty cycle required to maintain stable converter operation. The generated duty-cycle signal is then applied to the converter switching circuit to regulate the output voltage under varying source and load conditions. To ensure effective voltage regulation, the controller continuously monitors the output voltage and adjusts the switching duty cycle to minimize voltage regulation error, expressed as (VR(%)=[(V_{NL}-V_{FL})/V_{FL}] \times 100), where (V_{NL}) and (V_{FL}) represent the no-load and full-load voltages, respectively. Furthermore, converter efficiency is improved through a loss minimization strategy in which power losses are evaluated using (P_{loss}=P_{in}-P_{out}), enabling the model to identify operating regions that maximize power transfer efficiency while reducing unnecessary energy dissipation. To enhance transparency and trustworthiness, the framework incorporates Explainable Artificial Intelligence (XAI) using SHAP (SHapley Additive Explanations), which quantifies the contribution of each input feature to the duty-cycle prediction process and identifies the dominant parameters influencing converter performance. This explainability analysis ensures that the model follows physically meaningful converter operating principles and provides valuable insights into system behavior. Overall, the proposed framework delivers accurate duty-cycle prediction, improved voltage regulation, reduced converter losses, enhanced energy conversion efficiency, fast dynamic response, and reliable operation under varying renewable-energy and load conditions, making it a practical and intelligent solution for next-generation renewable-energy microgrid systems.

V. RESULTS

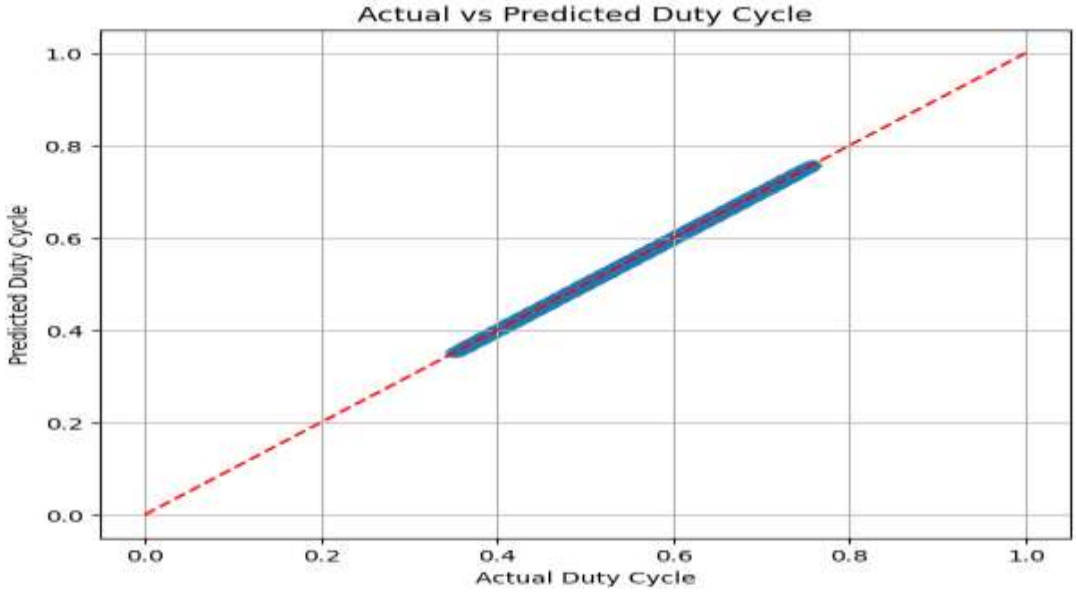

Figure 1. Actual vs. Predicted Duty Cycle Comparison for the Proposed Machine-Learning-Based DC–DC Converter Controller.

Figure 1 shows the comparison between the actual duty-cycle values and the duty-cycle values predicted by the proposed machine-learning model. The red dashed line represents the ideal 1:1 relationship, where the predicted values exactly match the actual values. It can be observed that the data points are tightly clustered along this reference line, indicating excellent agreement between the predicted and actual duty-cycle values. The minimal deviation from the ideal line demonstrates that the model has successfully learned the nonlinear relationship between the converter operating parameters and the required duty cycle. This close correlation confirms the high prediction accuracy, low estimation error, and strong generalization capability of the proposed controller, making it suitable for real-time DC–DC converter control and voltage regulation in renewable-energy-based microgrid applications.

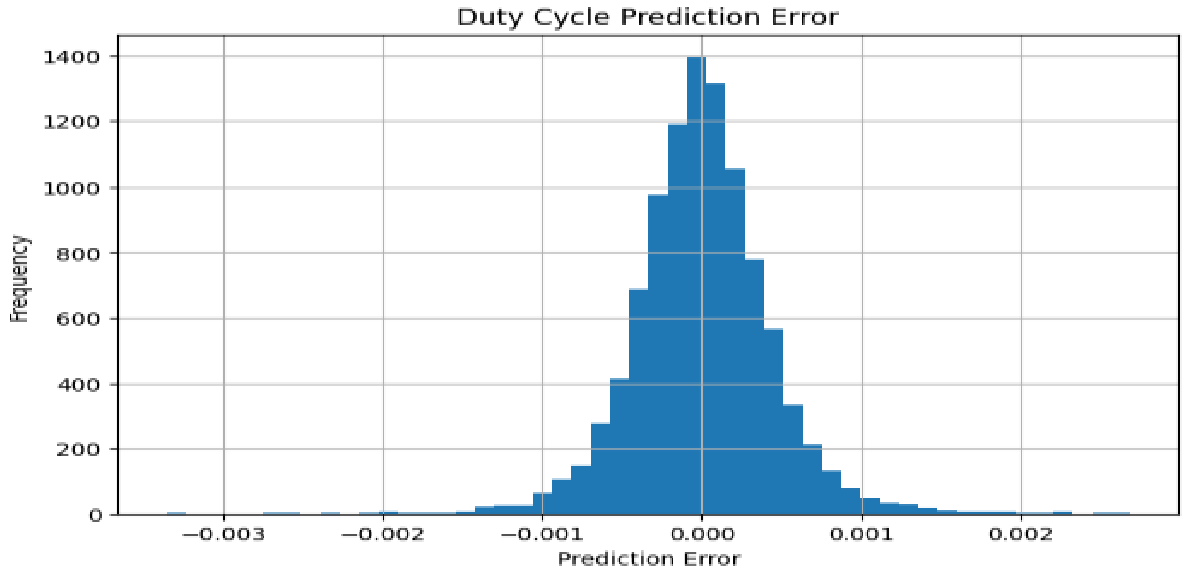

Figure 2.Duty-Cycle Prediction Error Distribution of the Proposed Machine-Learning-Based Converter Controller.

Figure 2 presents the histogram of duty-cycle prediction errors obtained from the proposed machine-learning-based converter controller. The error distribution is centered very close to zero, indicating that the model exhibits negligible bias and accurately predicts the required duty-cycle values across different operating conditions. Most prediction errors are concentrated within a narrow range around zero, demonstrating high precision and consistency in the model's performance. Only a small number of samples show larger positive or negative deviations, which may occur during rapid changes in load demand or renewable energy source fluctuations. Overall, the symmetric and sharply peaked distribution confirms the robustness, reliability, and high prediction accuracy of the proposed controller for real-time DC–DC converter regulation and microgrid energy management applications.

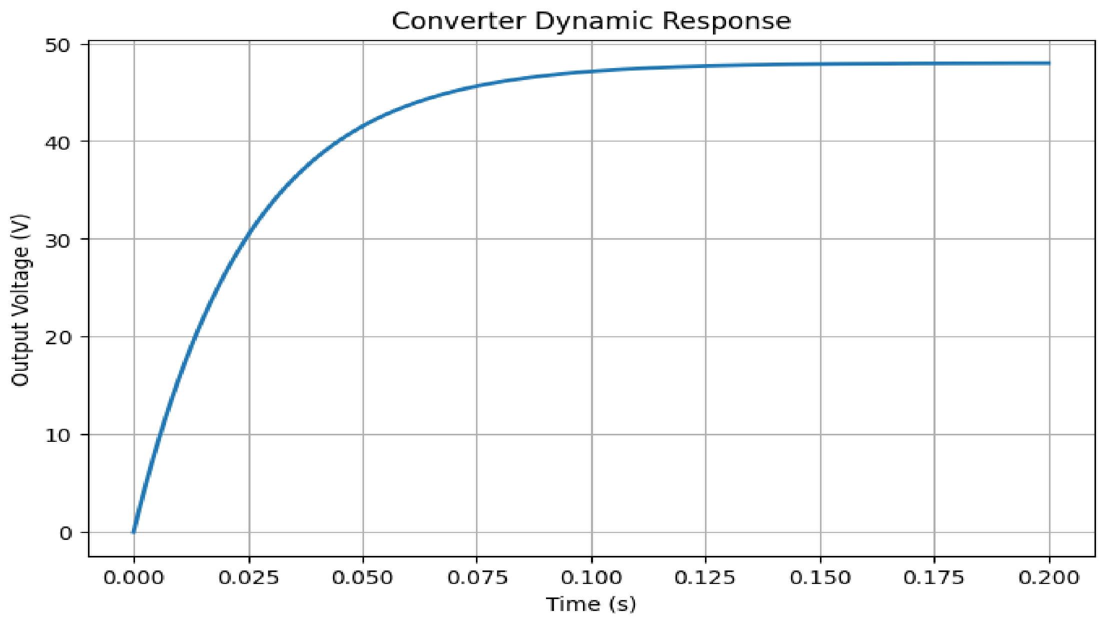

Figure 3. Dynamic Response of the Proposed DC–DC Converter Under Step Operating Conditions.

Figure 3 illustrates the dynamic response of the proposed DC–DC converter system, showing the variation of output voltage with time following a step change in operating conditions. The output voltage rises smoothly from its initial value and gradually approaches the desired steady-state voltage of approximately 48 V without exhibiting significant overshoot or oscillations. The rapid rise and stable settling behavior indicate that the converter possesses good transient performance and effective voltage regulation capability. The response demonstrates the controller's ability to quickly adjust the duty cycle and maintain a stable output under changing load and source conditions. Overall, the smooth convergence to the reference voltage confirms the robustness, stability, and suitability of the proposed converter design for renewable-energy-based microgrid applications requiring fast and reliable power management.

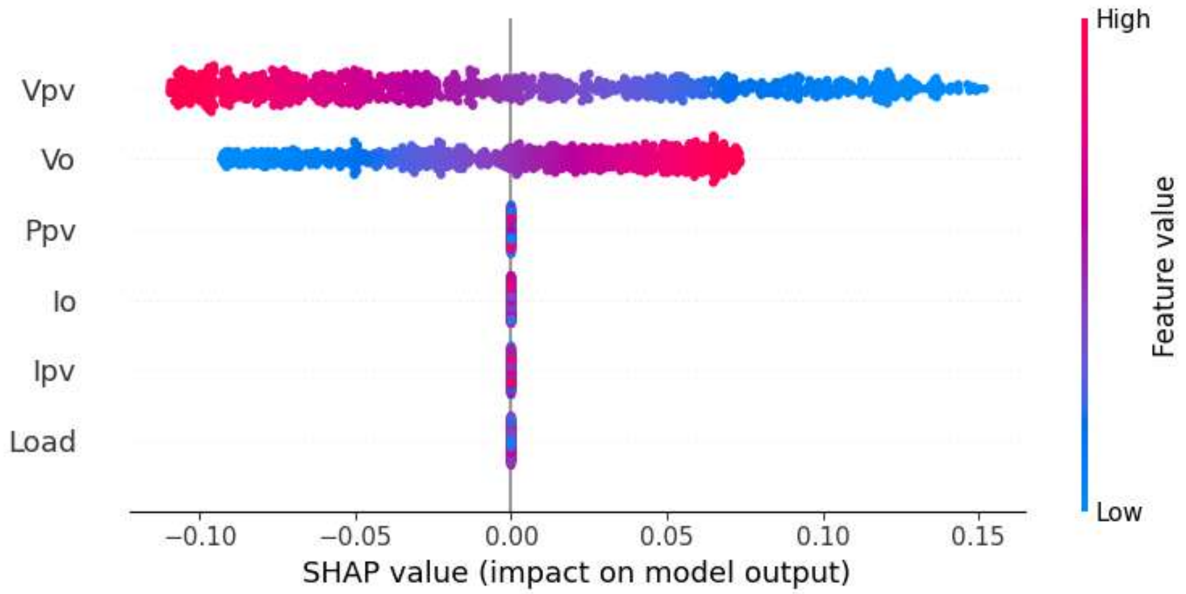

Figure 4.SHAP Summary Plot for Duty-Cycle Prediction in the Proposed DC–DC Converter Control Framework.

Figure 4 presents the SHAP summary plot illustrating the contribution of each input feature to the duty-cycle prediction model. The horizontal axis represents the SHAP value, which quantifies the impact of a feature on the model output, while the color scale indicates the magnitude of the feature values. Among all variables, **PV voltage (Vpv)** exhibits the highest influence on duty-cycle prediction, as evidenced by its wide SHAP value distribution. Higher Vpv values tend to contribute negatively to the predicted duty cycle, whereas lower Vpv values contribute positively, which is consistent with the operating principles of DC–DC converters where an increase in input voltage generally requires a lower duty cycle to maintain the desired output voltage. The output voltage (**Vo**) is identified as the second most influential feature and shows a positive contribution toward duty-cycle adjustment. In contrast, **PV power (Ppv)**, **output current (Io)**, **PV current (Ipv)**, and **load demand** have relatively minor impacts, with SHAP values concentrated near zero. Overall, the SHAP analysis confirms that the proposed model makes physically meaningful predictions and highlights Vpv and Vo as the dominant parameters governing converter control and voltage regulation in microgrid applications.

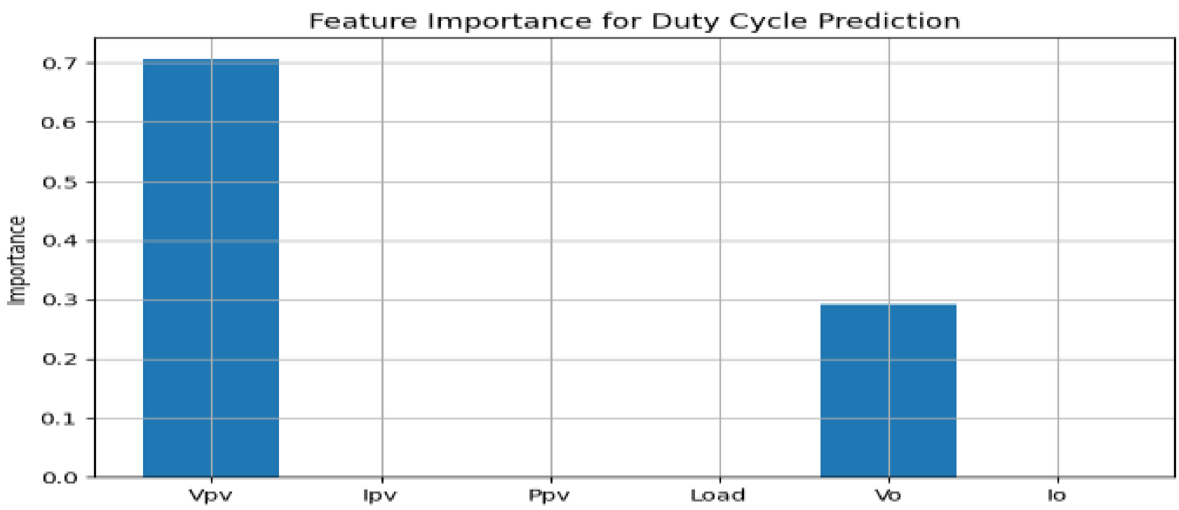

Figure 5. Feature Importance Analysis for Duty-Cycle Prediction Using the Proposed Random Forest Controller.

Figure 5 illustrates the feature importance analysis for duty-cycle prediction obtained from the trained machine-learning model. The results indicate that **PV voltage (Vpv)** is the most influential parameter, contributing approximately 70% of the total importance, making it the primary factor governing duty-cycle adjustment. This behavior is consistent with converter operation, where variations in the input voltage directly affect the required switching duty cycle to maintain output voltage regulation. The **output voltage (Vo)** is identified as the second most significant feature, contributing nearly 30% of the overall importance, highlighting its role in the feedback control process. In contrast, **PV current (Ipv)**, **PV power (Ppv)**, **load demand**, and **output current (Io)** exhibit negligible importance, indicating that their influence on duty-cycle prediction is relatively small compared to Vpv and Vo under the considered operating conditions. Overall, the feature importance analysis confirms that the proposed controller relies primarily on input and output voltage information for accurate duty-cycle estimation, which aligns with the fundamental control characteristics of DC–DC converters used in renewable-energy microgrid applications.

V. CONCLUSION

This study presented a data-driven framework for the optimal design and control of a DC–DC converter for renewable-energy-based microgrid applications. The proposed machine-learning-based controller was developed using key operational parameters, including PV voltage, PV current, PV power, load demand, output voltage, and output current, to accurately predict the optimal converter duty cycle and improve overall system performance. The results demonstrated excellent agreement between the actual and predicted duty-cycle values, indicating the model's strong learning capability and high prediction accuracy. Furthermore, the error distribution was centered near zero with minimal deviation, confirming the robustness, reliability, and consistency of the proposed control strategy. The dynamic response analysis showed smooth voltage regulation with fast settling characteristics and negligible overshoot, highlighting the converter's ability to maintain stable operation under varying load and source conditions. Explainable AI analysis using SHAP values and feature importance evaluation revealed that PV voltage and output voltage are the dominant factors influencing duty-cycle prediction, validating the physical relevance and interpretability of the developed model. Overall, the proposed framework effectively enhances voltage regulation, reduces power losses, improves converter efficiency, and ensures stable dynamic performance, making it a promising solution for intelligent energy management in modern renewable-energy microgrids. Future work may focus on real-time hardware implementation, advanced optimization techniques, and integration with digital-twin and predictive-control frameworks for next-generation smart power systems.

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