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Dual-Mode Neural Network Control for DC-DC Converters: Adaptive PI Tuning and Online Learning Strategies

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Abstract

This paper presents a dual-mode artificial intelligence-based control approach for robust regulation of DC-DC two-switch forward converters under wide input voltage fluctuations and dynamic load conditions. Two neural network-driven strategies are explored: (1) an adaptive PI controller whose gains are optimized offline via a genetic algorithm and predicted using a feedforward neural network, and (2) an online neural network controller that directly computes the duty cycle in real time using online learning. Extensive simulation studies compare these neural approaches against classical PI and adaptive fuzzy controllers using various quantitative performance metrics, including steady-state error, overshoot, peak time, settling time, and integral error indices (IAE, ISE, ITAE). Simulation results under nominal conditions and multiple disturbance scenarios—including sudden load changes and input voltage drops—demonstrate that both AI-based approaches outperform conventional PI and fuzzy controllers. While the offline-trained adaptive PI controller excels in nominal conditions with minimal steady-state error and overshoot, the online neural network controller offers superior dynamic adaptability and robustness in real-time scenarios. Comparative performance metrics and radar-based multi-criteria evaluations confirm the suitability of these intelligent control strategies for real-time power electronics applications requiring high precision and resilience

Keywords: Two-Switch Forward Converter; Neural Network Control; Adaptive PI Controller; Online Learning; Robust Control; DC-DC Converters; Genetic Algorithm (GA).

1. Introduction

DC-DC converters are essential components in modern electrical and electronic systems, providing efficient voltage regulation to meet the diverse demands of industrial automation, renewable energy integration, electric vehicles, and embedded applications [1–3]. Analogous to transformers in AC systems, these converters facilitate high-efficiency energy transfer in DC environments with minimal losses, making them indispensable in contemporary power electronics design. One of the principal challenges in deploying these converters is maintaining output voltage stability amid wide input voltage variations and unpredictable load conditions. These operational fluctuations, combined with the inherently nonlinear dynamics of switching converters and the presence of parasitic elements and component tolerances, often exceed the capabilities of conventional linear control methods [4,5]. Consequently, achieving robust dynamic performance requires advanced control strategies capable of adapting to real-time changes.

Among existing control architectures, closed-loop voltage-mode control remains widely adopted. This approach continuously monitors the output voltage and regulates it through a feedback mechanism. The Proportional-Integral-Derivative (PID) controller, owing to its simplicity, ease of implementation, and strong steady-state performance, continues to dominate industrial practice [6,7]. However, fixed-gain PID controllers are often inadequate in systems with varying operating points or strong nonlinear behavior, leading to poor transient performance and potential instability [8,9]. To overcome these limitations, adaptive PID controllers have been introduced, allowing for real-time tuning of control parameters in response to system variations. Although adaptive methods offer improved flexibility and performance, they can introduce implementation complexity and often fail to fully capture the nonlinear characteristics of power converters.

This has led to increased interest in artificial intelligence (AI)-based control methodologies. AI techniques have emerged as powerful tools for both system identification and control design in power electronics, particularly due to their ability to model complex, nonlinear, and time-varying behaviors. AI methods can be used to enhance conventional control structures, such as by automatically tuning PID parameters, or to develop entirely data-driven control strategies [10].

A wide variety of robust, adaptive, and intelligent control strategies have been proposed for DC-DC converters in recent years. Table 1 provides a comparative summary of the most prominent methods highlighting their main advantages, limitations, and representative references.

Conventional approaches such as PID controllers are widely used due to their simplicity and availability; however, their performance degrades in nonlinear regimes and under parameter uncertainties. Advanced methods like fuzzy logic, sliding mode control (SMC), model predictive control (MPC), and H-infinity control have been explored to address these limitations, each offering distinct advantages—such as robustness, constraint handling, or multivariable control. Nevertheless, these methods often suffer from inherent drawbacks including chattering, dependence on precise system models, tuning complexity, or high computational burden, limiting their practical deployment in real-time embedded applications. In this context, neural network-based controllers present a compelling alternative, offering the ability to approximate complex nonlinear mappings, adapt to varying conditions, and respond swiftly to disturbances—all without requiring explicit system modeling. These features make them particularly suitable for controlling power converters with non-ideal characteristics and fluctuating inputs.

Motivated by these developments, this paper presents a comprehensive study of two advanced intelligent control strategies for a two-switch forward converter: (1) an adaptive PI controller with ANN-based online gain tuning, and (2) a fully online neural network controller that generates the control signal directly in real time.

The performance of both approaches is rigorously evaluated and compared under wide input voltage variations and load disturbances, highlighting the benefits and limitations of each control paradigm for robust voltage regulation in medium-power applications.

The remainder of this paper is structured as follows:

Section 2 presents the system design and mathematical modeling of the two-switch forward converter. Section 3 describes the proposed artificial intelligence-based adaptive PI control strategy, incorporating genetic algorithm-based parameter optimization and neural network-based gain prediction, and introduces a fully online neural network controller. Section 4 discusses the simulation results and provides a comparative analysis of the two control strategies under various operating conditions. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. System Design

In medium-power applications requiring electrical isolation, voltage step-down, and reliable performance, selecting an appropriate DC-DC converter topology is crucial. Among isolated DC-DC converter topologies, the forward converter is a common choice for medium-power applications due to its efficiency and simplicity. However, the conventional single-switch design is prone to transformer core saturation and subjects the switch to high voltage stress. To mitigate these issues, the two-switch forward converter was introduced as an improved variant. By adding a second switch and diode, this topology ensures complete transformer demagnetization and limits switch voltage stress to the input voltage, enhancing both reliability and performance under varying input conditions.

Table1. Comparison of Control Strategies for Power Electronic Converters.

Control method	Main advantages	Main limitations	REF
Proportional–Integral–Derivative (PID)	Simple implementation; reliable for linear systems; widely available and understood	Poor performance in nonlinear systems; limited dynamic response; narrow operating range	[11]
Pid Optimized with Particle Swarm Optimization (PSO)	Simple structure; fast convergence	Susceptible to local minimum; potential instability	[12,13]
Pid Optimized with Genetic Algorithm (GA)	Improved robustness; maintains diversity in solutions	Computationally intensive; slow convergence rate	[12,14]
Fuzzy Logic Controller (FLC)	Simple control design; flexible and generalizable; effective for black-box systems	Highly dependent on rule base quality; potential complexity in rule management; requires expert knowledge	[15,16]
Artificial Neural Network (ANN)	Predictive control ability; fast adaptation to system changes	High computational cost; performance sensitive to training data quality; complex design	[17]
Neuro-Fuzzy Controller	Combines learning ability of neural networks and interpretability of fuzzy systems; reduced chattering; parameter tuning flexibility	Complex design and tuning; limited analytical transparency; high computational burden	[18]
H-Infinity Control (H∞)	Robust stability against uncertainties; suitable for multivariable systems; effective noise attenuation; flexible in reference tracking	Requires highly accurate modeling; complex synthesis and implementation	[19,20]
Model Predictive Control (MPC)	Handles constraints on variables and outputs; supports receding horizon policy; robust against disturbances; ensures optimal control sequence	High computational complexity; strong dependence on accurate model; tuning is challenging; implementation is nontrivial	[21,22]
Sliding Mode Control (SMC)	High robustness against parameter variations and disturbances; smooth mode transitions; fast and accurate dynamic response	Chattering effect; difficult implementation; sensitive to parameter tuning	[23,24]

Compared to alternatives such as push-pull, half-bridge, or full-bridge converters, the two-switch forward design offers a compelling balance between cost, complexity, and robustness—making it well-suited for intelligent control implementations such as neural network-based adaptive systems [25,26].

A schematic of the two-switch forward converter is shown in Fig. 1. Key components include two simultaneously operated switches (Q_1, Q_2), an isolation transformer, demagnetizing diodes (D_1, D_2), rectifier diodes (D_3, D_4), an output inductor (L), and a smoothing capacitor (C). The control circuit compares the output voltage with a reference and uses a PI controller to generate the pulse-width modulation (PWM) signal for switch control.

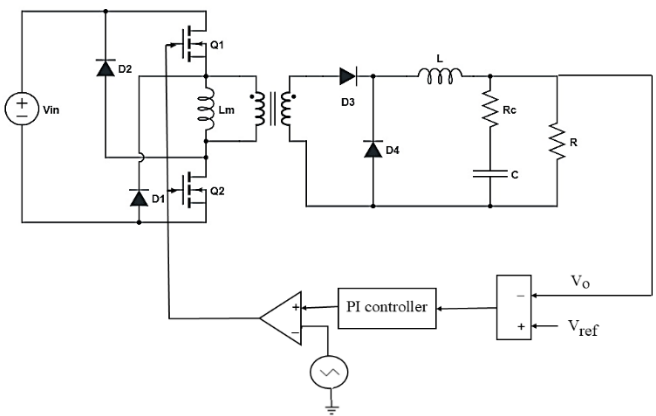


Fig 1. Two-switch forward converter with PI controller.

During the ON interval (T_o□), switches Q_1 and Q_2 conduct, applying the input voltage to the transformer's primary winding and inducing voltage across the secondary. Diode D_3 conducts, delivering current through the output inductor and load, while the output capacitor charges. Diode D_4 remains off. In the OFF interval ($T_o$ff), switches turn off, and the transformer's stored energy is returned to the source via D_1 and D_2. On the secondary side, D_4 conducts, continuing current flow to the load using the energy stored in the output inductor and capacitor.

For analysis and control design, the converter is modeled using the averaged state-space method under continuous conduction mode (CCM). By segmenting the operation into ON and OFF states and applying Kirchhoff's laws, time-domain equations are developed and averaged over a switching cycle. Small-signal perturbations are then introduced around a nominal operating point, yielding a linearized model.

Transforming this model into the Laplace domain gives a second-order transfer function of the form.

$$T_D(s)=\frac{V_o(s)}{D(s)}=\frac{nV_{in}(1+\frac{s}{\omega_z})}{1+\left(\frac{s}{Q\omega_0}\right)+\left(\frac{s}{\omega_0}\right)^2} \tag{1}$$

Here, n denotes the transformer's turns ratio, and V_{in} is the input voltage. The term $\omega_z=\frac{1}{R_cC}$ represents a zero introduced by the output capacitor and load resistance, while $\omega_0=\frac{1}{\sqrt{LC}}$ is the natural resonant frequency of the output LC filter. The quality factor Q, given by $Q=\frac{1}{\omega_0}(\frac{R}{RR_cC+L})$, reflects the damping characteristics of the system [27].

The PI controller regulates the output voltage V_o by comparing it to a reference V_{ref} and generating a control signal. This signal includes a proportional term for immediate error response and an integral term to eliminate steady-state error. The result is compared to a sawtooth waveform to produce the PWM signal, which modulates the duty cycle of Q_1 and Q_2. This closed-loop process ensures stable output despite input or load disturbances.

Precise tuning of Proportional-Integral-Derivative (PID) controller parameters is essential for achieving reliable and efficient control performance in dynamic systems. Despite their widespread use in industrial practice, conventional manual tuning methods often produce suboptimal results. These methods typically rely on iterative trial-and-error procedures and lack the adaptability needed to handle varying operating conditions [28,29]. Their limitations become particularly evident in nonlinear or time-varying systems, where fixed-gain controllers are unable to respond effectively to dynamic changes. This often results in excessive overshoot, prolonged settling times, and overall performance degradation [30–32]. To overcome these challenges, artificial intelligence (AI)-based tuning strategies have garnered increasing attention due to their inherent capabilities in adaptability, learning, and robustness.

3. Controller Design

To enhance the control performance of the two-switch forward converter under wide input variations, as seen in Fig. 2, artificial intelligence (AI)-based methods are considered. In this study, two different AI-based control strategies are explored and analyzed in the following subsections.

3-1. AI-Based Adaptive PID Controller

To achieve robust voltage regulation across a wide input voltage range, this study proposes a hybrid control strategy that integrates a genetic algorithm (GA) with an artificial neural network (ANN). The GA was chosen for its global optimization capability, independence from gradient information, and proven effectiveness in solving complex, nonlinear, and high-dimensional optimization problems [33,34]. By leveraging the exploratory power of GA and the adaptive learning capacity of ANN, the proposed approach facilitates dynamic and accurate control of the converter.

In the first stage, to facilitate controller design and performance analysis, a set of transfer function models was developed for the converter across a range of input voltages, from 254.56 V to 332.41 V in 0.75 V increments. Each model was derived in the Laplace domain based on the converter's electrical characteristics, incorporating parameters such as inductance L = 560 µH, capacitance of C = 318 µF, load resistance of R = 1 Ω, transformer turns ratio of n = 0.92, and a switching frequency of f□ = 50 kHz. To reflect real-world variability, ±5% perturbations were introduced to L, C, and R using Gaussian noise, simulating component tolerances and environmental effects. Each perturbed configuration yielded a small-signal transfer function approximated as a second-order system with an added zero, based on the converter's natural and zero frequencies. All models were stored in a .mat file for subsequent use in optimization and training.

In the second stage, for each modeled input voltage, a genetic algorithm (GA) was used to optimize the PI controller gains K_p and K_i. The objective was to minimize the tracking error between the output voltage and the 85 V reference, quantified by the cost function:

$$J = \sum(Vref - y(t))2 \quad (2)$$

where y(t) is the system's response to a unit step input.

The GA was initialized with 50 candidate solutions, each representing a unique (K_p, Ki) pair. Solutions were evaluated based on their performance in closed-loop simulations, and the best-performing candidates were selected through evolutionary operations (selection, crossover, and mutation) over successive generations. The resulting optimal gain values for each input voltage were stored and used to train the neural network.

In the third stage, a feedforward neural network was developed to predict the PI gains K_p and K_i as a function of the input voltage. The training dataset, generated from the GA-optimized parameters, was preprocessed by removing outliers using the interquartile range (IQR) method and smoothed with a moving average filter to reduce noise. The input–output pairs were normalized and divided into training (70%), validation (15%), and testing (15%) sets. The network architecture consisted of two hidden layers with 32 neurons each and was trained using the Bayesian Regularization algorithm to ensure generalization and prevent overfitting.

Fig. 3(a) illustrates the training progress of the neural network using the Mean Squared Error (MSE) across training (blue), validation (green), and test (red) datasets over 28 epochs. The minimum validation error (0.011839) is achieved at epoch 13, marking the optimal generalization point. Beyond this epoch, validation and test errors begin to increase, indicating the onset of overfitting. Although the training error continues to decrease, the lack of improvement in validation accuracy justifies early stopping at epoch 13 to preserve model generalization.

Fig. 3(b) presents the evolution of key training metrics using the Levenberg–Marquardt algorithm. The steadily decreasing gradient, reaching 0.031346, confirms effective convergence. The learning rate remains stable at 0.05 during the final epochs, suggesting consistent optimization dynamics. The network contains approximately 106.5 parameters, with a total weight magnitude of 9467.5146, reflecting moderate model complexity. Stabilization of parameters such as gamk and ssX further supports the attainment of a steady training state. Although the maximum number of failed validation checks (15) is reached at epoch 28, triggering early stopping, training was halted precisely at the point of best validation performance, avoiding significant overfitting and ensuring optimal generalization.

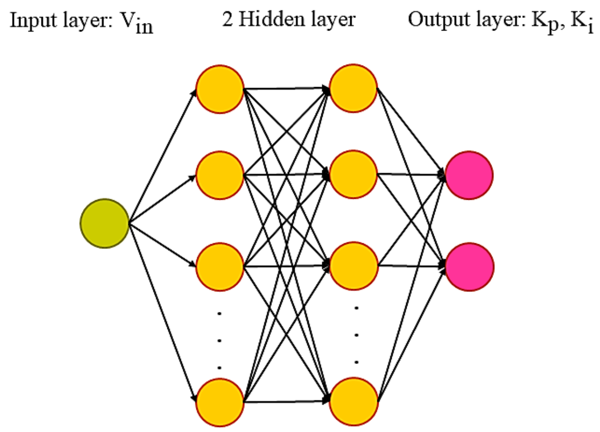
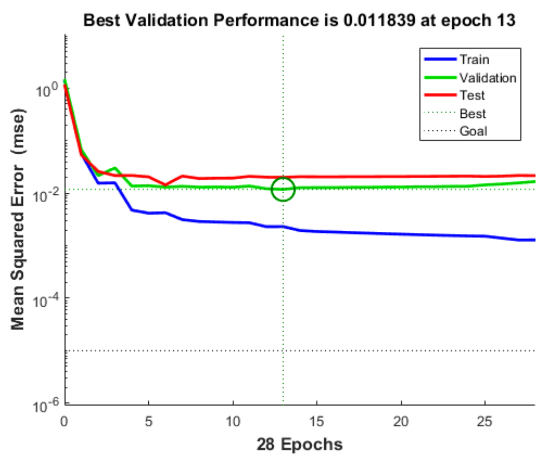
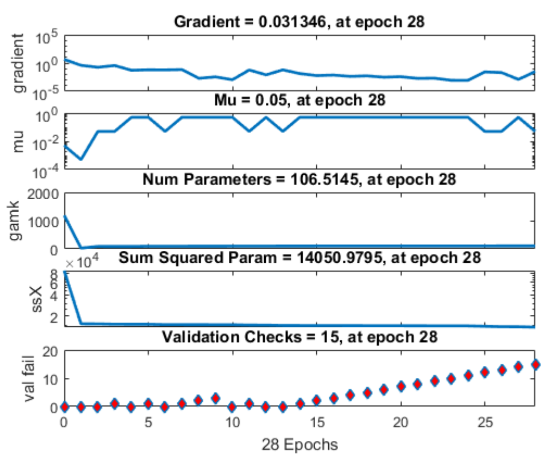


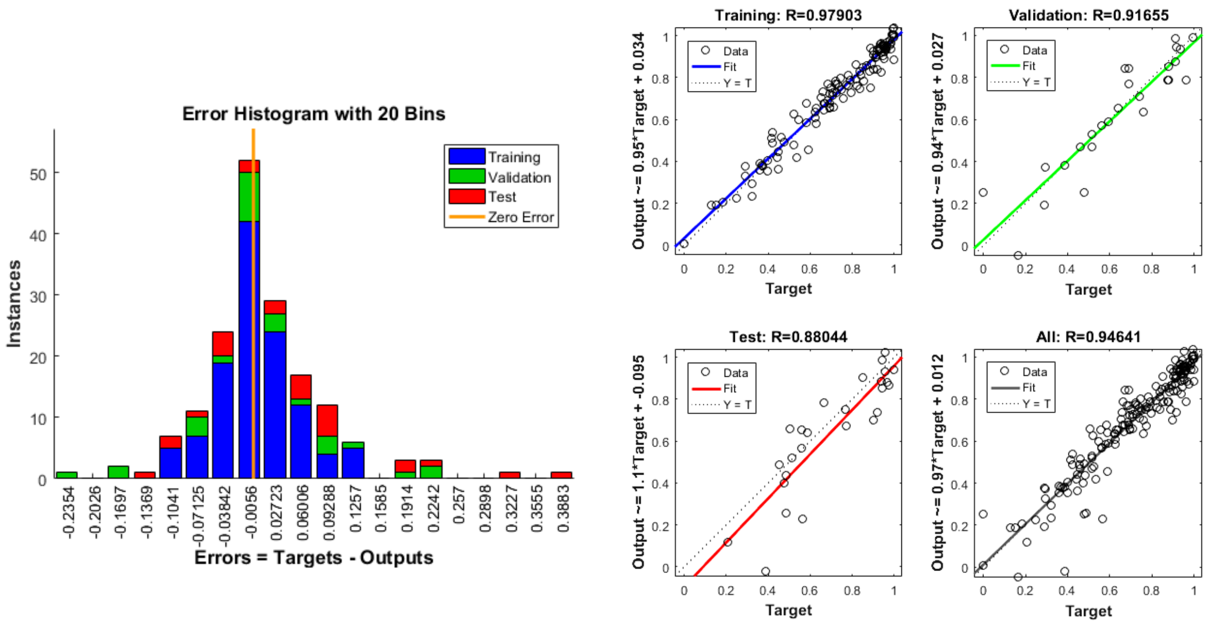
Fig 2. The feedforward neural network architecture includes input, output and hidden layers.



(a)



(b)



(c) (d)

Fig 3. Training and evaluation results of the online neural network controller. (a) Mean Squared Error (MSE) diagram. (b) Neural Network training state performance. (c) The error histogram diagram. (d) The regression for the training, validation, and test inputs, along with all the data.

Fig. 3(c) shows the error histogram with 20 bins, depicting the distribution of prediction errors across training, validation, and testing sets. The majority of errors cluster near zero, with a symmetric, bell-shaped distribution—indicating high predictive accuracy, minimal bias, and good generalization.

The regression plots in Fig. 3(d) further evaluate model performance across training, validation, testing, and combined datasets. High correlation coefficients (R = 0.97903, 0.91655, 0.88044, and 0.94641, respectively) confirm strong agreement between predicted and target values. The close alignment of the regression lines with the ideal diagonal (Y = T), along with the balanced distribution of data points, reinforces the model's reliability and robustness across both seen and unseen data.

The overall design framework—including system modeling, GA-based tuning of PI gains, and ANN-based gain predictions depicted in Fig. 4.

Ultimately, the proposed controller is interfaced with the converter as illustrated in Fig. 5.

The structure described in this section utilizes a neural network to determine the coefficients of the PI controller; however, the training process in that case is performed offline, prior to deployment. To enhance the flexibility and responsiveness of the controller to instantaneous changes in operating conditions, a real-time adaptive structure based on an online neural network is proposed in the following.

3-2. Online Neural Network-Based Controller Design

A real-time neural network-based controller is designed to dynamically regulate the duty cycle of the converter, ensuring convergence of the output voltage to the desired reference. The network is trained online, with its weights and biases updated during system operation.

The proposed controller employs a feedforward neural network with a single hidden layer. Its architecture is as follows:

- **Inputs:** Three signals—filtered error, error derivative, and error integral—are used as inputs to reflect the system's dynamic behavior and support adaptive control.
- **Hidden layer:** Consists of 5 neurons with hyperbolic tangent activation functions.
- **Output layer:** A single neuron with a sigmoid activation function generates the duty cycle.

Prior to input propagation, normalization is applied to prevent saturation and instability. The forward pass involves computing weighted sums and activations, resulting in a duty cycle output, which is then smoothed by a first-order low-pass filter:

$$D_{filtered}=\alpha_f D+(1-\alpha_f)D_{prev} \tag{3}$$

where $\alpha_f=\frac{dt}{\tau+dt}$ and τ is the filter time constant [33].

Online training is performed using the backpropagation algorithm. At each time step:

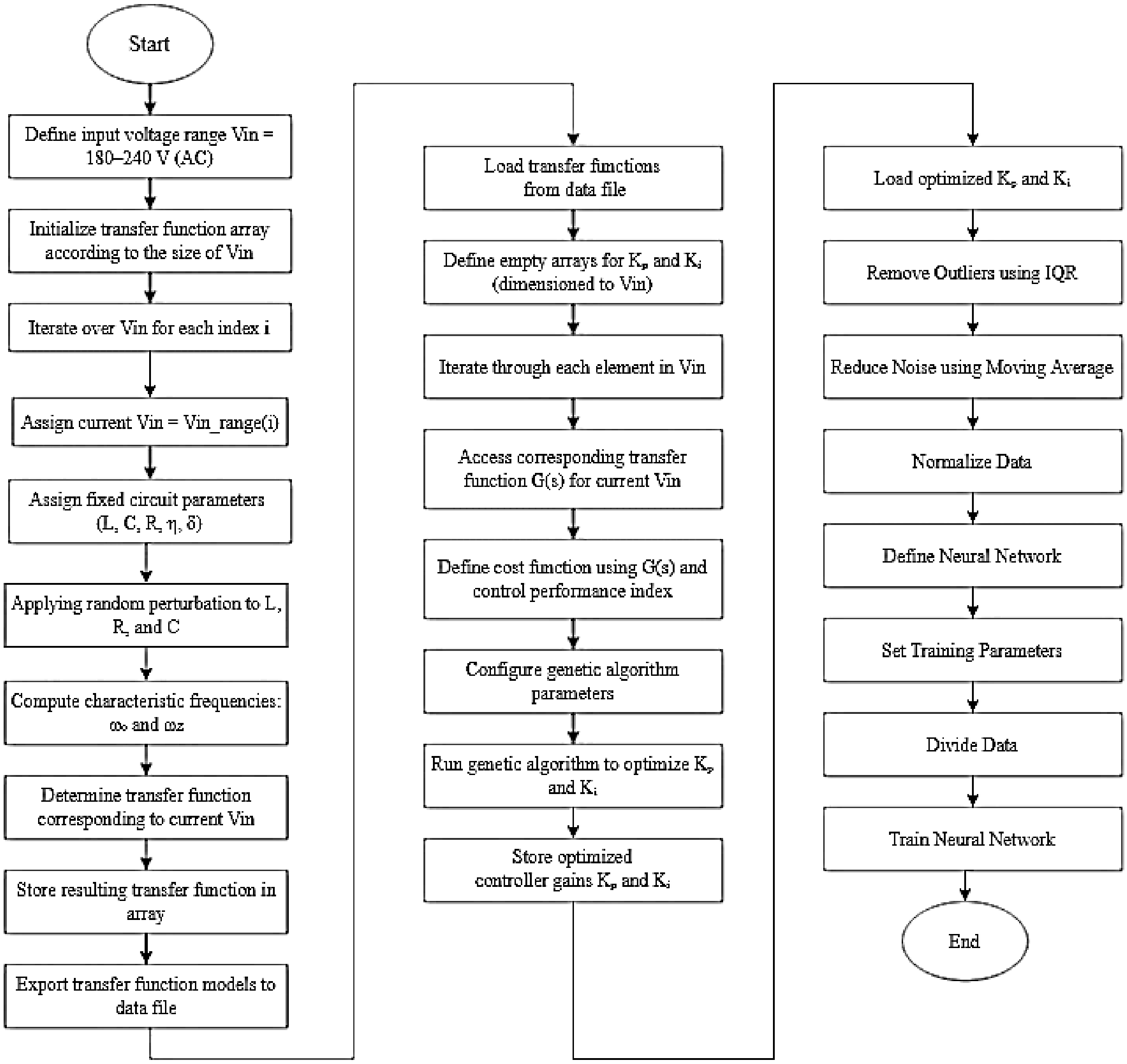


Fig. 4. Flowchart of the proposed AI-based adaptive PID controller design process.

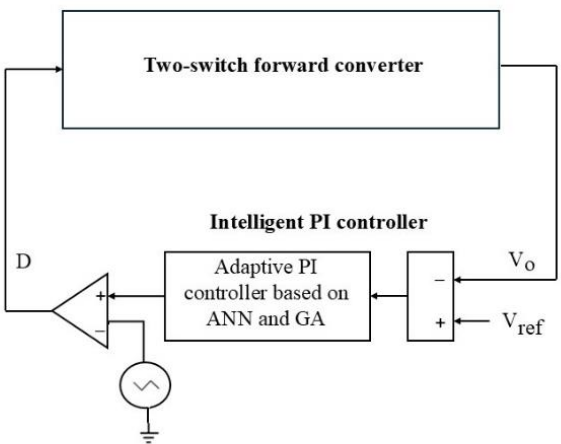


Fig. 5. DC-DC Converter System with Intelligent PI Controller.

1) **Error gradient** is computed using the derivative of the sigmoid function.
2) **Backpropagation** transmits the error to the hidden layer and calculates gradients.
3) **Weight updates with momentum** are applied to enhance convergence and suppress oscillations.
4) **Exponential decay of learning rate** is used to stabilize long-term training:
   1)

$$\eta_{step} = \eta_{int} \times \text{decay rate}^{(step-1)} \quad (4)$$

   2) **Weight and bias constraints** are imposed to prevent divergence.

Persistent variables are used to retain the network's state between iterations, including weights, biases, previous gradients, and filtered error components.

Fig. 6 illustrates the proposed controller design process.

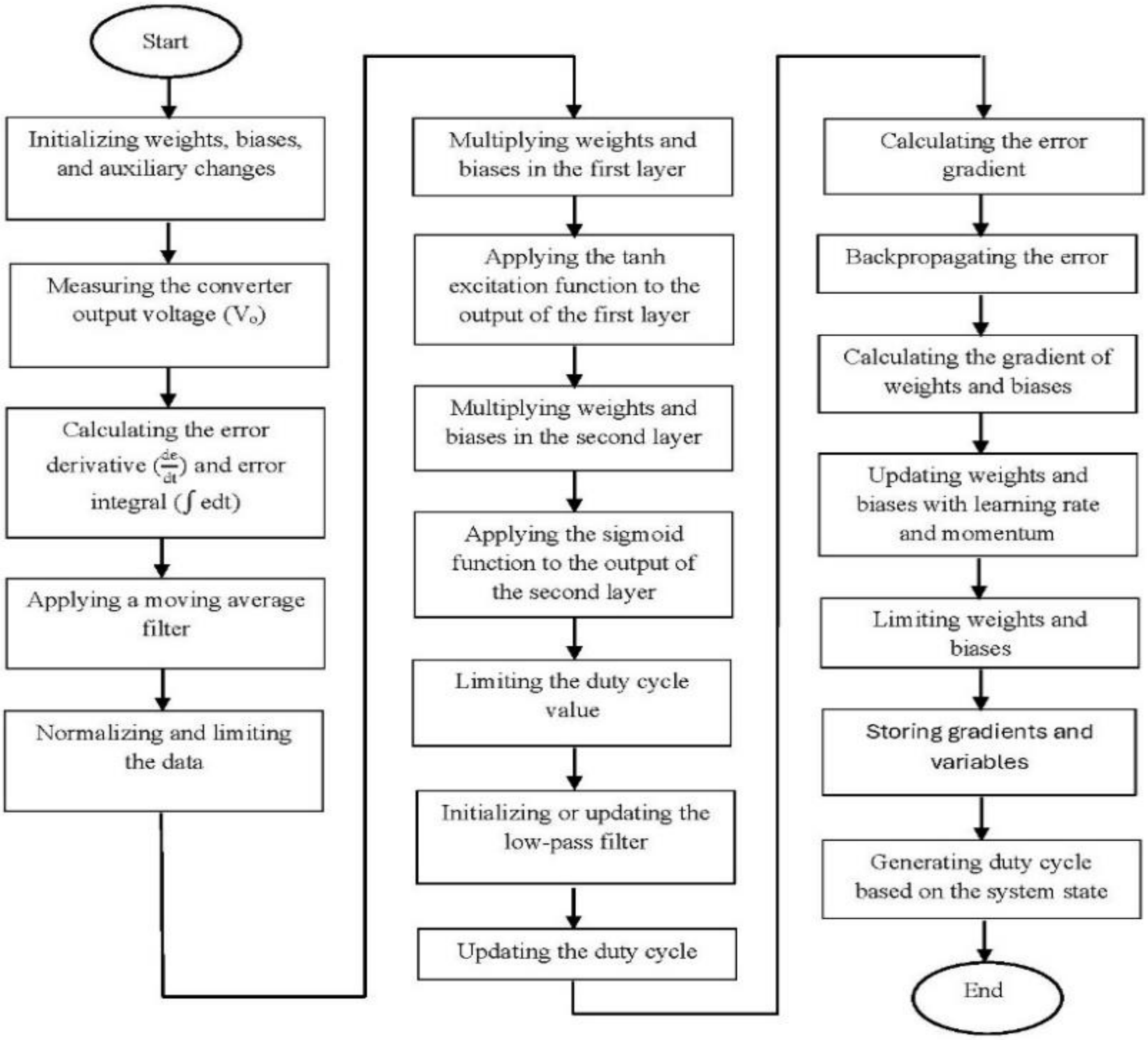


Fig 6. Flowchart of the proposed online NN controller design process.

In the final implementation, the proposed controller interacts with the converter according to the configuration shown in Fig. 7.

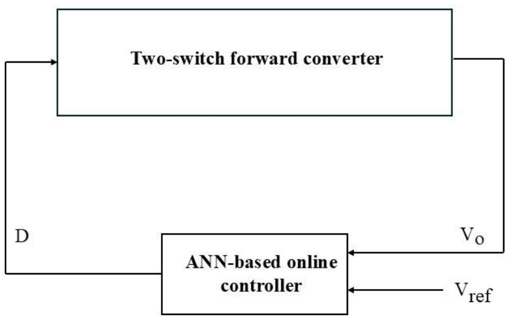


Fig 7. DC-DC Converter System with ANN-Based Online Controller.

4. Simulation Results and Discussion

This section initially outlines the real-time training process of the neural network-based controller, as depicted in Fig. 9.

The neural network was trained to model and control the converter under a randomly varying input voltage of 271.6 V. Fig. 4(2) illustrates the learning dynamics over 2000 training steps, including error convergence and the evolution of network parameters.

The top-left plot shows the network output error decreasing rapidly and stabilizing near zero, indicating successful learning. The top-middle and top-right plots depict the convergence of weights between the input-hidden and hidden-output layers, respectively. After initial fluctuations, the weights stabilize, demonstrating the network’s ability to extract relevant features and map them effectively to the output. The bottom-left and bottom-right plots show the evolution of biases in the hidden and output layers. Similar to the weights, the biases converge to steady values, indicating the network's internal structure has reached stability.

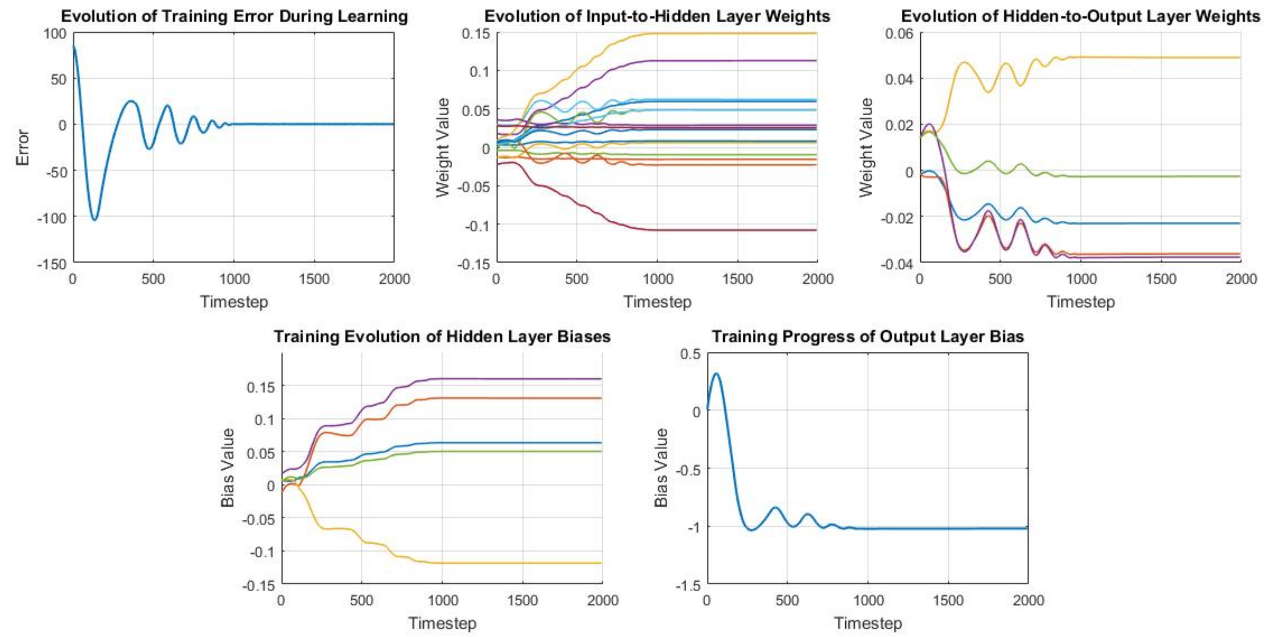


Fig 9. Evolution of the Error, Weights, and Biases During the Training Process of the Real-Time Neural Network Controller.

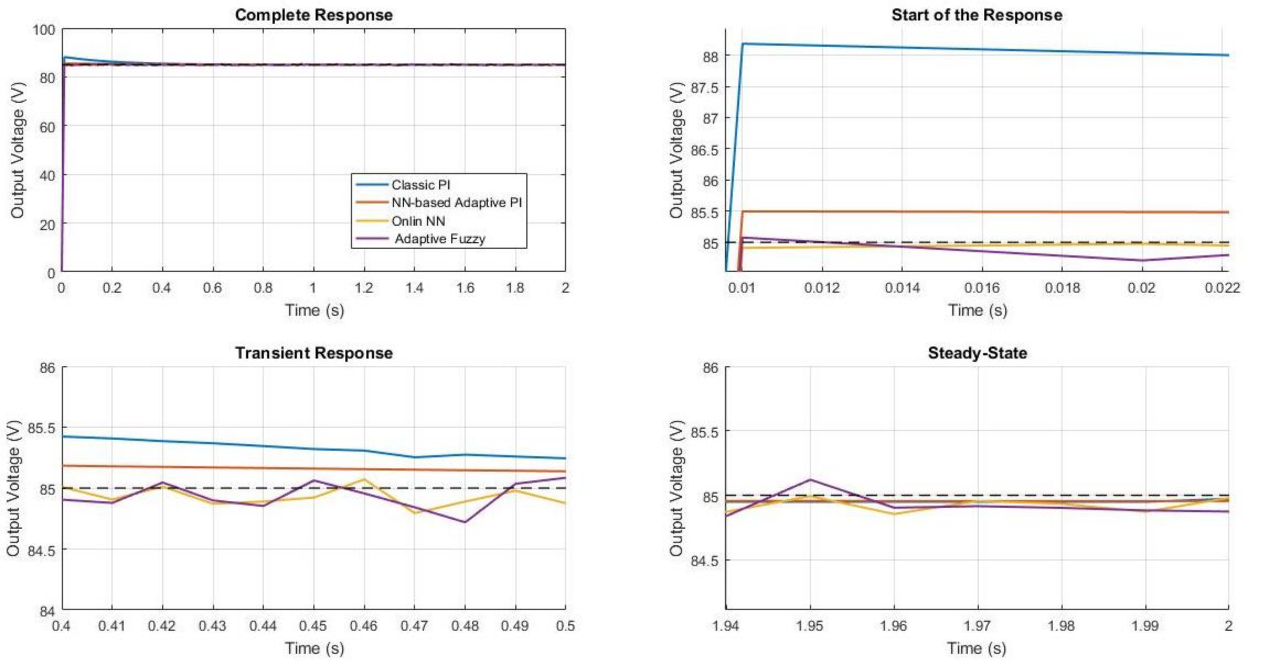


Fig 10. Output voltage of the circuit under the influence of different controllers in identical operating conditions.

Overall, the consistent reduction in error and convergence of weights and biases confirm the effectiveness of the training algorithm and the suitability of the network architecture for stable output control.

Fig. 10 presents the responses of four controllers under identical operating conditions.

In the initial phase (upper-right graph), the conventional PI controller shows the highest overshoot, while adaptive and neural network-based controllers achieve faster convergence with significantly lower overshoot, indicating superior transient performance. During the mid-transient period (lower-left graph), the adaptive neural network-based PI controller demonstrates the least oscillation and highest stability. The adaptive fuzzy and real-time neural network controllers also perform well, maintaining the output voltage close to the reference with limited fluctuations. In the steady-state phase (lower-right graph), both the conventional and adaptive neural network-based PI controllers maintain high accuracy with minimal error and oscillation. The real-time neural controller shows similar behavior, whereas the adaptive fuzzy controller exhibits a comparatively larger steady-state error.

Table 2. Performance indices of the circuit under the influence of various controllers under identical operating conditions.

Controller	Steady state error (V)	Overshoot (%)	Peak time (S)	Settling time (S)	Standard deviation	IAE	ISE	ITAE
Classic PI	0.048	3.750	0.010	0.140	0.006	1.524	73.310	0.188
Adaptive fuzzy	0.092	0.590	0.950	0.010	0.091	1.102	72.290	0.239
NN-based Adaptive PI	0.044	0.580	0.010	0.010	0.001	1.051	72.30	0.094
Online NN	0.060	0.110	0.130	0.010	0.058	0.987	72.264	0.139

Detailed performance metrics for all controllers are summarized in Table 3, highlighting their respective strengths and limitations under identical operating conditions.

Overall, based on the results presented in Table 2, it can be concluded that the adaptive PI controller based on a neural network outperforms the other methods across most performance metrics. The real-time neural network controller, despite exhibiting some reduction in accuracy, demonstrates a fast response with minimal overshoot, indicating its suitability for real-time applications.

In the next stage, the system's performance was evaluated under three distinct perturbation scenarios. The objective of this analysis is to assess the controllers' ability to maintain stability and regulate the output voltage under non-nominal and disruptive operating conditions:

- **Scenario 1** involves a sudden increase in load, where the system load instantaneously doubles at a specific moment. This case evaluates the controller's responsiveness and its ability to maintain the output voltage at the desired level.
- **Scenario 2** corresponds to a severe input voltage drop from 300 V to 250 V. This scenario is designed to examine system stability and control performance in response to substantial variations in the power supply.
- **Scenario 3** combines both disturbances described above, where the load increases and the input voltage decreases simultaneously. This represents the most challenging condition and serves as a critical benchmark for evaluating the adaptability and robustness of the controllers under extreme operating circumstances.

For each of these scenarios, the variations in output voltage are depicted in Fig. 11. The controllers’ performances are analyzed and compared both quantitatively and qualitatively.

Under Scenario 1, both the classical PI controller and the adaptive neural network-based PI controller effectively regulate the output voltage at the reference level, exhibiting minimal oscillations and demonstrating high stability. In contrast, the real-time neural network and adaptive fuzzy controllers, while able to maintain the voltage near the reference, show greater oscillatory behavior, indicating lower stability. Table 4 presents the various performance metrics for this operating condition.

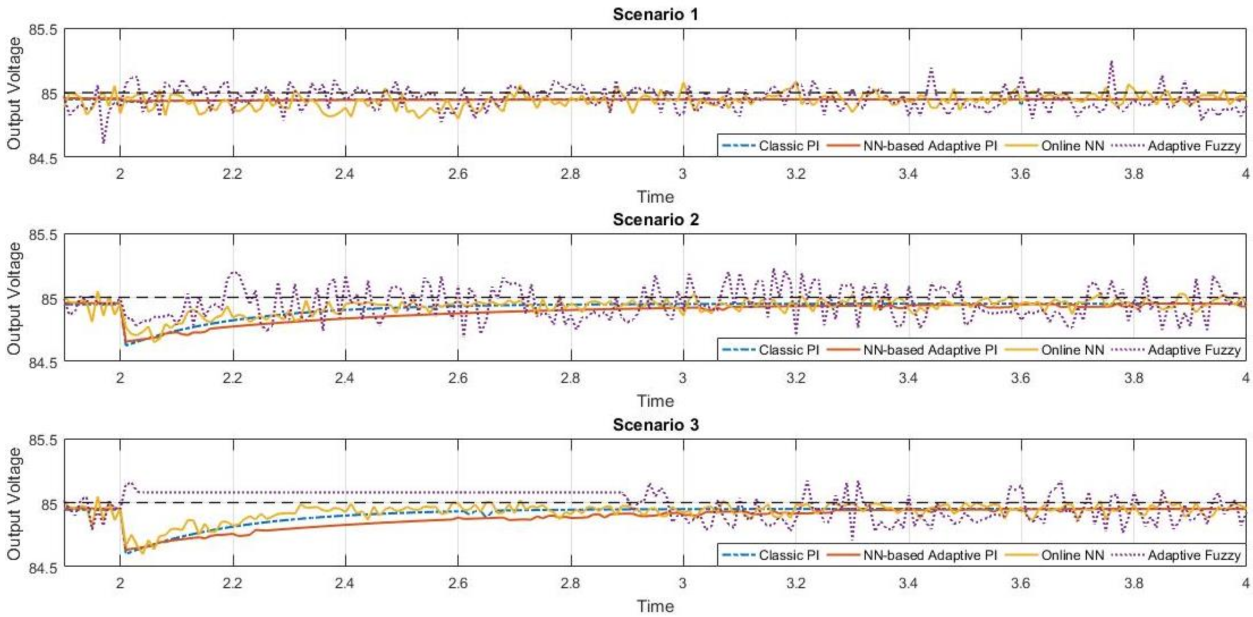


Fig 11. Output voltage response of the system under different controllers during various disturbance tests.

Table 3. Performance indices of the system under different controllers during the load step disturbance.

Controller	Steady state error (V)	Overshoot (%)	Peak time (S)	Settling time (S)	Standard deviation	IAE	ISE	ITAE
Classic PI	0.050	0	-	0	0.006	0.108	0.006	0.104
Adaptive fuzzy	0.087	0.290	1.76	0	0.084	0.162	0.019	0.17
NN-based Adaptive PI	0.052	0	-	0	0	0.110	0.006	0.106
Online NN	0.037	0.1	1.2	0	0.040	0.140	0.014	0.118

The results indicate that the PI and neural network-based adaptive PI controllers outperform the others in most performance metrics, showing zero overshoot, minimal steady-state error, and high stability. In contrast, the adaptive fuzzy controller exhibits the highest overshoot, error, and standard deviation. All controllers achieve zero settling time, but overall, the PI-based controllers demonstrate the most effective and stable performance.

In Scenario 2, following a sharp input voltage drop, the PI controller sustains a stable response with minor deviations and low oscillations. The adaptive neural network-based PI controller performs similarly, often surpassing the classical PI in terms of reduced oscillations and steady tracking. The real-time neural network controller shows moderate initial oscillations that quickly settle, while the adaptive fuzzy controller exhibits the highest oscillations and frequent deviations, reflecting reduced stability under input voltage disturbances.

The results show that the online neural network controller achieves the lowest steady-state error and outperforms others in all integral error indices (IAE, ISE, ITAE), especially under severe input disturbances. Although it has the highest peak time, it maintains strong overall performance. The PI and neural network-based adaptive PI controllers also perform well in terms of stability and low oscillation. In contrast, the adaptive fuzzy controller exhibits the highest overshoot, steady-state error, and error indices, indicating the weakest performance in this scenario.

In Scenario 3, which combines both increased load and decreased input voltage, the PI and adaptive neural network-based PI controllers maintain output voltage near the reference with acceptable oscillation levels. The real-time neural controller initially dips but recovers rapidly and stabilizes effectively. Conversely, the adaptive fuzzy controller shows the greatest instability, with significant and persistent deviations from the reference. Overall, the adaptive neural network-based PI controller consistently demonstrates strong performance and robustness across all scenarios.

Table 4. Performance indices of the system under different controllers in response to input voltage step disturbance.

Controller	Steady state error (V)	Overshoot (%)	Peak time (S)	Settling time (S)	Standard deviation	IAE	ISE	ITAE
Classic PI	0.049	0	-	0	0	0.168	0.023	0.113
Adaptive fuzzy	0.050	0.27	1.6	0	0.008	0.251	0.04	0.242
NN-based Adaptive PI	0.052	0	-	0	0	0.230	0.036	0.159
Online NN	0.044	0.03	1.74	0	0.043	0.153	0.019	0.112

Table 5. Performance indices of the system under different controllers during load and input voltage disturbance.

Controller	Steady state error (V)	Overshoot (%)	Peak time (S)	Settling time (S)	Standard deviation	IAE	ISE	ITAE
Classic PI	0.049	0	-	0	0	0.172	0.025	0.113
Adaptive fuzzy	0.071	0.2	1.22	0	0.095	0.200	0.024	0.216
NN-based Adaptive PI	0.050	0	-	0	0	0.235	0.039	0.155
Online NN	0.047	0.02	1.71	0	0.041	0.148	0.020	0.109

Table 5 reveals that the online neural network controller offers the best steady-state accuracy and the lowest peak time among all controllers. It also achieves the lowest error values in IAE, ISE, and ITAE indices. In contrast, the adaptive fuzzy controller shows the highest overshoot, peak time, steady-state error, and standard deviation, indicating the weakest overall performance. The PI and neural network-based adaptive PI controllers show no overshoot and minimal standard deviation, reflecting strong stability. Overall, the online neural network controller demonstrates superior accuracy and effectiveness compared to the other control strategies.

Fig. 12 presents a comparative analysis of the performance of four controllers using a radar chart. Initially, the performance data are normalized using the Z-score method. Given that lower criterion values correspond to superior performance, the normalized values are subsequently inverted to ensure that better-performing points lie closer to the outer boundary of the chart.

For each controller, a corresponding polygonal region is constructed on the radar chart. The area enclosed by each polygon is then computed using the Gaussian sweep (shoelace) method. The controller associated with the largest enclosed area is considered to exhibit the most favorable overall performance among the compared controllers.

The analysis of quantitative performance indices indicates that the neural network-based adaptive PI controller demonstrates high accuracy and favorable transient performance under nominal operating condition and load step disturbance. In most evaluated criteria, it outperforms conventional control strategies. Nonetheless, under severe disturbances, its effectiveness diminishes in certain metrics, particularly ITAE and steady-state error.

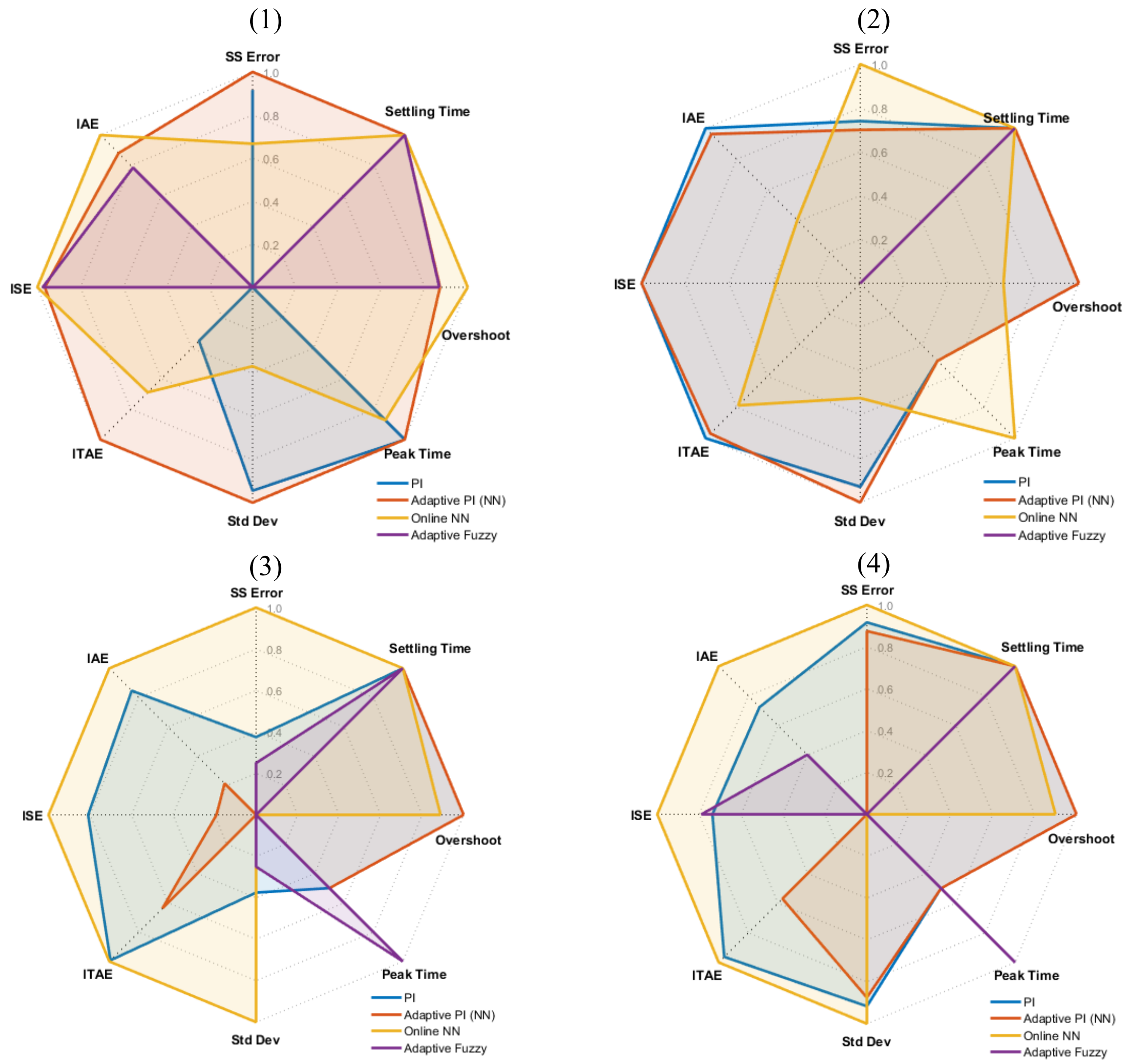


Fig 12. Multi-Criteria Performance Evaluation of Controllers Using Radar Chart Under Different Operating Scenarios: (1) Nominal Condition, (2) Scenario 1, (3) Scenario 2, (4) Scenario 3.

Conversely, the neural network-based real-time controller, despite exhibiting a marginal decline in metrics such as peak time and final accuracy, consistently delivers a fast, stable, and reliable response across complex and time-varying operating scenarios. This controller exhibits superior performance in critical conditions, achieving minimal steady-state error, reduced overshoot, and lower values in integral error indices. Owing to its adaptive and smooth dynamic behavior, it is particularly well-suited for real-time applications operating under non-nominal and uncertain conditions.

In summary, the following conclusions can be drawn:

- Under normal and predictable operating conditions, the adaptive PI controller based on neural networks offers high precision and satisfactory transient behavior, making it a suitable and efficient choice;
- In contrast, under disturbed, uncertain, or real-time conditions, the neural network-based real-time controller, by leveraging online learning mechanisms, provides enhanced stability and improved dynamic performance relative to conventional approaches.

5. Conclusion

This study investigated and compared two neural network-based control strategies for enhancing the performance of a two-switch forward DC-DC converter operating under variable conditions. The first method, an adaptive PI controller trained offline with a genetic algorithm and neural network, demonstrated excellent performance in nominal and mildly disturbed environments, offering high accuracy, minimal overshoot, and stable voltage regulation. The second method, an online neural network controller with real-time weight adaptation, proved more effective in complex and highly dynamic operating scenarios. It achieved faster convergence, lower steady-state error, and improved disturbance rejection, particularly under simultaneous voltage and load perturbations.

Simulation results confirmed that both AI-based methods outperform traditional PI and fuzzy controllers in transient and steady-state metrics. Notably, the online neural controller exhibited superior real-time adaptability without requiring prior system modeling or predefined gain values, making it ideal for embedded applications with time-varying or uncertain conditions.

Overall, the findings suggest that a hybrid control architecture, leveraging offline optimization for baseline performance and online learning for adaptive refinement, holds significant promise for future high-efficiency, intelligent power converter designs. Future work may focus on hardware implementation, training acceleration techniques, and the integration of reinforcement learning or meta-learning for enhanced real-time adaptability.

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Biography

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