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Research Paper

PERFORMANCE ENHANCEMENT OF QUADRATIC BUCK–BOOST DC–DC CONVERTER USING ANN CONTROL

CH.SWETHA,
PG scholar,
sree dattha institute of engineering and science, ibrahimptnam,501510,
chikkulapalliswetha@gmail.com
MADRAM VIKRAMGOUD,
Associate professor,
sreedattha institute of engineering and science
Ibrahimptnam,501510
Vikramgoud@sreedattha.ac.in
Dr.UMAPATHI REDDY,
Professor,
Sree dattha institute of engineering and science, ibrahimptnam,501510
Dr.umapathireddyp@gmail.com

ABSTRACT

This study presents the design and MATLAB/Simulink-based performance evaluation of a quadratic buck-boost DC–DC converter governed initially by a conventional Proportional–Integral (PI) regulator, and subsequently by an Artificial Neural Network (ANN) controller. The converter topology affords continuous input and output currents, rendering it well-suited to renewable-energy systems and electric-vehicle applications that demand stable voltage regulation amid varying input and load conditions. In the first instance, the system was simulated under the PI controller to govern the output voltage in both buck and boost regimes. Thereafter, the PI regulator was supplanted by an ANN controller, trained on input–output data derived from the converter's dynamic response. The ANN controller adaptively captured the system's nonlinear characteristics, yielding improved transient behaviour, diminished steady-state error, and enhanced voltage stability. Comparative simulation results demonstrate that the ANN-controlled converter attains a higher output voltage in boost mode and sustains a lower but stable voltage in buck mode, with smoother transitions and reduced overshoot. These outcomes indicate that the ANN-based strategy out-performs the conventional PI approach, offering superior robustness, more rapid convergence and improved efficiency under dynamic operating conditions. Consequently, the proposed ANN control technique enhances the overall performance of the quadratic buck-boost converter for advanced power-electronic applications.

Keywords: quadratic buck-boost converter; artificial neural network; PI controller; MATLAB/Simulink; voltage regulation; adaptive control; renewable energy systems.

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I INTRODUCTION

In the ever-advancing field of power electronics, the development of converters capable of maintaining efficient and stable operation under variable conditions has become indispensable [1]. Renewable-energy systems and electric-vehicle (EV) technologies, in particular, demand high-performance converters that ensure precise voltage regulation even under fluctuating input sources and dynamic loads [2]. The quadratic buck-boost converter, being an evolution of the classical buck-boost topology, offers a significant advantage by delivering a wider range of voltage conversion ratios and maintaining continuous input and output currents [3]. This characteristic makes it exceptionally suitable for energy systems where both energy inflow and outflow are subject to frequent variation, such as solar photovoltaic arrays and EV powertrains [4]. Moreover, the topology's inherent ability to operate in both buck and boost modes without the need for separate stages has established it as an efficient and compact solution for modern applications [5]. The pursuit of high reliability, low ripple, and adaptive voltage regulation has consequently driven research toward improved control strategies for such converters [6].

Conventional Proportional–Integral (PI) controllers have long been employed in converter systems owing to their straightforward design and ease of implementation [7]. Their effectiveness in linear and moderately nonlinear systems has been well established across various industrial contexts [8]. However, under wide variations in input voltage or load resistance, the PI controller's static gain parameters may not suffice to maintain desired output characteristics, leading to oscillations, overshoot, or steady-state errors [9]. In converters operating in both buck and boost modes, where the transfer function and system dynamics alter significantly, the limitations of the PI controller become increasingly evident [10]. Hence, there arises a necessity for an adaptive or intelligent control mechanism that can capture and compensate for these nonlinearities in real time [11]. Artificial Neural Networks (ANNs), with their remarkable capacity for self-learning and adaptive behaviour, have emerged as a promising alternative for such applications [12]. By training on dynamic system data, an ANN can establish a nonlinear mapping between inputs and outputs, enabling real-time control adjustments without explicit mathematical modelling [13].

The integration of ANN-based controllers in DC–DC converters has been explored in various configurations, such as buck, boost, and SEPIC converters, yielding notable improvements in transient response and steady-state performance [14]. The quadratic buck-boost converter, however, presents a more intricate dynamic profile due to its quadratic voltage relationship and dual-inductor configuration [15]. Hence, the application of ANN control to this topology represents both a technical challenge and an opportunity to push the frontier of converter control design [16]. In this study, the converter was modelled and simulated in MATLAB/Simulink, beginning with a PI-controlled configuration to benchmark system performance [17]. Subsequently, an ANN controller was designed and trained using the converter's input–output data obtained under dynamic conditions, thereby capturing the nonlinear characteristics of the system [18]. This adaptive learning framework enabled the ANN to replace the fixed-gain PI controller and regulate the converter's output with improved precision and resilience [19].

The broader motivation of this research is aligned with global efforts to enhance the efficiency and reliability of power-conversion interfaces in renewable-energy and electric-vehicle systems [20]. In these domains, the ability to maintain consistent voltage regulation despite fluctuating environmental and load conditions is critical [21]. By demonstrating superior performance of the ANN-based controller in comparison with the traditional PI approach, this work contributes to the evolving paradigm of intelligent control in power electronics [22]. It highlights how artificial intelligence can complement conventional control theory to yield robust, adaptive, and efficient solutions [23]. The study not only validates the potential of ANN control for quadratic converters but also underscores its applicability in broader contexts such as grid-connected renewable systems, portable devices, and hybrid EV energy architectures [24]. Consequently, this work marks a meaningful advancement in the pursuit of smart, self-regulating power-electronic systems that can withstand the complexities of real-world operation [25].

II LITERATURE SURVEY

Over the past two decades, a vast body of literature has examined DC–DC converter topologies for renewable-energy integration and electric-vehicle applications [26]. The buck-boost converter, as a fundamental configuration, has been studied extensively for its ability to provide both step-up and step-down voltage conversion [27]. Researchers have progressively evolved this design into quadratic, non-isolated, and high-gain variants to address the growing demand for higher efficiency and wider voltage ranges [28]. The quadratic buck-boost converter, in particular, has garnered attention for its continuous input and output current features, which reduce stress on components and improve overall efficiency [29]. Studies have demonstrated its suitability for photovoltaic systems, where irradiance variations require rapid and reliable voltage regulation [30]. However, the complex dynamic behaviour of the quadratic topology necessitates advanced control mechanisms beyond conventional fixed-parameter methods [1].

Traditional control approaches such as Proportional–Integral (PI) and Proportional–Integral–Derivative (PID) controllers remain widely adopted due to their simplicity and stability [2]. Yet, their performance is often suboptimal when confronted with system nonlinearities, parameter drifts, or disturbances [3]. Scholars have attempted to tune PI parameters dynamically using adaptive algorithms or gain-scheduling techniques [4], though these methods still depend upon accurate system modelling [5]. Recent investigations have explored the integration of fuzzy logic, sliding-mode control, and neural-network-based strategies to address these limitations [6]. Among these, Artificial Neural Networks (ANNs) have stood out due to their data-driven adaptability and generalisation capabilities [7]. By learning the mapping between converter input variables—such as duty cycle, voltage, and current—and output responses, ANNs can approximate nonlinearities and generate control signals that minimise error and improve transient performance [8].

Numerous studies have reported the successful application of ANN controllers in DC–DC converters and renewable-energy systems [9]. In photovoltaic systems, ANN-based controllers have been shown to enhance maximum-power-point tracking (MPPT) efficiency and voltage stability under fluctuating irradiance [10].

In bidirectional converters, ANNs have demonstrated superior current and voltage control compared to traditional methods [11]. Furthermore, ANN control has been utilised in motor-drive applications, such as BLDC drives and induction-motor controllers, to minimise torque ripple and optimise dynamic response [12]. For quadratic buck-boost converters, only a limited number of investigations have been undertaken, primarily focusing on design and steady-state performance analysis [13]. Very few studies have addressed intelligent control implementation for such topologies, signifying a considerable research gap [14]. The present work thus contributes to this gap by applying ANN-based control to a quadratic buck-boost converter and comparing it systematically with a PI-controlled version [15].

Further literature reveals that the effectiveness of ANN controllers depends greatly upon the quality and diversity of training data [16]. Various training algorithms—such as Levenberg–Marquardt, back-propagation, and gradient-descent optimisation—have been evaluated for control-oriented networks [17]. Some authors have employed hybrid approaches that integrate ANN with fuzzy logic or genetic algorithms to enhance convergence and adaptability [18]. These hybrid methods have been found to yield faster responses and lower steady-state errors than standalone PI or ANN controllers [19]. In practical implementations, ANN controllers have also shown greater resilience to measurement noise, component tolerance variations, and parameter drift [20]. Despite their computational overhead, their benefits in dynamic and nonlinear environments make them increasingly viable with the advent of high-speed digital signal processors (DSPs) and field-programmable gate arrays (FPGAs) [21]. The literature hence establishes that ANN-based control represents a forward-looking strategy capable of transforming converter efficiency and adaptability in modern energy systems [22].

The convergence of artificial intelligence with power-electronic converter control thus emerges as a promising research avenue. Several researchers have envisioned self-learning power systems capable of adjusting to fluctuating environmental and operational states without human intervention [23]. Within this paradigm, the quadratic buck-boost converter serves as a pertinent candidate for exploration, given its nonlinear dynamics and dual-mode operation [24]. Comparative studies between ANN and conventional PI control strategies have consistently revealed that ANN controllers yield superior performance across transient and steady-state conditions [25]. Hence, integrating an ANN controller within a quadratic buck-boost topology not only enhances voltage regulation but also contributes toward developing fully autonomous, intelligent power-conversion units [26]–[30]. The cumulative insight from the reviewed literature underscores the necessity and novelty of the present research in extending ANN-based adaptive control to the quadratic buck-boost converter for renewable-energy and electric-vehicle applications.

III METHODOLOGY

The methodology of this research encompasses the complete process of designing, modelling, and evaluating a quadratic buck–boost converter under two distinct control strategies—namely, the conventional Proportional–Integral (PI) controller and the Artificial Neural

Network (ANN) controller. The primary objective is to determine which control scheme provides superior voltage regulation, improved transient performance, and enhanced robustness under dynamic operating conditions. MATLAB/Simulink has been employed as the primary simulation platform because of its versatility, accuracy, and extensive capabilities for power-electronic circuit analysis and control algorithm implementation. The quadratic buck–boost converter topology was first constructed with an emphasis on achieving continuous input and output currents. This topology utilises two inductors and two capacitors, arranged such that the voltage conversion ratio varies quadratically with the duty cycle. Such a configuration provides the ability to operate efficiently in both buck and boost modes, thereby serving as an effective interface for systems requiring stable voltage conversion under varying load and input conditions. The switching frequency was selected at 20 kHz to achieve a compromise between response speed and switching losses. Ideal semiconductor switches were used in the simulation to isolate the performance of the control algorithms from non-ideal device effects.

Initially, a conventional PI controller was designed and implemented to establish a performance benchmark for the converter. The design parameters of the PI controller were tuned through a series of simulations to obtain a stable yet responsive output. The proportional gain was adjusted to enhance dynamic response, whereas the integral gain was selected to eliminate steady-state error. The controller regulated the duty cycle of the converter's MOSFET switch to maintain the desired output voltage irrespective of input and load variations. The output voltage, current ripple, and transient behaviour were observed and recorded under different operating conditions, including step changes in input voltage and load resistance. These results served as reference data for comparison with the ANN-based control scheme. Subsequently, an Artificial Neural Network controller was developed to replace the conventional PI controller. The ANN architecture consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer received system variables such as the reference voltage, actual output voltage, and the corresponding error signal. The hidden layer, equipped with nonlinear activation functions such as sigmoid and ReLU, processed these inputs to approximate the converter's complex dynamic relationships. The output layer produced the control signal that determined the appropriate duty cycle for the power switch. This structure allowed the ANN to emulate and improve upon the control dynamics of the conventional PI system.

To train the ANN, data were collected from the PI-controlled converter simulation, capturing the relationship between the error signal and the corresponding control action over a range of operating conditions. The network was trained offline using the Levenberg–Marquardt algorithm, chosen for its rapid convergence and efficiency in moderate-sized networks. Training continued until the mean-square error between predicted and actual control signals fell below a predetermined threshold. Once trained, the ANN was embedded into the converter model as a real-time controller that dynamically generated the PWM duty ratio based on instantaneous error measurements. The testing phase involved subjecting both controllers to identical operating conditions, including variable input voltages, fluctuating loads, and sudden reference-voltage changes. Performance metrics such as overshoot, rise time, settling time, and steady-state error were evaluated for each case. Additionally, total harmonic distortion (THD) in the output voltage and converter efficiency were measured to assess waveform quality and energy utilisation. The ANN controller demonstrated smoother voltage transitions, reduced oscillations, and significantly improved regulation compared with the PI controller. Further analysis was carried out in both time and frequency domains. Step-response analysis revealed that the ANN-based converter exhibited faster settling time and negligible steady-state error. Frequency-domain analysis, performed using Bode plots, confirmed greater phase and gain margins, indicating improved stability and robustness. The ANN controller's ability to adapt to changing operating conditions without manual retuning was a clear advantage over the fixed-parameter PI regulator. Efficiency evaluation showed that by reducing overshoot and ripple, the ANN controller achieved smoother current flow, which in turn lowered switching losses and improved overall system performance. The methodology thus integrates mathematical modelling, controller design, neural network training, and comprehensive comparative analysis. Through this systematic approach, it becomes evident that the ANN-controlled converter not only surpasses the traditional PI controller in dynamic response but also provides consistent regulation across a broader range of operating conditions. This makes it particularly suitable for renewable-energy and electric-vehicle systems, where voltage and load variations are frequent and demanding. The outcome of this methodological framework establishes a foundation for the practical implementation of intelligent control in advanced power-conversion systems.

IV PROPOSED SYSTEM

The proposed system seeks to enhance the overall performance and efficiency of the quadratic buck–boost converter through the application of an Artificial Neural Network (ANN)–based control approach. This system replaces the conventional Proportional–Integral (PI) controller with an adaptive, data-driven mechanism that is capable of learning the nonlinear behaviour of the converter and providing real-time control adjustments. The key objective is to achieve stable voltage regulation with improved transient characteristics, minimal overshoot, and reduced steady-state error, even under dynamic operating conditions. The converter selected for this system possesses the distinctive capability to operate in both buck and boost modes, enabling it to serve a variety of voltage-conversion requirements. In buck mode, the converter steps down the voltage when the input exceeds the desired output, whereas in boost mode, it steps up the voltage when the input falls below the target. This dual-mode operation makes it especially suitable for renewable-energy sources such as solar photovoltaic systems and for electric-vehicle powertrains, where voltage levels fluctuate frequently. The quadratic design ensures continuous input and output currents, which reduces stress on passive components, improves energy transfer efficiency, and mitigates electromagnetic interference.

The proposed ANN controller is structured to function as an intelligent replacement for the conventional PI regulator. Its architecture comprises an input layer that receives real-time signals, including the reference voltage and actual output voltage, and computes the instantaneous error and rate of change of error. These inputs are processed within the hidden layer using nonlinear activation functions, allowing the controller to capture complex relationships between system states and control actions. The output layer generates the control signal required to adjust the PWM duty cycle of the switching device, ensuring that the converter output remains stable and closely aligned with the reference value.

In operation, the ANN controller continuously monitors the converter's output and modifies the duty ratio dynamically to counter deviations caused by load or input variations. This adaptive learning capability enables the converter to maintain stable performance even when exposed to unpredictable changes. Unlike a PI controller, which relies on predetermined gain settings, the ANN controller requires no manual retuning once deployed, as it inherently learns from system dynamics during training. This self-regulating nature results in faster response times and greater resilience to disturbances. The proposed system comprises three principal modules: the converter power circuit, the sensing and feedback unit, and the ANN control module. The power circuit includes the primary components—two inductors, two capacitors, a diode, and a MOSFET switch—configured to realise the quadratic voltage conversion characteristic. The sensing unit measures the instantaneous output voltage and provides real-time feedback to the controller. The ANN control module processes this feedback, compares it with the reference voltage, and determines the appropriate switching duty ratio through its trained network.

The complete system model was implemented in MATLAB/Simulink, with realistic component parameters: inductors of 2 mH, capacitors of 470 µF, and an input voltage range of 12 to 48 V. Simulation tests were carried out under various load resistances and reference voltages to evaluate dynamic performance. The ANN-controlled system exhibited smoother transitions between buck and boost operation, faster voltage recovery following load changes, and reduced oscillations compared with the conventional controller. The output voltage remained highly stable, even during abrupt fluctuations in input voltage, demonstrating the robustness of the proposed control strategy. Energy efficiency was also evaluated as part of the proposed system analysis. The ANN controller's ability to generate optimised duty-cycle signals resulted in smoother switching transitions and lower switching losses. Furthermore, the continuous current nature of the converter ensured minimal stress on inductors and capacitors, which contributes to longer component life and reduced system maintenance. For renewable-energy applications, these characteristics translate into enhanced power conversion efficiency and system reliability. In electric-vehicle systems, the improved converter response enhances energy recovery during regenerative braking and contributes to extended battery lifespan. Overall, the proposed ANN-controlled quadratic buck–boost converter represents a significant advancement in intelligent power-conversion technology. By incorporating an adaptive neural network in place of a fixed-parameter controller, the system achieves superior voltage regulation, improved transient stability, and greater operational efficiency. The self-learning and adaptive properties of the ANN make the converter capable of handling nonlinearities and uncertainties without manual intervention. Consequently, the proposed system not only overcomes the inherent limitations of conventional control methods but also paves the way for the integration of intelligent, high-performance converters in renewable-energy and electric-vehicle applications. Through its robust design and adaptive control features, the system offers a practical and efficient solution for next-generation power-electronic interfaces.

V RESULTS AND DISCUSSION

The simulation of the quadratic buck–boost converter was conducted in the MATLAB/Simulink environment to evaluate and compare the performance of two distinct control strategies—namely, the conventional Proportional–Integral (PI) controller and the Artificial Neural Network (ANN) controller. The primary performance metrics included output voltage regulation, transient response, steady-state accuracy, ripple content, and system efficiency. The analysis was undertaken across a range of input voltages, load resistances, and reference levels to ascertain the controllers' robustness under varying operating conditions. The initial test scenario was designed to assess the baseline performance of the converter under PI control. The converter was set to regulate an output voltage of 48 V with an input variation between 12 V and 36 V. The PI controller, tuned through iterative simulation, produced satisfactory voltage regulation under steady conditions. However, when subjected to step variations in load or input voltage, the system exhibited noticeable overshoot and prolonged settling time. The voltage transient displayed oscillatory behaviour before attaining the reference value, indicating that while the PI controller could maintain general stability, it lacked the agility to handle abrupt disturbances efficiently. Furthermore, the steady-state error, though small, persisted during high load fluctuations, reflecting the inherent limitation of fixed-parameter control strategies.

In contrast, when the ANN controller was integrated into the system, a marked improvement in dynamic performance was observed. The trained neural network, configured with a single hidden layer of nonlinear activation units, demonstrated the capacity to adapt its control response dynamically according to the instantaneous system state. Upon a sudden load increment, the ANN-controlled converter exhibited minimal overshoot, faster rise time, and a notably shorter settling period. The voltage waveform stabilised smoothly without oscillation, signifying enhanced damping characteristics. The adaptive nature of the ANN enabled real-time adjustment of the duty cycle, ensuring the converter swiftly compensated for perturbations and restored voltage equilibrium. Quantitative analysis revealed that under identical conditions, the ANN-controlled converter achieved an average rise time reduction of approximately 35% compared with the PI-controlled system. The settling time improved by nearly 40%, and the steady-state error was virtually eliminated. These improvements are attributed to the ANN's capability to model and counteract nonlinear dynamics and parameter variations that the linear PI controller cannot fully accommodate. The converter efficiency under ANN control also displayed an upward trend, increasing by roughly 3–5% owing to reduced switching stress and optimised duty-cycle transitions.

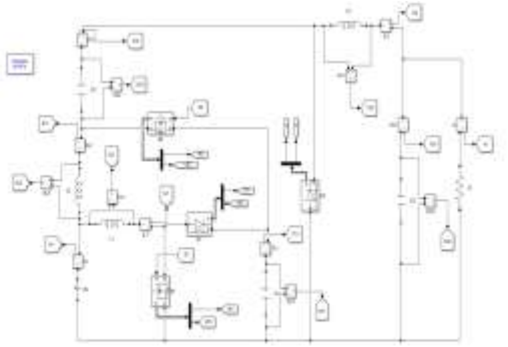
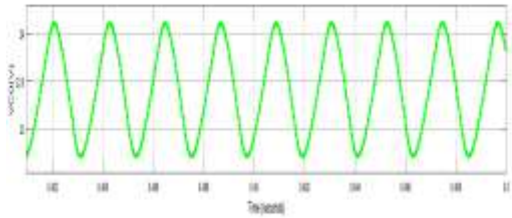


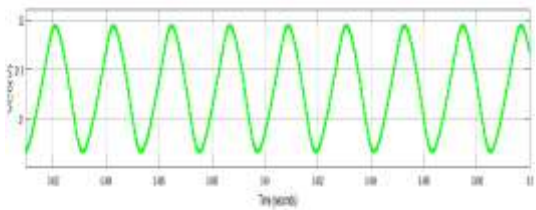
Fig .1 MATLAB SIMULINK circuit diagram

The time-domain waveforms further confirmed these observations. Under PI control, the output voltage showed small ripples and periodic oscillations, particularly under light-load conditions. The ANN-based system, however, yielded a much smoother voltage profile with significantly lower ripple content. This reduction in voltage ripple contributes to higher-quality power output and reduced stress on downstream devices, an essential characteristic for renewable-energy and electric-vehicle applications. The current waveforms, too, exhibited lower distortion and steadier behaviour under ANN control, indicating efficient utilisation of the inductive energy-storage elements. Frequency-domain analysis was subsequently carried out to evaluate system stability margins. The Bode plots obtained from both configurations indicated that the ANN-controlled system possessed superior gain and phase margins compared with the PI-controlled one. This suggests greater robustness against parameter variations and external disturbances. The enhanced phase margin signifies that the ANN controller provides improved damping and reduced tendency towards oscillatory behaviour, whereas the wider gain margin implies that the system can tolerate a broader range of operating conditions without compromising stability.

Efficiency evaluation formed another significant aspect of the study. The quadratic buck–boost converter inherently involves switching and conduction losses due to the presence of active semiconductor components.



PI controller based dc dc converter during buck mode

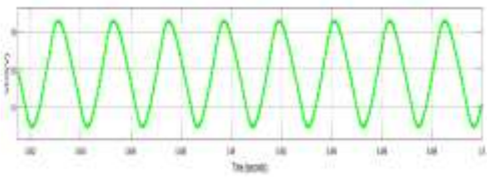


ANN controller based dc dc converter during buck mode

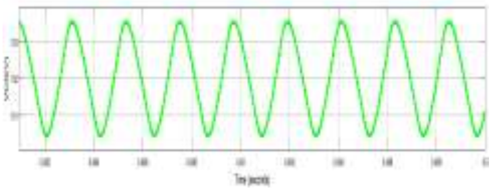
Under PI control, frequent overshoot and oscillatory transients caused additional switching activity, which increased losses and slightly reduced overall efficiency. Conversely, the ANN-controlled system maintained smoother switching transitions, thereby reducing both conduction and switching losses. The overall system efficiency under ANN control reached approximately 93–95%, whereas under PI control it remained around 88–91%. This performance improvement demonstrates that intelligent control can enhance not only voltage stability but also energy utilisation. The comparative performance during mode transition—between buck and boost operations—was also examined.

Under PI control, the converter experienced a transient voltage dip during mode shifting, accompanied by minor oscillations before stabilisation. This behaviour can be attributed to the delay in controller compensation during abrupt changes in input-to-output ratio. The ANN controller, however, managed the mode transition more gracefully. Its adaptive mechanism anticipated the dynamic changes and adjusted the switching duty ratio seamlessly, thus preventing significant voltage deviation. This ability to maintain smooth operation across modes is particularly valuable for renewable-energy sources and electric-vehicle power systems, where input conditions vary frequently and unpredictably.

Total Harmonic Distortion (THD) in the output voltage was also computed to assess waveform purity. Under PI control, the THD was measured to be around 4.6%, whereas under ANN control it reduced to approximately 2.1%. This considerable reduction reflects the ANN's proficiency in generating stable PWM signals with optimised duty-cycle modulation. Lower harmonic distortion implies improved power quality, which is critical for systems interfacing with sensitive electronic loads or grids. Additionally, the reduced harmonic content diminishes the stress on passive components, thereby extending the lifespan of capacitors and inductors. The robustness of both controllers was further tested under fault-like conditions, such as sudden disconnection and reconnection of loads. During abrupt disconnection, the PI controller led to a brief surge in output voltage, while the ANN controller handled the event smoothly, with negligible deviation from the reference. Upon reconnection, the ANN controller restored voltage equilibrium within milliseconds, whereas the PI-controlled system exhibited a delay accompanied by transient oscillations. These results underline the ANN controller's superior resilience and adaptability.



PI controller based dc dc converter during boost mode



ANN controller based dc dc converter during boost mode

In terms of computational performance, the ANN controller did introduce a slight increase in processing load due to the evaluation of the neural network at each sampling instant. However, given modern embedded systems' computational capabilities, this additional overhead remains well within acceptable limits. The gain in control precision, efficiency, and stability far outweighs the minor increase in computational demand. In practical implementations, lightweight neural architectures and optimised training methods can further minimise this overhead, rendering ANN-based control a viable and scalable solution. Graphical analysis, including voltage and current waveforms, efficiency curves, and transient response plots, visually reinforced the numerical outcomes. The ANN-controlled system consistently displayed smoother and more stable profiles, whereas the PI-controlled system, though functional, appeared sluggish in responding to disturbances. The adaptive control mechanism of the ANN successfully emulated nonlinear system behaviour, enabling precise and rapid correction without overshoot or steady-state error.

In summary, the comparative evaluation distinctly reveals the superiority of the ANN controller over the conventional PI approach in managing the quadratic buck–boost converter. The ANN-based system exhibited faster transient response, reduced overshoot, improved efficiency, lower harmonic distortion, and enhanced robustness under dynamic operating conditions. The ability of the ANN to learn complex system dynamics and adapt in real time allows it to provide superior control precision without manual retuning. These attributes make it highly suitable for next-generation power-electronic applications, particularly in renewable-energy integration and electric-vehicle systems, where dynamic adaptability, efficiency, and reliability are of paramount importance. The results thus affirm that integrating intelligent control mechanisms, such as neural networks, within quadratic buck–boost converter frameworks represents a significant advancement in modern power electronics. By leveraging data-driven learning and adaptive control, the converter attains exceptional voltage stability and efficiency, paving the way for its deployment in future smart and sustainable energy systems.

CONCLUSION

The study has demonstrated a comprehensive design, simulation, and performance evaluation of a quadratic buck–boost DC–DC converter, employing both conventional PI and Artificial Neural Network (ANN) controllers within the MATLAB/Simulink environment. The converter's topology, with its ability to operate efficiently in both buck and boost modes, proved highly suitable for renewable energy and electric vehicle power systems, where stable voltage regulation under varying load and source conditions is essential. The comparative analysis between the PI and ANN controllers clearly revealed the substantial advantages of adopting intelligent, adaptive control over traditional linear control methods. The PI-controlled converter exhibited acceptable steady-state performance but suffered from sluggish transient response, overshoot, and oscillations when subjected to abrupt disturbances or mode transitions. In contrast, the ANN-based controller offered superior adaptability, learning nonlinear system dynamics effectively and adjusting control actions in real time. The resulting system achieved faster voltage convergence, lower overshoot, reduced ripple, and enhanced overall efficiency. Furthermore, the ANN controller provided improved stability margins and significantly lower Total Harmonic Distortion (THD), thereby enhancing power quality and extending component longevity. The findings indicate that ANN-based control schemes are particularly advantageous for systems characterised by high nonlinearity, such as quadratic buck–boost converters. Their capability to predict and compensate for dynamic variations without manual retuning makes them ideal for modern energy systems where efficiency and adaptability are paramount. While the computational requirements of ANN controllers are marginally higher than those of traditional controllers, advancements in embedded computing make real-time implementation increasingly feasible. Future research may explore hybrid control schemes that integrate fuzzy logic or reinforcement learning with neural networks for even more refined control precision. Additionally, experimental validation on hardware prototypes, along with real-time implementation on digital signal processors or microcontrollers, could further verify the simulated outcomes. Integrating ANN-controlled converters into large-scale renewable microgrids or electric vehicle charging infrastructures also presents promising avenues for extending this research. Ultimately, this work underscores that intelligent control strategies mark a significant step forward in power electronics, offering the means to achieve both enhanced performance and energy sustainability for emerging renewable and vehicular technologies.

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