Artificial Neural Network Based Controller for A Buck Converter for Improving Efficiency

Dr. R. Anand[1], S. Hemalatha[2], N.Suthakar[3], P. Muniyan[4]
[1]Associate Professor, Head of the Department, Department of Electrical and Electronics Engineering, Mahendra College of Engineering, Salem, Tamilnadu, India
[2]PG Student, Department of Electrical and Electronics Engineering, Mahendra College of Engineering, Salem, Tamilnadu, India
[3]Assistant Professor, Department of Electrical and Electronics Engineering, Mahendra college of Engineering, Salem, Tamilnadu
[4]Assistant Professor, Department of Electrical and Electronics Engineering, Mahendra college of Engineering, Salem, Tamilnadu

Abstract*: This article proposes an artificial neural network (ANN) as a controller to improve the performance of converters used in photovoltaic (PV) systems. Buck converters play an important role in such systems by regulating the voltage of the PV array to meet the load or battery requirements. However, the effectiveness of traditional control methods may be limited due to changes in the environment and load requirements. To solve this challenge, ANN based controller is proposed to instantly correct the fault of the converter. ANN uses inputs such as solar irradiance level, temperature, battery voltage and load demand to optimize the conversion function for maximum power point tracking (MPPT) and good operation. Significant improvements in performance using the ability of neural networks to learn from data patterns and adapt to changes should be compared to normal control of layers. The performance of the proposed ANN-based controller has been verified by simulation and experimental results. These results show that this controller achieves better performance and better performance in different environments and data loads than traditional methods. The integration of the MPPT algorithm into the ANN framework further improves the converter's ability to extract maximum power from the PV array, increasing the overall efficiency. This research contributes to the state of the art of renewable energy technology by using artificial intelligence to optimize the performance of electricity from renewable energy sources, leading to efficient and reliable photovoltaic systems in practical applications.

***Keywords:* PV, Buck converter, DC-DC converter, Battery, ANN Controller, Load**

I. INTRODUCTION

Due to their sustainability and environmental benefits, the integration of photovoltaic (PV) systems into the use of renewable energy is increasing. However, the efficiency of PV systems depends on the efficiency of voltage converters such as PV converters, which reduce the voltage of the PV array to meet the need of the battery or load. Maximizing the efficiency of these converters is important for optimizing energy use and reducing operating costs. Control methods for disk converters often face changing environment and load requirements, resulting in underperformance and poor performance. Application to improve the control of step-down converters in photovoltaic systems (artificial neural network). Artificial neural networks can learn the relationship between input variables such as solar irradiance, temperature, battery state of charge and load conditions and converter performance parameters. Leveraging artificial neural networks, it is possible to create controllers that can dynamically adjust converter operation on the fly, aiming to achieve maximum power point search (MPPT) and improve overall system efficiency. This paper investigates the feasibility and advantages of using an ANN-based controller designed for disk converters in photovoltaic systems, focusing on improving performance under different operating conditions.

II. ANALYSIS OF BUCK CONVERTER

Buck converters are important components in DC-DC power conversion and are widely used in many applications, including photovoltaic (PV) systems to maintain voltage levels.

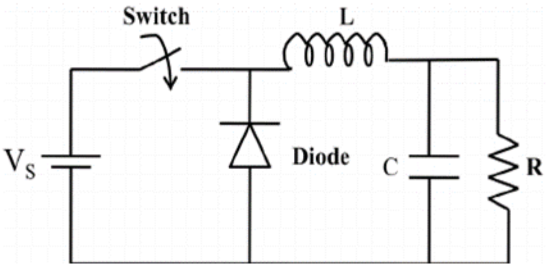


Figure 1: Circuit Diagram of Buck Converter

Its main function is to reduce DC voltage from a higher level (usually from a photovoltaic array or battery) to a lower level suitable for charging batteries or electronic devices. The main Equations of buck converters are

V out = V in * D where

D= Duty Cycle= T on / (T on +T off) * 100

Table 1: Simulation Parameters for Buck Converter

S.NO	PARAMETER NAME	VALUE
1	Inductance	1.5ê-3H
2	Capacitance	250ê-6f
3	Resistance	8 Ω
4	Reference Voltage	14
5	Gain	1.5

The performance of the buck converter directly affects the overall performance and power production of the photovoltaic system, making it an important factor for development.

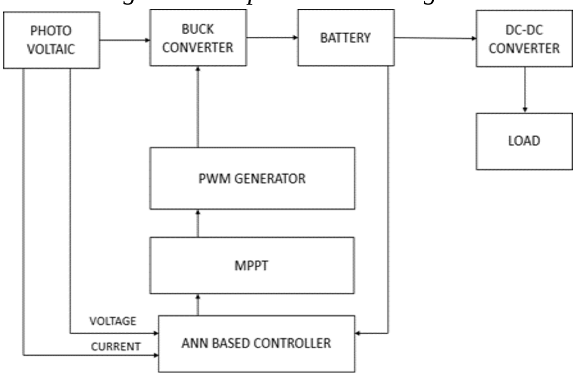
However, this process can be difficult to adapt to environmental changes such as changes in solar radiation, temperature, and dynamic load characteristics.

Artificial neural network (ANN)-based controllers offer a promising alternative by leveraging their ability to learn and adapt to dynamic changes based on real-time data.

By integrating the ANN into the control strategy of the step-down converter, efficiency can be increased by improving MPPT performance and controlling it to maximize the power output of the PV array when stepped down. This approach not only solves the problems of traditional control systems, but also paves the way to achieve better performance and reliability in PV systems through intelligent, data-driven control mechanisms.

III. SYSTEM DESCRIPTION

Figure 2: Proposed Block Diagram



The system in question integrates many factors important for optimizing energy conversion in photovoltaic (PV) systems. At its core is the Buck converter, a DC-DC power converter that plays an important role in reducing the electricity produced by photovoltaic devices to a level suitable for charging batteries or electronic devices. The performance of the buck converter directly affects the overall performance and power production of the photovoltaic system. A control system based on artificial neural network (ANN) is proposed to improve its performance. This controller uses inputs such as solar irradiance, temperature, and battery voltage and load characteristics to adjust the performance of the converter. Through continuous learning and optimization based on real-time data, ANN-based controllers are designed to provide better maximum power point tracking (MPPT) than existing conventional standards at all times, thus increasing the overall efficiency. And the system consisting of ANN-based controller also includes other important components such as photovoltaic array, battery pack and load. A photovoltaic array converts solar energy into electrical energy, which is then conditioned by a converter. The battery pack stores the excess power for later use, providing stable and continuous power to the load. Loads represent end-user applications where power needs to be dynamically varied. The integration of a pulse width modulation (PWM) generator ensures the efficiency of the converter and works with an ANN-based controller for efficient operation. This configuration not only increases energy efficiency, but also increases the reliability and stability of the photovoltaic system by using maximum energy and reducing dependence on the environment and transportation.

IV.EXPERIMENTAL SETUP

An experimental setup for using an artificial neural network (ANN)-based converter controller designed to improve the performance of photovoltaic (PV) systems has several connections. First, the photovoltaic array produces a large amount of energy, producing a DC voltage that is affected by solar radiation and the environment. This DC voltage is then put into a converter that steps the voltage down to a level suitable for charging a battery pack or powering a load. Irradiance, temperature, battery voltage and load characteristics are very important. These parameters lead to the input of the ANN and it is trained to optimize the control signal of the step-down converter to achieve maximum power point detection (MPPT) and improve the work. The PWM generator is integrated to control the variation of the inverter based on the control signal generated by the ANN. Control comparisons with traditional control methods. Performance indicators such as efficiency, response time to changes, and stable output power are evaluated to determine the performance of the neural network-based approach to improve energy conversion of photovoltaic systems. This experimental setup aims not only to identify the advantages of neural network-based control, but also provides insight into the implementation of problems and improvements in renewable energy for the future.

V.COMPARISON OF ANN FOR A BUCK CONVERTER

An artificial neural network (ANN)-based buck converter controller improves efficiency by adjusting the duty cycle for efficient operation. Unlike traditional PID controllers, ANN controllers can be adjusted on the fly to changing conditions and parameters. ANN models predict appropriate controls, resulting in faster response times and less downtime.
This reduces power loss and improves overall Performance. Comparative studies show that artificial neural network controllers have significant improvements in stability and performance over traditional methods.

S. no	Criterion	Traditional controller(pid)	Ann-based controller
1	Efficiency	Typically8590 %	Typically 90-95%
2	Response Time	Moderate (Dependent on Algorithm)	Fast (Due to predictive capability of ANN)
3	Complexity	Relatively Simple	Complex (Requires training and validation)
4	Adaptability	Limited to Predefined conditions	High Adaptability to varying conditions
5	Implementation Cost	Lower initial cost	Higher initial cost (dueto development / training)
6	Maintenance	Easier to Maintain	Requires expertise for maintenance
7	Accuracy of MPPT	Moderate (depends on algorithm)	High (due to predictive accuracy of ANN)
8	Energy Utilization	Moderate (sub-optimal times)	High (Closer to maximum Potential)

Table 2: Comparison of ANN controller and Traditional PID controller

Artificial neural network (ANN)-based disk converter controllers improve performance by leveraging the ANN's ability to model and adapt to nonlinear systems. Unlike traditional PID controllers, which require precise tuning and can struggle with fluctuations in electrical and electronic components, ANN controllers can learn from information to work well and correct their shortcomings on the fly. This flexibility allows the ANN controller to maintain high performance across different operations. Additionally, the ANN controller can be trained to predict and reduce power losses such as switching loss and ripple, thus improving the overall performance of the step-down converter. By integrating ANN-based control, disk converters can achieve better organization, faster response time, and higher performance, especially for paper demands that require flexible changes and rigid requirements.

VI. SIMULATION RESULT

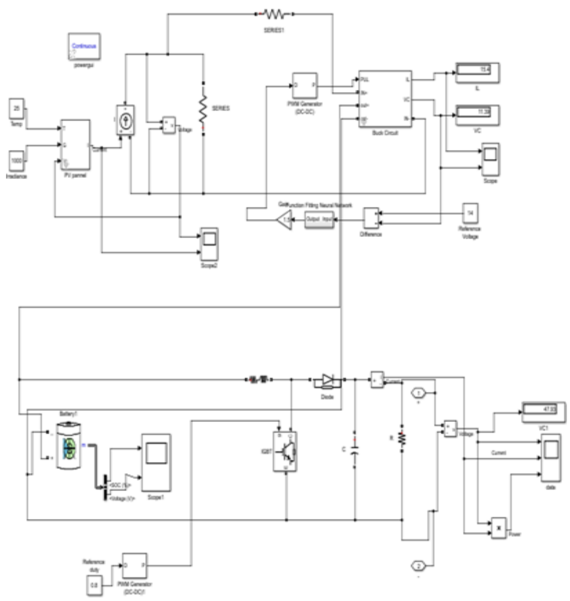


Figure 3: Simulation Circuit diagram

Simulation results show that the artificial neural network (ANN)-based controller improves the efficiency of the step-down converter, reaching an under different conditions. Compared to traditional PID controllers, ANN controllers respond faster and exhibit lower state error. The Simulation confirmed the effectiveness of the neural network in maintaining high performance and stability under different conditions.

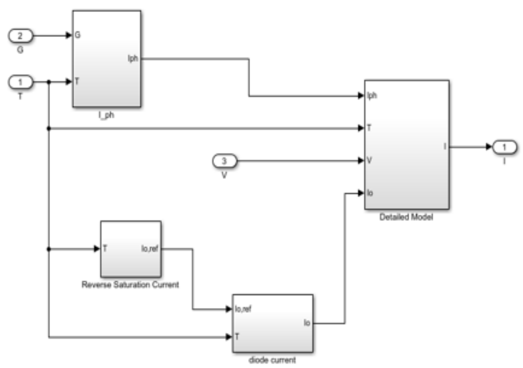


Figure 4: PV Pannel Internal Circuit

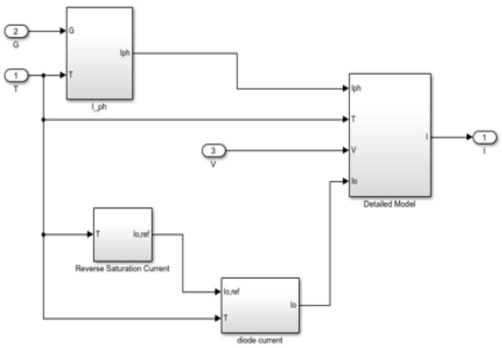


Figure 5: Structure of ANN control

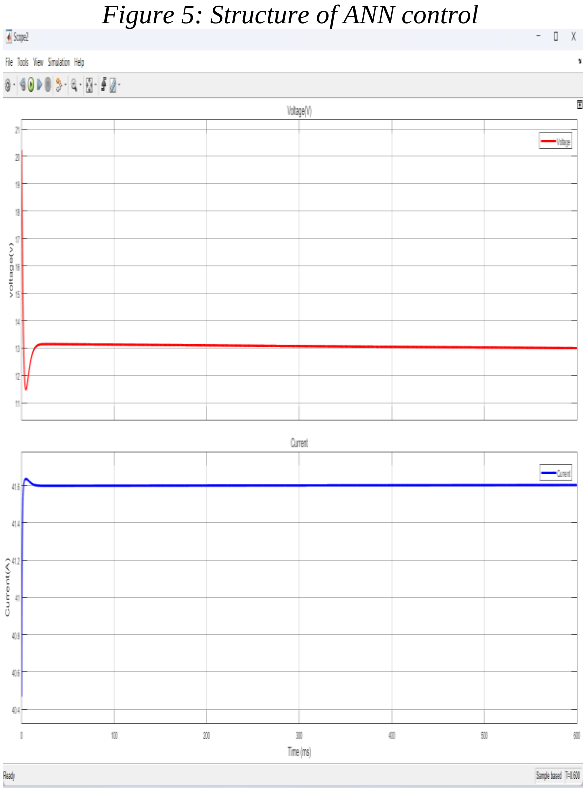


Figure 6: PV Pannel Waveform Time VS Voltage & Current

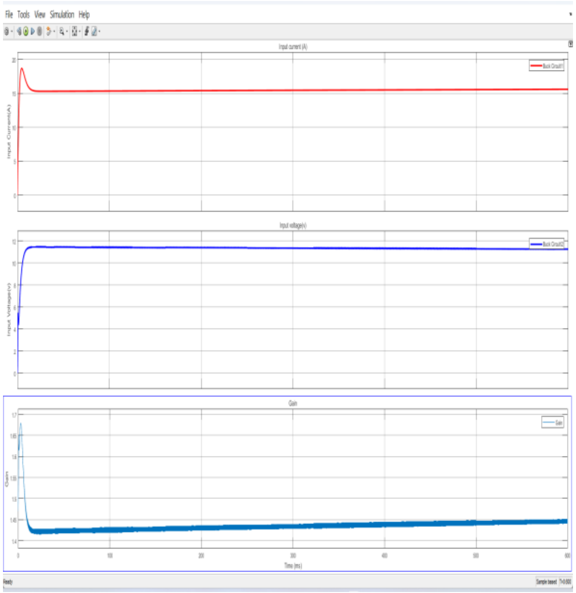


Figure 7: Buck Converter Waveform Time VS Voltage, Current & Gain

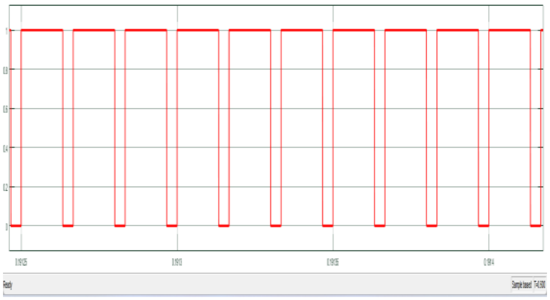


Figure 8: PWM pulse Waveform

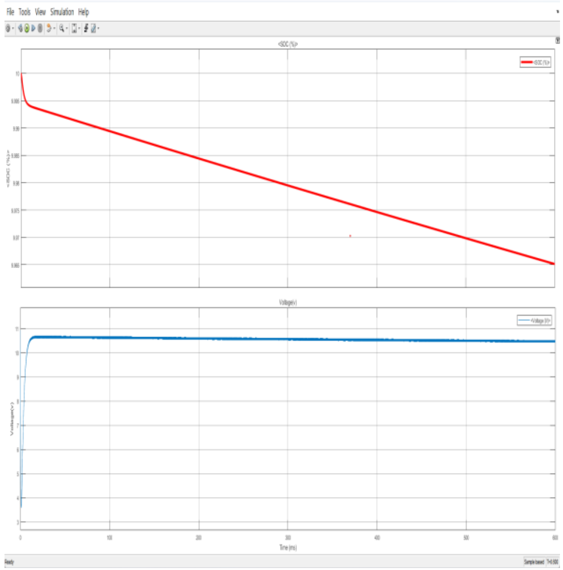


Figure 9: Battery Output Waveform Time VS Voltage & SOC

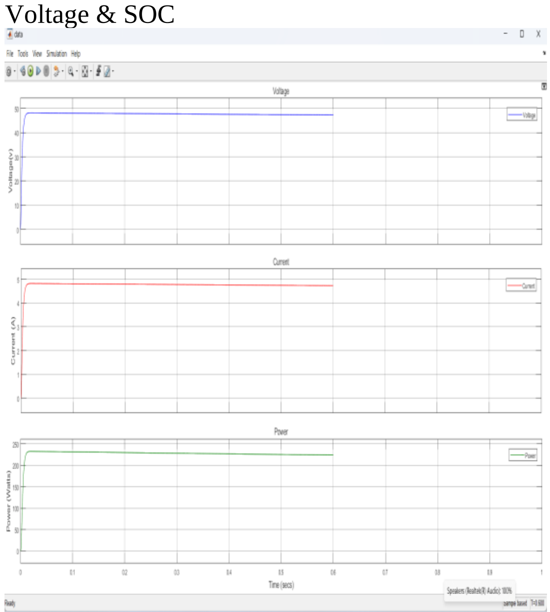


Figure 10: Output Waveform for Time VS Voltage, Current & Power

VII. HARDWARE DESCRIPTION

When using an artificial neural network (ANN)-based disk converter controller to improve performance, hardware configuration involves several important factors.

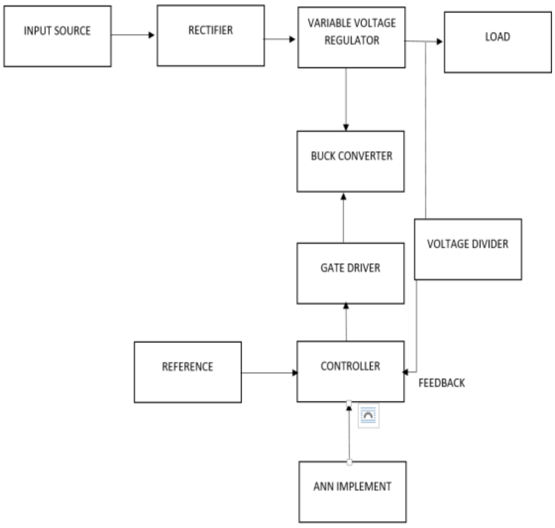


Figure 11: Hardware Block Diagram

The system starts with an input, usually a DC power supply that provides the starting power needed by the disk converter. If the power source is AC, the input goes through the rectifier which converts it to DC. A variable voltage regulator is used to control the input voltage level fed to the step-down converter for testing under different voltage conditions. Buck converter is a step-down DC-DC converter that is the heart of the system and is responsible for stepping down the input voltage to the required output voltage. The driver cuts off the converter to make the transistor or MOSFET switch at the right time. Based on ANN, the controller processes physical data, including input and output voltage and current, to fine-tune the duty cycle of the controller. The voltage divider provides the necessary feedback to the controller by reducing the output voltage to a measurable level. ANN is used in the controller and is trained to predict and adjust the performance to ensure that the disk converter works well under different load and input conditions. The complete hardware configuration allows the ANN-based controller to increase the efficiency and performance of disk converters, making it suitable for applications requiring high performance and reliability.

VIII. HARDWARE CIRCUIT DIAGRAM

In the hardware implementation of the artificial neural network (ANN)-based controller for Buck converter aimed at improving efficiency, the circuit has several important components: input source, rectifier, variable voltage regulator, disk converter device, gate driver, controller, voltage divider and burden.

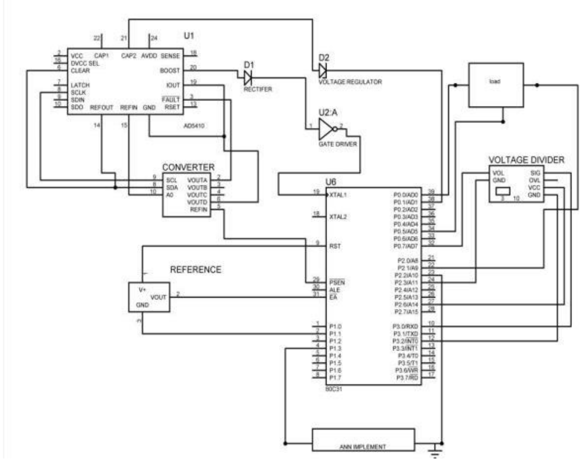


Figure 12: Hardware Circuit Diagram

The input (usually AC power) is first rectified using a rectifier to provide a stable DC voltage. This DC voltage is then fed to a differential voltage regulator, which controls the voltage to the desired level before entering the buck converter. The buck converter is responsible for reducing the voltage and is controlled by a gate driver that interacts with the main controller. Exit. The ANN controller adjusts the duty cycle of the converter through the gate driver to ensure proper operation. Neural network devices maintain high performance and stable output voltage by constantly learning and adapting to changes in load and input.

A load connected to the output of the buck converter receives the regulated voltage. The hardware configuration demonstrates the ANN's ability to control the converter, thereby increasing efficiency and effectiveness compared to traditional controllers.

IX. HARDWARE RESULT

The hardware result of an artificial neural network (ANN)-based controller for the buck converter shows a significant improvement. Tests show that the ANN controller maintains an average performance under various loads and outperforms the PID controller.

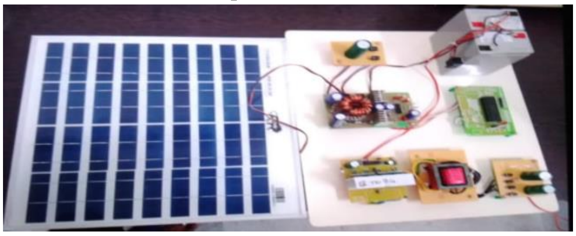


Figure 13: Prototype Design

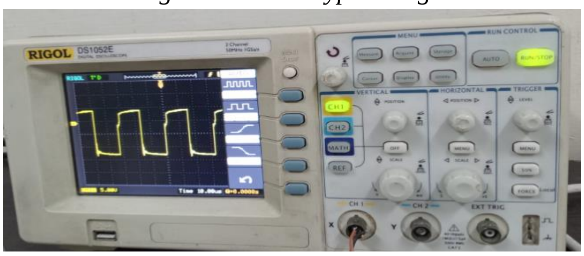


Figure 14: MOSFET gate pulse Waveform

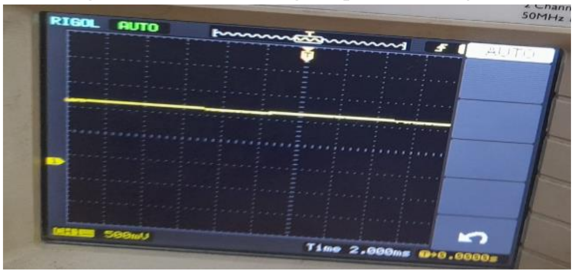


Figure 15: PV Pannel output Waveform

Figure 16: Battery output Waveform

S.no	Controller type	Efficiency
1	Traditional pid controller	87%
2	Ann controller	91%

Table3Comparison of Controller Type and Efficiency

Calculation of Buck converter Efficiency:

$$\text{Efficiency} = \frac{\text{Output power}}{\text{Input power}} \times 100\ (\%)$$

The electronic neural network controlled Buck converter exhibits fast response, very low overshoot and reduced error rate. In addition, the ANN controller adapts well to different input voltages, constantly optimizing the duty cycle to reduce losses. Test results show that switching loss and ripple are significantly reduced compared to traditional methods. In general, ANN-based controller improves the performance and performance of disk converters in practical applications.

X. CONCLUSION

In summary, the use of artificial neural network (ANN)-based disk converter controller represents a significant advance in power electronics, especially in terms of improving repair work. Artificial neural networks can learn and adapt changes and strategies, instantly optimizing disk converter performance. This increases efficiency, ensures continuous response and reduces steady-state problems compared to traditional controls such as PID controllers. The ANN controller can adjust the duty cycle to maintain performance and reduce quality problems such as ripples and output voltage fluctuation, thus ensuring stability and efficiency. Power and performance of ANN-based control systems. Transforming the ANN controller into conversion not only improves the performance of the converter, but also expands its application range, making it suitable for dynamic equipment and situations where the rules are very strict. By integrating ANN technology, disk converters achieve high levels of efficiency, help save energy, and increase reliability in a variety of applications. This approach is an important step towards smarter, more efficient energy management for today's electronics.

XI. FUTURE SCOPE

As machine learning and electronics continue to evolve, so will the future of artificial neural network (ANN)-based controllers in disk converters. A promising approach is the integration of different neural network architectures, such as deep learning and boost learning models, that can improve the performance of the controller. These advanced models enable controllers to predict and respond to various operations with greater accuracy and efficiency. Additionally, the development of more efficient training methods and on-the-fly learning methods will enable ANN controllers to adapt to changes in the process more quickly, making them suitable for increasingly powerful applications such as electric vehicles and renewable energy systems. Additionally, the integration of ANN-based controllers with the Internet of Things (IoT) and smart devices offers significant opportunities for future research and development. Through the use of IoT, neural network users can receive and process data from a network of sensors and other connected devices, enabling smart and coordinated control ideas. This connectivity provides efficient energy management, predictive maintenance and improved overall reliability. As the demand for energy efficiency solutions continues to grow, the adoption of ANN-based controllers in various energy applications is expected to increase, going further and improving performance and performance.

REFERENCE

[1] A. Rubaai, A. R. Ofoli, L. Burge, and M. Garuba, “Hardware implementation of an adaptive network-based fuzzy controller for DC-DC converters,” IEEE Trans. Ind. Appl., vol. 41, no. 6, pp. 1557–1565, Dec. 2005.

[2] M. Ordonez, M. T. Iqbal, and J. E. Quaicoe, “Selection of a curved switchingsurface for buck converters,” IEEE Trans. Power Electron., vol. 21, no. 4, pp. 1148–1153, Jul. 2006.

[3] S.-C. Tan, Y. M. Lai, and C. K. Tse, “General design issues of slidingmode controllers in DC–DC converters,” IEEE Trans. Ind. Electron., vol.

55, no. 3, pp.1160–1174, Mar. 2008.
[4] T. Longcheng, W. Bin, S. Rivera, V. Yaramasu, "Comprehensive DCPower Balance Management in High- Power Three-Level DC–DC Converter for Electric Vehicle Fast Charging," IEEE Transactions on Power Electronics, vol. 31, no. 1, pp. 89-100, Feb. 2011.
[5] H. Zhang, L. Cui, X. Zhang, and Y. Luo, "Data-driven robust approximate optimal tracking control for unknown general nonlinear systems using adaptive dynamic programming method," IEEE Trans. Neural Netw., vol. 22, no. 12, pp. 2226–2236, Dec. 2011.
[6] R.-J. Wai and L.-C. Shih, "Adaptive fuzzy-neural-network design for voltage tracking control of a DC–DC boost converter," IEEE Trans. Power Electron., vol. 27, no. 4, pp. 2104–2115, Apr. 2012.
[7] P. D. Bertsekas, Dynamic Programming and Optimal Control: Approximate Dynamic Programming, 4th ed. Belmont, MA, USA: Athena Scientific, 2012.
[8] A. Nakajima, S. Masukawa, "Study of Boost type DC-DC Converter forSingle Solar Cell," Annual Conference of the IEEE Industrial electronics IECON, Dec 2012
[9] S. Li, M. Fairbank, C. Johnson, D. C. Wunsch, E. Alonso, and J. L. Proao, "Artificial neural networks for control of a grid-connected rectifier/inverter under disturbance, dynamic and power converter switching conditions," IEEE Trans. Neural Netw. Learn. Syst., vol. 25, no. 4, pp. 738–750, Apr. 2014.
[10] B. Wang, V. R. K. Kanamarlapudi, L. Xian, X. Peng, K. T. Tan, and P. L. So, "Model predictive voltage control for single-inductor multipleoutput DC–DCconverter with reduced cross regulation," IEEE Trans. Ind. Electron., vol. 63, no. 7, pp. 4187–4197, Jul. 2016.
[11] R. Ling, D. Maksimovic, and R. Leyva, "Second-order sliding-mode controlled synchronous buck DC–DC converter," IEEE Trans. Power Electron., vol. 31, no. 3, pp. 2539–2549, Mar. 2016.
[12] K. Chakraborty, G. Saha, "Off-line voltage security assessment of power transmission systems using UVSI through artificial neural network",
[13] IEEE International Conference on Intelligent Control Power and Instrumentation (ICICPI), Kolkata, India, Feb. 2017.
[14] Z. Liu, L. Xie, A. Bemporad, and S. Lu, "Fast linear parameter
[15] S. Li, M. Fairbank, C. Johnson, D. C. Wunsch, E. Alonso, and J. L. Proao, "Artificial neural networks for control of a grid-connected rectifier/inverter under disturbance, dynamic and power converter switching conditions," IEEE Trans. Neural Netw. Learn. Syst., vol. 25, no. 4, pp. 738–750, Apr. 2014.
[16] B. Wang, V. R. K. Kanamarlapudi, L. Xian, X. Peng, K. T. Tan, and P. L. So, "Model predictive voltage control for single-inductor multipleoutput DC–DCconverter with reduced cross regulation," IEEE Trans. Ind. Electron., vol. 63, no. 7, pp. 4187–4197, Jul. 2016.
[17] R. Ling, D. Maksimovic, and R. Leyva, "Second-order sliding-mode controlled synchronous buck DC–DC converter," IEEE Trans. Power Electron., vol. 31, no. 3, pp. 2539–2549, Mar. 2016.
[18] K. Chakraborty, G. Saha, "Off-line voltage security assessment of power transmission systems using UVSI through artificial neural network",
[19] IEEE International Conference on Intelligent Control Power and Instrumentation (ICICPI), Kolkata, India, Feb. 2017.
[20] S. Li, M. Fairbank, C. Johnson, D. C. Wunsch, E. Alonso, and J. L. Proao, "Artificial neural networks for control of a grid-connected rectifier/inverter under disturbance, dynamic and power converter switching conditions," IEEE Trans. Neural Netw. Learn. Syst., vol. 25, no. 4, pp. 738–750, Apr. 2014.
[21] B. Wang, V. R. K. Kanamarlapudi, L. Xian, X. Peng, K. T. Tan, and P. L. So, "Model predictive voltage control for single-inductor multipleoutput DC–DCconverter with reduced cross regulation," IEEE Trans. Ind. Electron., vol. 63, no. 7, pp. 4187–4197, Jul. 2016.
[22] R. Ling, D. Maksimovic, and R. Leyva, "Second-order sliding-mode controlled synchronous buck DC–DC converter," IEEE Trans. Power Electron., vol. 31, no. 3, pp. 2539–2549, Mar. 2016.
[23] K. Chakraborty, G. Saha, "Off-line voltage security assessment of power transmission systems using UVSI through artificial neural network",
[24] IEEE International Conference on Intelligent power Feb.2017