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ENHANCING MICRO-GRID RENEWABLE ENERGY SYSTEMS WITH NEURAL NETWORK-BASED CONTROLLERS FOR SOLAR AND WIND

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ABSTRACT

This study presents a Simulink-based simulation model designed to optimize the performance of renewable energy systems using neural network-based controllers. The model integrates two key controllers: a Maximum Power Point Tracking (MPPT) controller for solar photovoltaic (PV) systems and a pitch angle controller for wind farms. Neural networks are employed in both controllers to enhance their adaptive capabilities and improve efficiency under varying environmental conditions. The MPPT controller utilizes neural network algorithms to dynamically adjust the operating point of the solar PV array, ensuring maximum power extraction at all times. Similarly, the pitch angle controller employs neural networks to optimize the blade angle of wind turbines, thereby maximizing energy capture from wind resources while maintaining system stability. The simulation results demonstrate the effectiveness of the neural network-based controllers in enhancing the overall performance and reliability of renewable energy systems, highlighting their potential for real-world applications in sustainable energy generation.

Keywords: Microgrid, Artificial Neural Network, MPPT.

I. INTRODUCTION

Solar and wind-based microgrids are increasingly recognized as essential components in the transition to a sustainable energy future. These microgrids leverage localized, renewable energy sources, integrating photovoltaic panels and wind turbines to provide a decentralized, reliable, and efficient power supply. The synergy between solar and wind energy within a microgrid addresses the intermittent nature of these resources, enhancing overall energy security and reducing dependence on fossil fuels. Solar panels generate electricity during the day, particularly during sunny periods, while wind turbines can produce power both day and night, often complementing periods of low solar output. This dual-source approach ensures a more consistent energy supply.

The performance and efficiency of these microgrids are significantly enhanced through the integration of neural networks, a sophisticated form of artificial intelligence. Neural networks are adept at handling large datasets and recognizing patterns, making them highly suitable for managing the complexities of energy systems. By analyzing historical data and current operational metrics, neural networks can predict potential equipment failures, facilitating predictive maintenance and reducing unexpected downtime. This predictive capability not only enhances the reliability of the microgrid but also lowers maintenance costs by allowing for timely interventions.

Neural networks also play a crucial role in optimizing energy management within the microgrid. By forecasting energy demand and supply based on variables such as weather conditions, historical usage patterns, and market prices, these AI systems enable the efficient allocation of resources. For instance, during periods of high solar output but low demand, neural networks can manage the storage of excess energy in batteries, ensuring its availability during peak demand times or when production is low. This optimization reduces energy waste and enhances the overall efficiency of the microgrid.

Neural networks contribute to effective load balancing and demand response. By learning and predicting consumption behaviors, these systems can adjust the energy distribution in real-time, ensuring that the microgrid operates efficiently without overloading any component. This balancing act not only improves the performance of the microgrid but also prolongs the lifespan of its infrastructure, reducing the need for frequent replacements and repairs.

Grid stability is another critical area where neural networks prove invaluable. The inherent variability in solar and wind power generation can pose challenges to maintaining a stable energy supply. Neural networks can

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quickly analyze and respond to fluctuations in energy production and consumption, making real-time adjustments to the energy mix. This rapid responsiveness ensures a stable and reliable energy supply, even in the face of sudden changes in generation or demand. Neural networks facilitate advanced energy trading strategies. By accurately predicting energy prices and demand, these systems can make informed decisions about when to buy or sell energy, maximizing economic benefits for the microgrid. This capability is particularly valuable in deregulated energy markets where prices can fluctuate significantly. The integration of neural networks into solar and wind-based microgrids also supports the development of smart grid technologies. By enabling seamless communication between different components of the energy system, neural networks help create an intelligent, responsive grid that can dynamically adjust to changing conditions. This smart grid capability enhances the overall resilience of the energy system, making it better equipped to handle disruptions and ensure continuous power supply.

Solar and wind-based microgrids, enhanced by neural network integration, represent a significant advancement in the pursuit of sustainable, efficient, and resilient energy systems. Neural networks' predictive, analytical, and optimization capabilities transform the management and operation of these microgrids, ensuring a reliable and consistent energy supply. As technology continues to evolve, the role of AI in energy systems is likely to expand, offering even greater potential for innovation and efficiency in the renewable energy sector.

1 Solar system modelling in Simulink

1.1 MPPT Controller;

A Maximum Power Point Tracking (MPPT) controller is a vital component in a solar panel system, designed to maximize the efficiency and energy output of photovoltaic (PV) panels. It accomplishes this by continuously tracking and adjusting the electrical load to ensure that the panels operate at their Maximum Power Point (MPP), the point where they generate the most electricity.

MPPT controllers are crucial because they enhance the overall efficiency of solar power systems. They adapt to varying environmental conditions such as cloud cover or shading, ensuring that the PV panels consistently produce the maximum possible power output. This boost in efficiency results in increased electricity generation and shorter payback periods for solar installations.

MPPT controllers help extend the lifespan of batteries in off-grid or hybrid solar systems. By delivering the appropriate voltage and current levels, they prevent overcharging and deep discharging, which can damage batteries and reduce their longevity. MPPT controllers are indispensable for optimizing the performance, efficiency, and longevity of solar panel systems, making them a crucial component in fully harnessing the potential of solar energy. In our design, we have implemented the perturbation and observation algorithm for the MPPT controller.

1.2 Simulink model with the MPPT controller with P&O algorithm

Here we have a Simulink model that integrates a solar panel, a Maximum Power Point Tracking (MPPT) controller, and a DC-DC converter, serving as a powerful tool for simulating and optimizing photovoltaic (PV) energy systems. The solar panel component simulates the electrical behavior of the PV module, converting incident sunlight into electrical energy. It takes into account factors such as irradiance, temperature, and the panel's characteristics to generate output voltage and current.

The MPPT controller plays a crucial role in the Simulink model by continuously adjusting the operating point of the solar panel to extract the maximum available power. It employs algorithms like Perturbation and Observation (P&O) or Incremental Conductance to locate the Maximum Power Point (MPP). The DC-DC converter module regulates the voltage and current levels to match the requirements of the load or battery, ensuring efficient energy transfer between the solar panel and the target storage or consumption system.

Overall, this Simulink model provides a comprehensive platform for analyzing and optimizing the performance of solar PV systems under various conditions. It allows engineers and researchers to fine-tune the system for maximum energy harvesting and efficiency. The discussed Simulink model is illustrated in the figure below.

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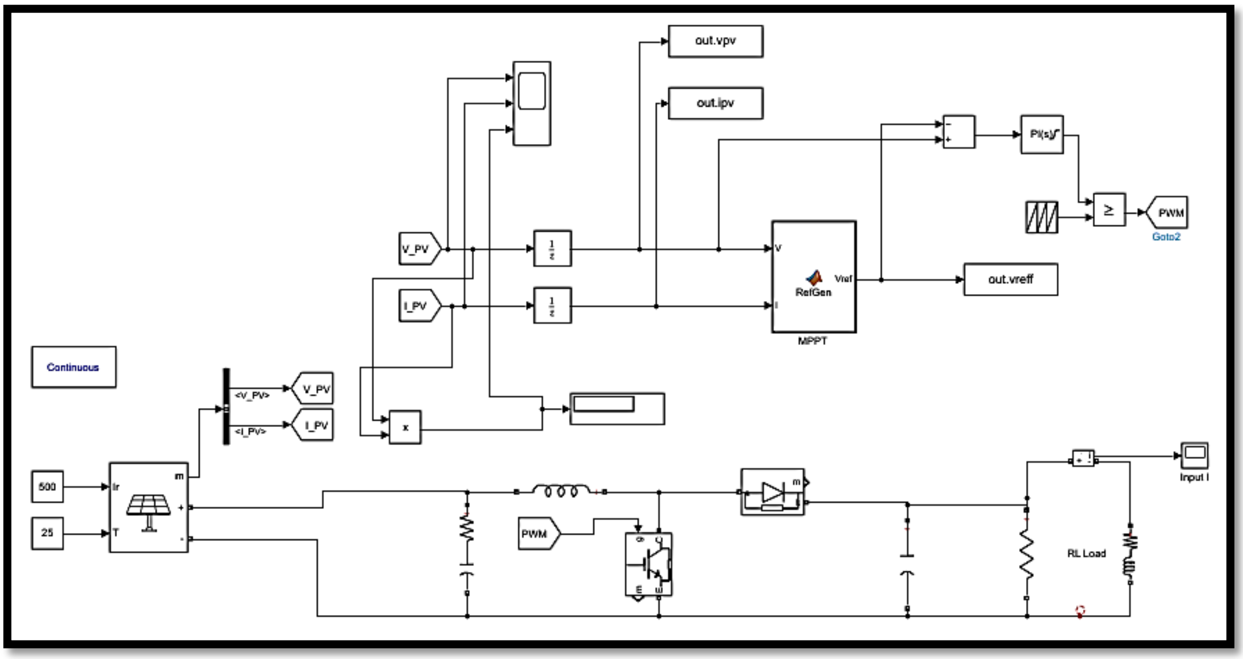

Figure 1: Simulink model with P&O based MPPT

It can be seen the P&O algorithm has been implemented inside a MATLAB function. The solar panel has the maximum voltage of 29V. We have used 10 module in series So the maximum voltage would be 290V. We have inputted the same rating in out perturbation and observation based MPPT controller. The results obtained from this model is found to be in limits. This model is used to generate the dataset for the ANN controller.

1.3 Creation of dataset to design ANN controller

From the above mentioned model, the dataset has the input parameter solar voltage and output parameter as Vref.

1.4 Simulink model with the developed ANN controller

Given below is the developed Simulink model with the developed ANN controller

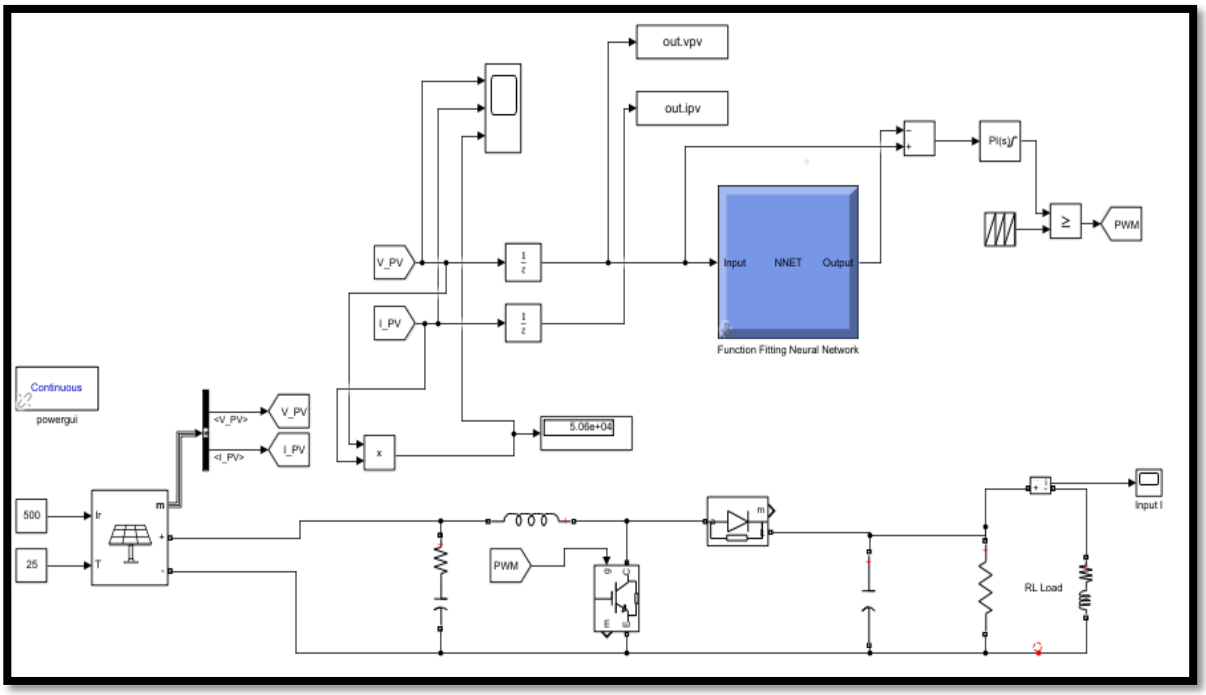

Figure 2: Simulink solar model with ANN Controller

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Here the neural network controller has been used to generate the Vref. The result obtained are found to be satisfactorily.

2 Simulink Model for the pitch angle controlling of wind farm

A Simulink model of wind turbine is used in the microgrid as shown in the figure below.

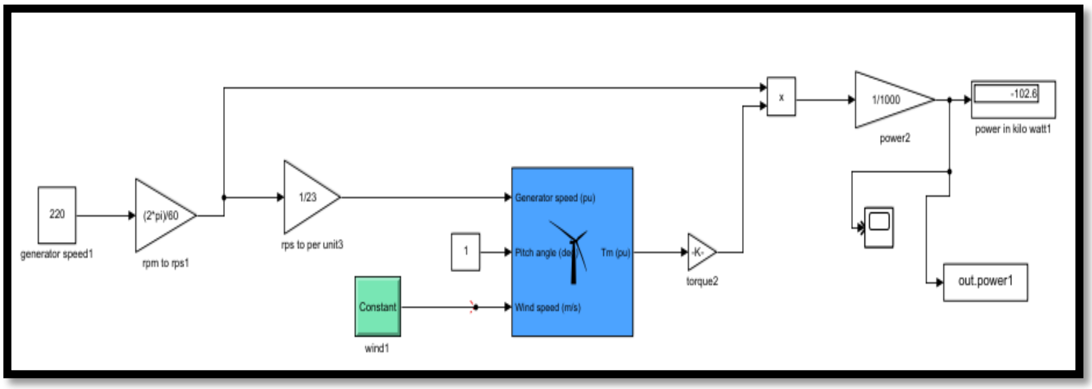

Figure 3: Model to get the optimum pitch angle

Here the rated power of wind turbine is to be chosen as 50kW. The rpm of the wind turbine is taken as 220. Converting this rpm to rps we get

$$\text{RPS} = \frac{\text{RPM}}{\frac{60}{2\pi}} = \frac{220 * 2\pi}{60} = 23$$

Torque to per unit conversion $P = wT$

Here P=rated power 50kW, w=23 So, $T = \frac{50000}{23} = 2174$

The dataset is created from the above mentioned model where the windspeed is taken as the input parameter and optimum pitch angle is taken as the output parameter. This model is then exported as the Simulink block and used as a pitch angle controller as shown below.

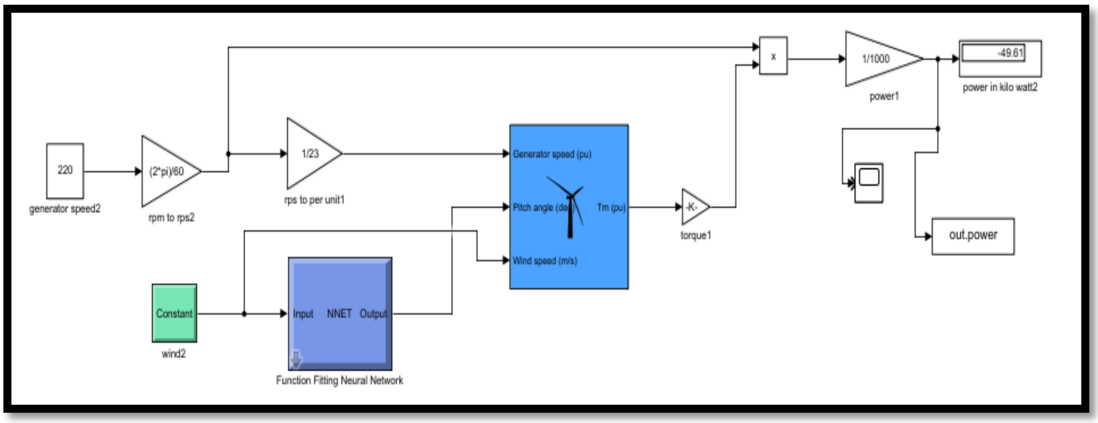

Figure 4: Wind turbine modelling with ANN controller

II. RESULTS AND DISCUSSION

2.1 Neural Network performance for the pitch angle control

The performance of the neural network based pitch angle controller is shown below

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	Observations	MSE	R
Training	17	0.0656	0.9995
Validation	4	1.7922	0.9973
Test	4	44.1311	0.9694

Figure 5: performance of pitch angle NN controller

It can be seen that the regression coefficient is very close to unity. The error histogram of the controller is shown below and the maximum error is found to be 0.09342

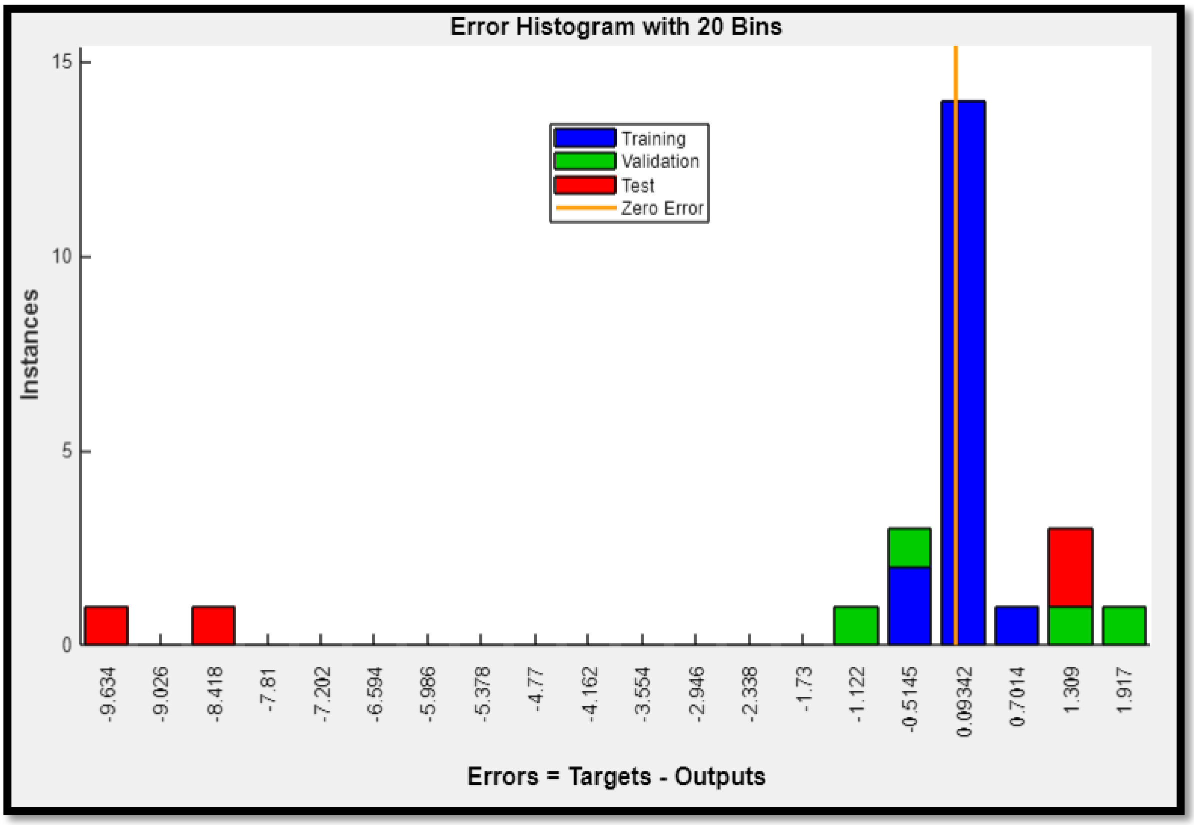

Figure 6: Error histogram of wind turbine NN controller

2.2 Real time performance evaluation of pitch angle controller

As shown in the figure below the performance of the wind turbine is evaluated with and without the ANN controller. Here it can be seen that there is large deviation in power when the neural network based controller is not used.

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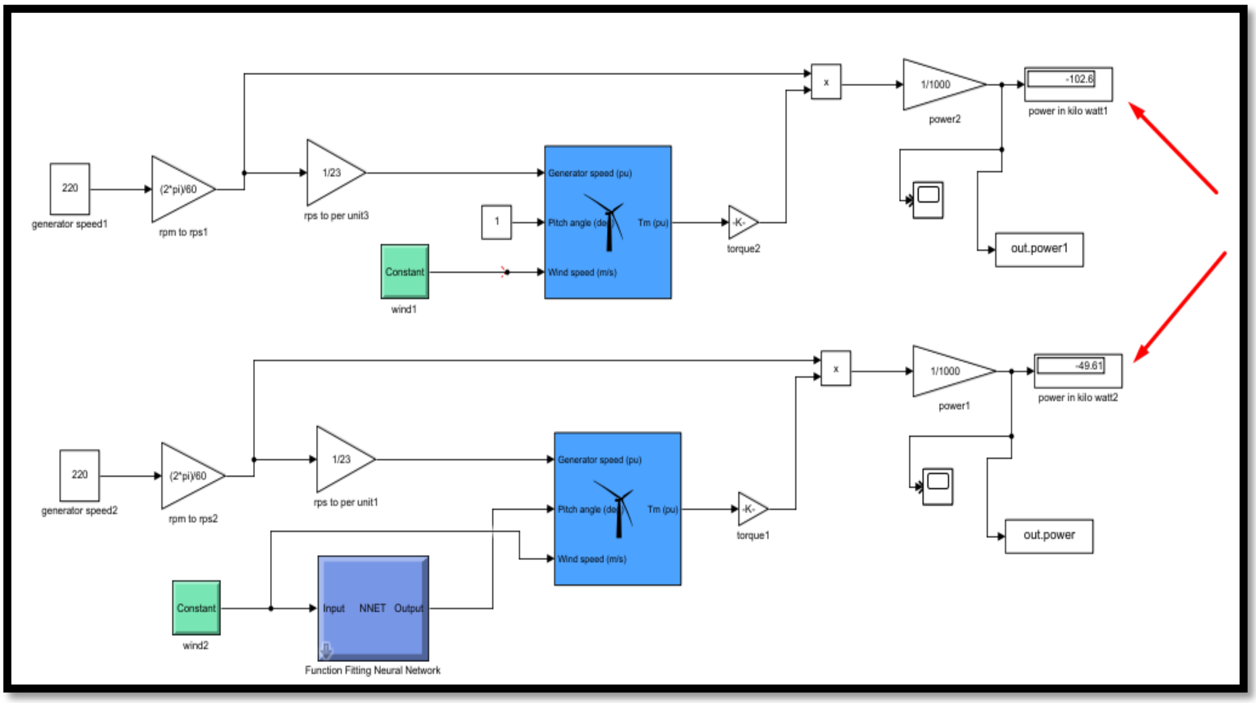

Figure 7: Power output comparison

2.3 Neural Network performance for the MPPT tracking

A neural network has been trained with the data obtained from the P&O algorithm and the performance is shown below.

	Observations	MSE	R
Training	757	53.3383	0.3296
Validation	162	46.7081	0.1997
Test	162	46.0569	0.4116

Figure 8: Performance of solar NN controller

2.4 MPPT using ANN controller

The traditional MPPT controller is now replaced with the developed trained ANN controller. The voltage, current and power waveform is shown below

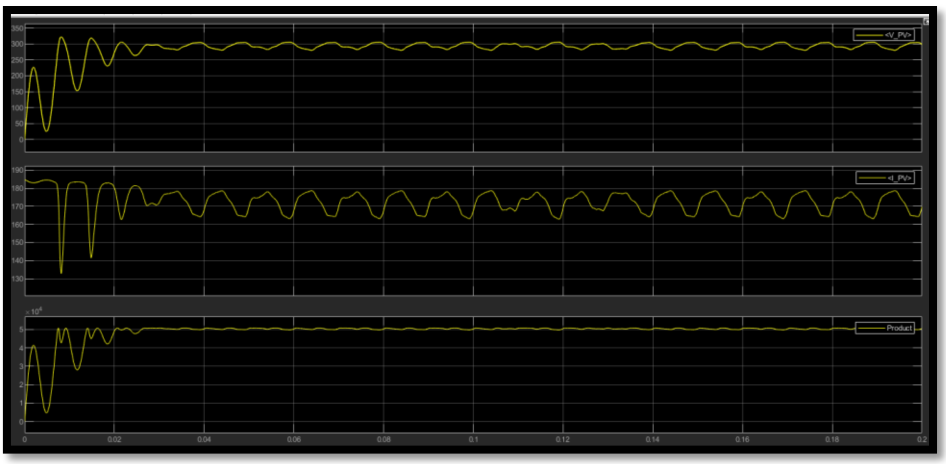

Figure 9: voltage, current and power waveforms using NN based controller

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It can be seen in the above waveform that the Maximum power point is reached using this controller

2.5 Comparative analysis

As mentioned in the [19], the MPPT peak to peak deviation comparison is shown below

Model	Peak-peak MPPT deviation	Difference(P_{max} - P_{min})
Model used in [19]	power generated is maintained between 5000-13000W	8000W
Our proposed model	power generated is maintained between 49000-52000W	3000W

III. CONCLUSION

This study successfully developed a Simulink-based simulation model to optimize renewable energy systems by integrating neural network-based controllers. The model incorporates two critical controllers: a Maximum Power Point Tracking (MPPT) controller for solar photovoltaic (PV) systems and a pitch angle controller for wind farms. The use of neural networks in both controllers significantly enhances their adaptability and efficiency under varying environmental conditions. The MPPT controller dynamically adjusts the operating point of the solar PV array to ensure maximum power extraction, while the pitch angle controller optimizes the blade angle of wind turbines to maximize energy capture and maintain system stability. Simulation results confirm the effectiveness of these neural network-based controllers in improving the performance and reliability of renewable energy systems, demonstrating their considerable potential for real-world applications in sustainable energy generation. The promising results of this study open several avenues for future research and development. Firstly, further refinement of neural network algorithms could enhance their predictive accuracy and response times, leading to even more efficient energy extraction. Additionally, expanding the model to incorporate other renewable energy sources, such as hydro and geothermal, could provide a more comprehensive solution for integrated energy systems. Investigating the real-world implementation of these controllers, including hardware-in-the-loop (HIL) simulations and pilot projects, would be valuable to assess their practical viability and scalability. Moreover, exploring the integration of advanced machine learning techniques, such as deep learning, could further improve the controllers' performance under diverse and complex environmental conditions. Finally, developing robust cybersecurity measures to protect these intelligent control systems from potential threats is crucial for ensuring the safe and reliable operation of future smart grids.

IV. REFERENCES

[1] Carrasco, J. M., Franquelo, L. G., Bialasiewicz, J. T., Galván, E., PortilloGuisado, R. C., Prats, M. M.,& Moreno-Alfonso, N. (2006). Power-electronic systems for the grid integration of renewable energy sources: A survey. IEEE Transactions on industrial electronics, 53(4),1002-1016.

[2] Ganechari, S. M., & Kate, S. (2005). Alternative energy sources. Alternative Energy Sources, 5

[3] Crutzen, P. J., Mosier, A. R., Smith, K. A., & Winiwarter, W. (2016). N 2 O release from agro-biofuel production negates global warming reduction by replacing fossil fuels. In Paul J. Crutzen: A pioneer on atmospheric chemistry and climate change in the anthropocene (pp. 227-238). Springer, Cham

[4] Crutzen, P. J., Mosier, A. R., Smith, K. A., & Winiwarter, W. (2007). N 2 O release from agro-biofuel production negates global warming reduction by replacing fossil fuels. Atmospheric Chemistry and Physics Discussions, 7(4), 11191-11205

[5] Tsang, M. B., Friedman, W. A., Gelbke, C. K., Lynch, W. G., Verde, G., & Xu, H. S. (2001). Isotopic scaling in nuclear reactions. Physical Review Letters, 86(22), 5023

[6] A. A. Hossam El-din and C. F. Gabra, A Comparative Analysis Between the Performances of Monocrystalline,Polycrystalline and Amorphous Thin Film in Different Temperatures at Different Locations in Egypt-Conference paper 2014, researchgate

[7] Mekhilef, S., Saidur, R., & Safari, A. (2011). A review on solar energy use in industries. Renewable and Sustainable Energy Reviews, 15(4), 1777–1790. doi:10.1016/j.rser.2010.12.018

[8] A Mohapatra and S Tripathy 2018 IOP Conf. Ser.: Mater. Sci. Eng. 377 012135, A Critical Review of the use of Fuel Cells Towards Sustainable Management of Resources

[9] Midilli, A.; Ay, M.; Dincer, I.; Rosen, M.A. On hydrogen and hydrogen energy strategies. I: Current status and needs. J. Renew. Sustain. Energy Rev. 2005, 9, 255–271.

[10] Aditi and Dr. Ashok Kumar Pandey, A Review Paper on Hybrid Power System with Different Controllers and Tracking Methods, nternational Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 IJERTV5IS010022 www.ijert.org, Vol. 5 Issue 01, January-2016.

[11] Md. Habibur Rahman, Kamanashis Barua, Simulation of a Solar Power System with Fuel Cell backup Source for Hybrid Power System Application, 978-1-7281-1126-1/19/$31.00 ©2019 IEEE

[12] Y.S. Mohammed, M.W. Mustafa, N. Bashir, I.S. Ibrahem, "Existing and recommended renewable and sustainable energy development in Nigeria based on autonomous energy and microgrid technologies", Renewable and Sustainable Energy Reviews, vol. 75, pp. 820, 2017.

[13] W. Kellog, M. H. Nehrir, G. Venkataramanan, V. Gerez, Electric Power Systems Research, 39, 35-38, (1996)

[14] S. Kamaruzzaman, Z. Azami, A. Yusoff , M. N. Zulkifli, A. R. Juhari, S. M. Nor, Transactions on Mathematics 4 (7),130-140 (2008)

[15] Bhandari, B., Lee, KT., Lee, GY. et al. Optimization of hybrid renewable energy power systems: A review. Int. J. of Precis. Eng. and Manuf.-Green Tech. 2, 99–112 (2015). https://doi.org/10.1007/s40684-015-0013-z

[16] Mellit A, Kalogirou SA, Hontoria L, Shaari S. Artificial intelligence techniques for sizing photovoltaic systems: a review. Renew Sust Energ Rev 2009;13(2):406–19

[17] Modelling in MATLAB. https://www.mathworks.com/help/simulink/gs/create-a-simple-model.html

[18] Sudha Bala Gupta, 'A review paper on modelling of hybrid power system using solar power and fuel cell.' International Journal of Scientific Research in Engineering and Management (IJSREM) Volume: 05 Issue: 08 | Aug - 2021

[19] Ahmed Aziz, "Hybrid Wind/PV/Battery Energy Management-Based Intelligent Non-Integer Control for Smart DC-Microgrid of Smart University', IEEE 2024