International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 16s,2025
https://theaspd.com/index.php

Advanced Control Strategies Design And Simulation Of Pi, Fuzzy And Anfis Controller For Pv And Wind

Ravi Bukya[1], A. Vijendar[2], M. Sunitha[3], G. Jagan Naik[4]
[1]Assistant Professor, Department of Computer Science and Electrical Engineering, Nalla Malla Reddy Engineering College, Divyanagar, Hyderabad-39, Telangana, India, ravibhukya.cse@nmrec.ac.in.
[2]Associate Professor, Department of CSE (AIML), CMR Engineering College, Kandlakoya, Hyderabad-39, Telangana, India, vijendar.amgothu@cmrec.ac.in.
[3]Associate Professor, Department of CSE (DS), Marri Laxman Reddy Institute of Technology and Management, Hyderabad-39, Telangana, India, sunitha.m@mlrtm.ac.in
[4]Associate Professor, Department of CSE (DS), CMR Institute of Technology, Kandlakoya, Hyderabad-39, Telangana, India, gjnaik1106@gmail.com.

Abstract:
This study focuses on the design and implementation of algorithms for regulating and synchronizing voltage source inverters (VSIs) used as power conditioners in grid-connected photovoltaic (PV) systems for renewable energy applications. The primary objective is to develop robust control strategies that ensure reliable inverter performance under challenging grid conditions, including voltage imbalances, frequency fluctuations, and harmonic distortions. By addressing these issues, this research makes a significant contribution to advancing both the knowledge and technology of grid-connected solar systems, offering a comprehensive framework to maintain optimal performance and compliance with power quality standards, even during grid disturbances. To overcome inherent limitations of conventional approaches, the study introduces an innovative control scheme that combines Incremental Conductance (INC) and Perturb and Observe (P&O) techniques for Maximum Power Point Tracking (MPPT). Additionally, to enhance system stability and dynamic response, the proposed method replaces traditional Proportional-Integral (PI) voltage regulators with advanced Fuzzy Logic Controllers (FLCs). These fuzzy regulators are designed to achieve faster dynamic response, suppress grid current fluctuations, and maintain voltage stability in the constant current operating range. The proposed strategy has been rigorously analyzed through detailed mathematical modeling and extensive MATLAB simulations. Comparative results demonstrate superior dynamic performance and enhanced grid power utilization, validating the effectiveness and practicality of the control approach.
Keywords: *Compensation topology, efficiency, power transfer capability, Inductive power transfer, series-series and parallel-series topology.*

INTRODUCTION

In modern solar photovoltaic (SPV) systems, the integration of Artificial Intelligence (AI) techniques—particularly Fuzzy Logic (FL) and Artificial Neural Networks (ANN)—has gained significant traction due to their unique capabilities. These advanced methodologies are widely employed to optimize Maximum Power Point Tracking (MPPT) in SPV modules, thereby enhancing overall system performance. As discussed in previous sections, SPV modules exhibit complex non-linear characteristics, which often challenge conventional MPPT algorithms in accurately locating and extracting the Maximum Power Point (MPP). In this context, AI-based techniques, such as FL-driven MPPT, offer a highly effective alternative [1].This study adopts a Fuzzy Logic Controller (FLC), The choice of FLC is primarily motivated by its proven ability to manage systems characterized by nonlinearities and uncertainties. This strength stems from the controller's reliance on expert knowledge and heuristic rules, which imbue the system with an added layer of intelligence. Crucially, FLC does not require an explicit mathematical model of the system, making it inherently more robust and adaptable compared to conventional controllers [2].The distinctive advantage of FLC lies in its ability to represent control strategies through linguistic rules defined on fuzzy sets. This allows the controller to effectively manage the inherent imprecision and uncertainty of SPV systems—an area where traditional control methods often fall short. By leveraging linguistic variables and rule-based reasoning, FLC mirrors human-like decision-making, enabling it to handle the complex, non-linear behavior typical of SPV modules without the need for a precise mathematical formulation [3].Implementing FLC-based MPPT in SPV systems thus represents a strategic approach to overcoming the challenges posed by the modules' non-linear dynamics. By harnessing the flexibility and intelligence of fuzzy logic, this technique significantly enhances the robustness and efficiency of SPV systems. Moreover, it underscores the broader potential of AI-driven control in advancing the performance and optimization of renewable energy technologies.

1 Fuzzy Logic

Fuzzy Logic (FL) extends conventional Boolean logic, which operates on binary outcomes (0 or 1), by introducing a continuous spectrum of values between 0 and 1. This enables the expression of degrees of truth, rather than rigid binary distinctions, making FL an intuitive framework that mirrors natural human reasoning and communication. The foundational concepts of FL were introduced by Lotfi Zadeh in the late 1960s [4], who developed the notions of fuzzy sets and fuzzy control to address challenges in controlling systems that are difficult to model using traditional techniques. By facilitating the representation of imprecise and vague information, FL aligns closely with the nuances of human decision-making [5].A significant milestone in FL's practical application came in 1974, when Ebrahim Mamdani implemented one of the first fuzzy control systems [4]. Since then, fuzzy control has become a well-established and actively researched domain within fuzzy set theory. The original motivation for fuzzy control was to manage systems with complex dynamics or those lacking precise mathematical models. Fuzzy Logic Controllers (FLCs) leverage linguistic variables and rule-based reasoning, incorporating qualitative knowledge into the control process [6]. This adaptability makes FLCs particularly effective for dynamic, non-linear systems where conventional controllers may struggle [7] [8].The practical viability of fuzzy controllers is evidenced by their widespread use in commercial products, ranging from video cameras and air conditioners to televisions and washing machines. Their broad adoption in consumer electronics underscores their robustness and ability to handle real-world complexities [9].Over time, fuzzy logic has evolved into a powerful tool for managing uncertainty and imprecision in control systems. Its success across a variety of applications highlights its value in capturing the richness of human reasoning, making it a preferred choice for designing controllers, especially for dynamic systems where conventional approaches may be inadequate [10][11].FLCs typically reside within knowledge-based systems structured around IF-THEN rules that incorporate vague predicates and employ fuzzy inference mechanisms. These rules guide the decision-making process: each rule contains an antecedent (IF) and a consequent (THEN) [12]. When the conditions in the antecedent are met, the conclusions in the consequent are activated. In effect, FLCs function as state-variable controllers, using a combination of rules and inference mechanisms to govern the behavior of the system being controlled [13].Unlike traditional controllers that rely on precise numerical values, fuzzy systems use linguistic variables such as "small," "medium," or "high." These terms represent values within a fuzzy domain, defined over a universe of discourse. At the heart of an FLC lies a set of linguistic rules, which encapsulate the knowledge and heuristics of the system. FLCs have demonstrated superior or comparable performance to other control algorithms across a wide range of real-world applications [14].The application of fuzzy logic is particularly advantageous in problems that are mathematically challenging or where FL offers enhanced performance, simpler implementation, or faster computation [15]. FL excels in environments characterized by uncertainty, imprecision, and complexity. By accommodating linguistic values and employing rule-based decision-making, FLCs capture the subtleties and uncertainties inherent in many real-world systems. The flexibility of fuzzy logic supports its use across diverse domains, from consumer electronics to industrial control processes. Its capacity to handle non-linearities and imprecise information makes it a highly valuable tool where conventional control methods fall short [16]. Furthermore, the interpretability and ease of implementation of FL have contributed to its widespread adoption in practical applications. In summary, FL's unique ability to manage uncertainty and imprecision positions it as an indispensable tool in the design of modern control systems and intelligent decision-making frameworks [17-23].

2 Fuzzy Logic Controller-Flc

The FLC has four fundamental stages: fuzzification, the fuzzy rule-base system, the fuzzy inference system, and defuzzification, as depicted in figure.1.These stages collectively enable the controller to process and interpret linguistic variables for effective decision-making and simulation model of the PV system with

Fuzzy controller as shown in figure 2 also Incremental conductance MPPT algorithm Simulink as shown in figure 3.

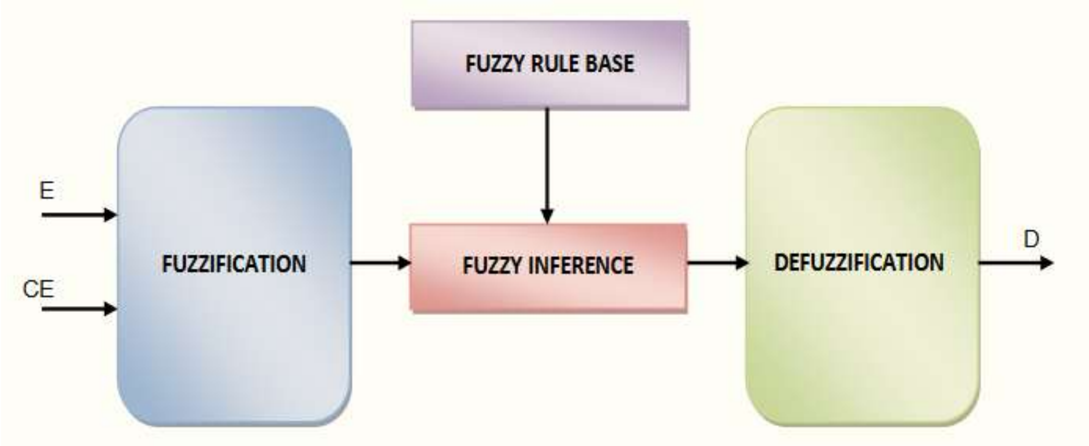

Fig.1. Diagram illustrating the structure of a fuzzy logic controller.

Simulation & Results

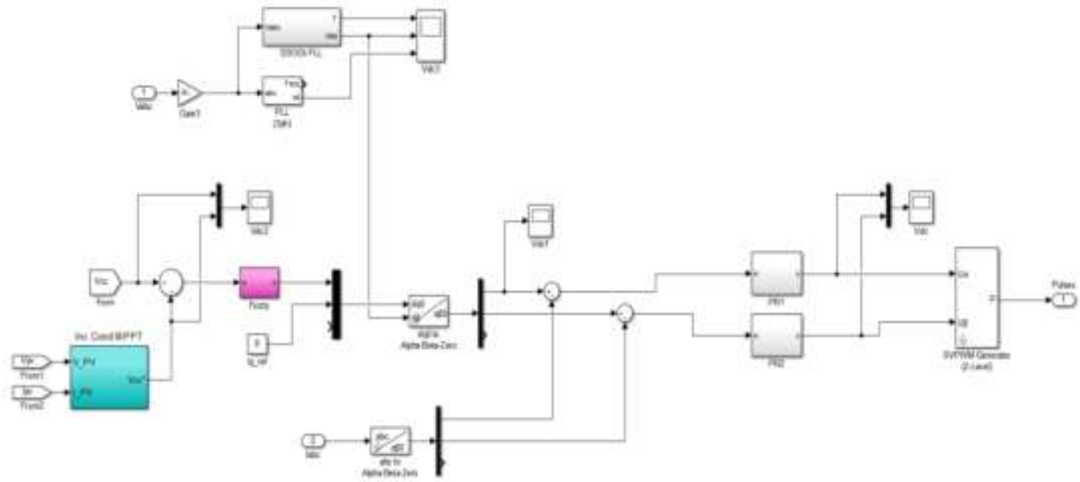

Fig. 2. Simulink diagram of grid-connected P-V system with fuzzy-controller.

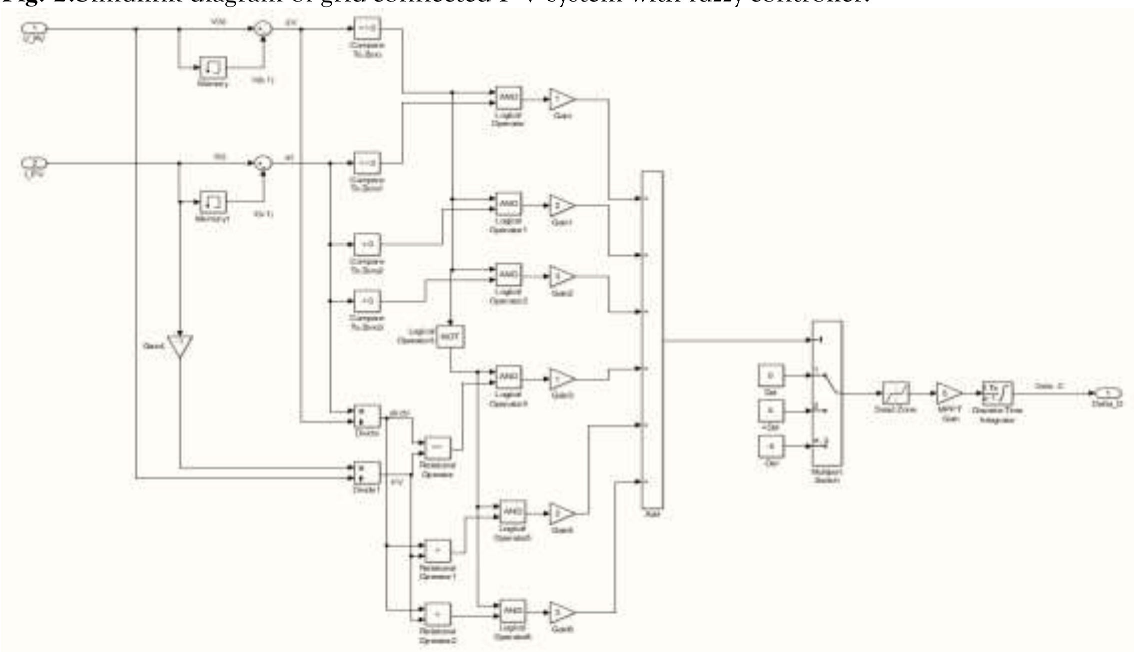

Fig. 3. The Simulink model of the Incremental Conductance MPPT algorithm

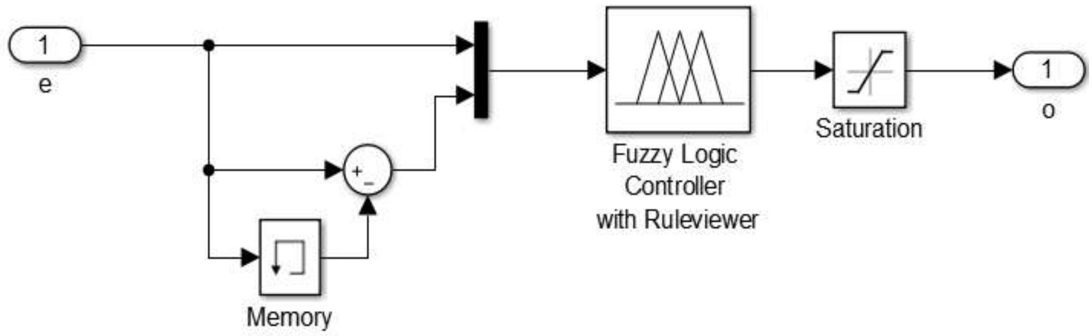

Fig. 4. Displays the Simulink model depicting the Fuzzy Controller.

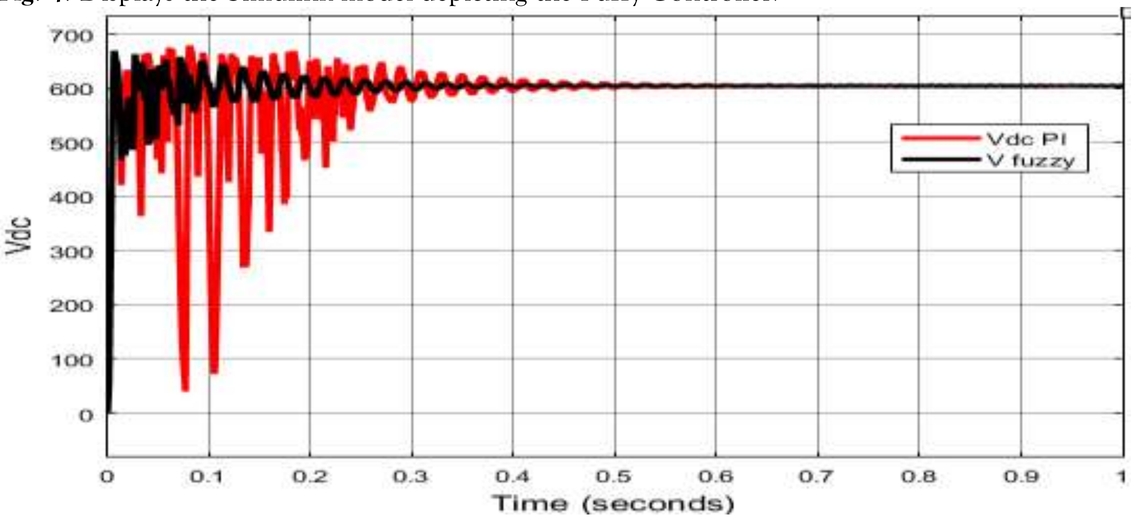

Fig. 5. DC voltage wave form with PI and Fuzzy controller.

From the above figure 5 DC voltage output wave form with PI and Fuzzy Controller, it is evident that the peak overshoot and the ripples in the dc voltage is reduced with the use of Fuzzy Controller in figure 4 the controller of the Simulink model as in figure 4.

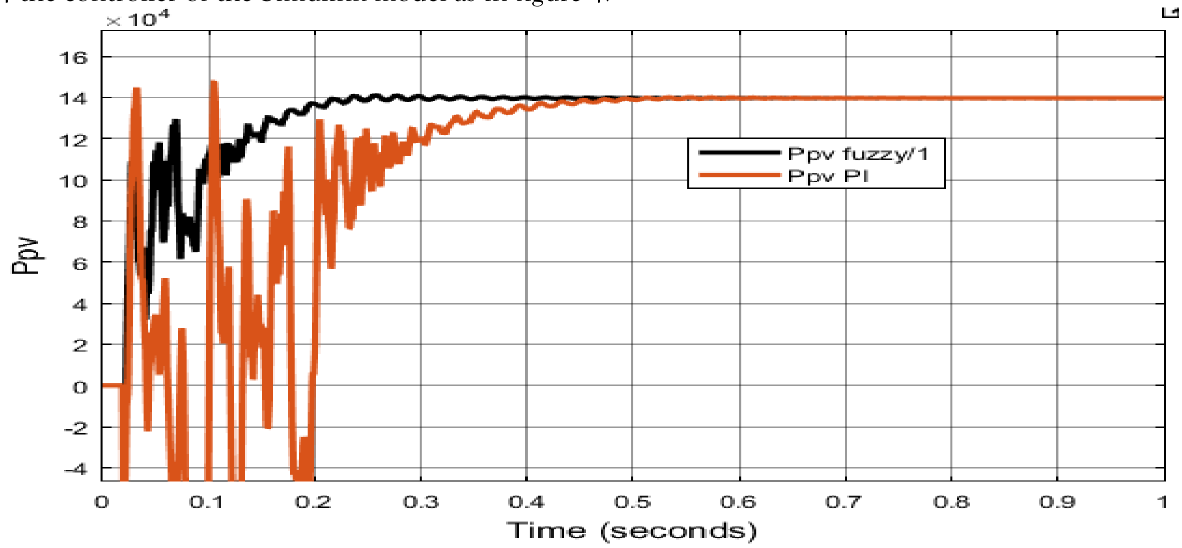

Fig. 6. The power generated by PV systems can be efficiently regulated using both a PI controller and a FC. The graphic above compares the electricity generated by photovoltaic (PV) systems using both proportional-integral (PI) and fuzzy controllers. The utilisation of a fuzzy controller leads to a reduction in both overshoot and ripples in the waveform. The utilisation of fuzzy logic also leads to a decrease in settle time. The PI controller requires approximately 0.55 seconds reaching a stable state, while the FC reduces the settling period to 0.25 seconds figure 6 and figure 7.

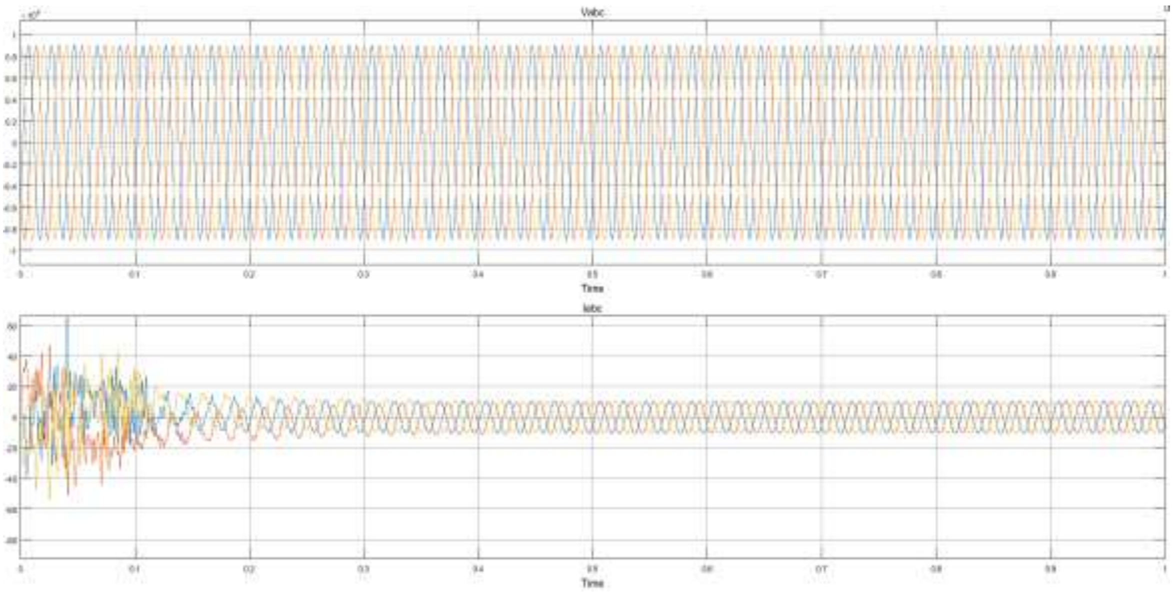

Fig. 7. Waveforms of voltage and current controlled by a fuzzy controller.

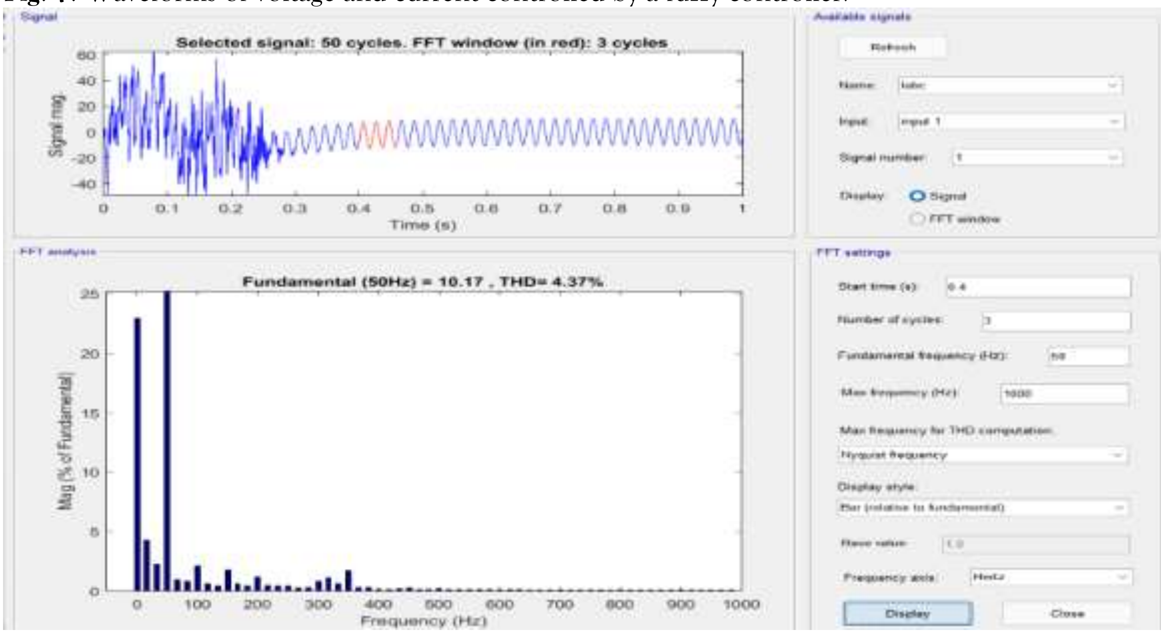

Fig. 8. Total Harmonic Distortion with PI controller

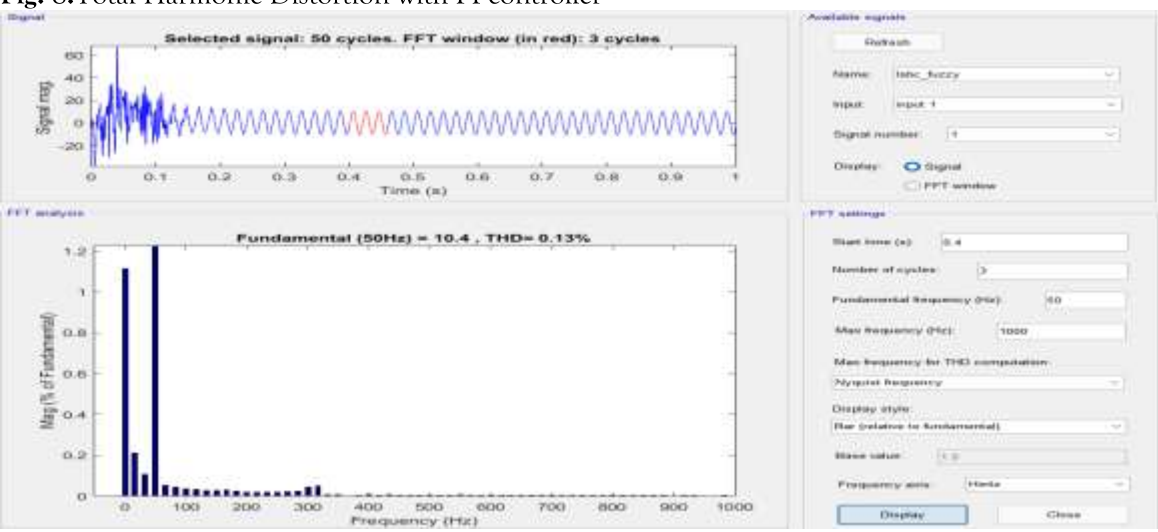

Fig. 9. Calculation of Total Harmonic Distortion using a fuzzy controller.
Here three cases are considered and tested as shown in figure 8 and Figure 9 as follows the factors
1.When there is sudden change in load.
2.When three phase fault is occurred.
3.when there is change in irradiance.

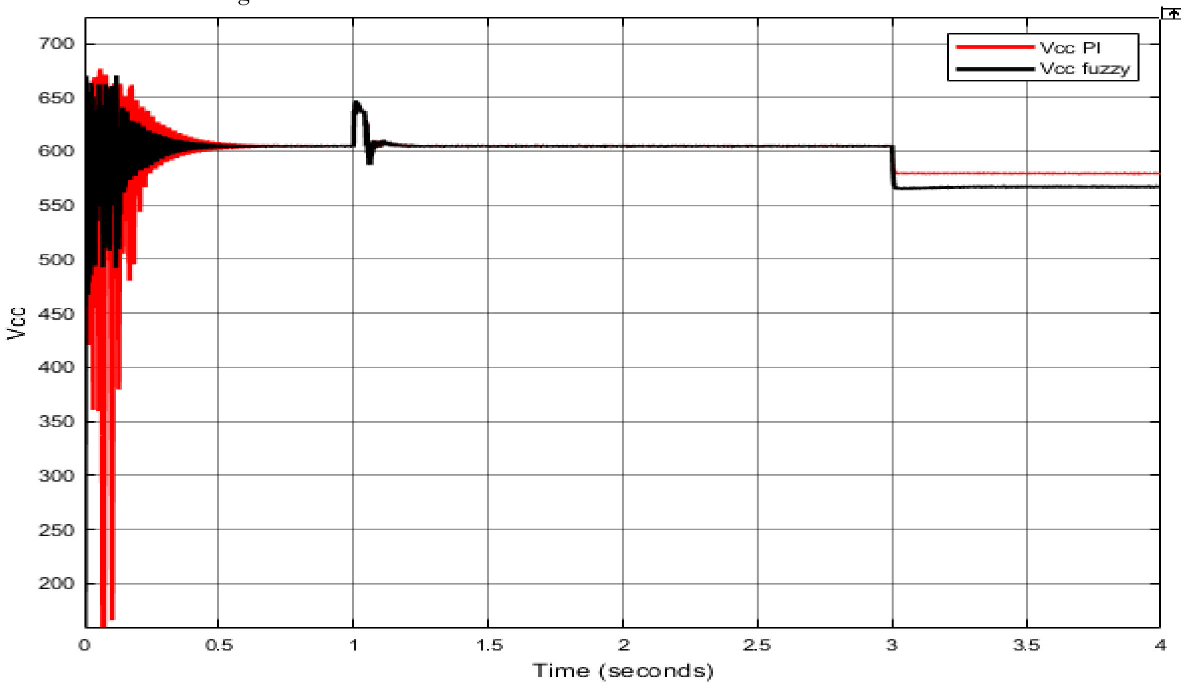

Fig. 10. DC link Voltage with Sudden load at 1s And Fault at 3s.

The load is evaluated at 1 second, whereas the three-phase fault is evaluated at 3 seconds. At the 1-second mark, when the load is abruptly applied, the voltage experiences a minor increase from 600V to 645V till 1.05 seconds. From 1.05 seconds to 1.055 seconds, there is a voltage drop from 600V to 588V. Ultimately stabilising at a duration of 1.25 seconds.At a fault occurrence of 3 seconds, the voltage drops from 600V to 580V when using a PI controller. However, while using a fuzzy controller, the voltage drops from 600V to 640V. When comparing the two, the voltage loss is greater with the fuzzy controller in figure 10 and figure 9.

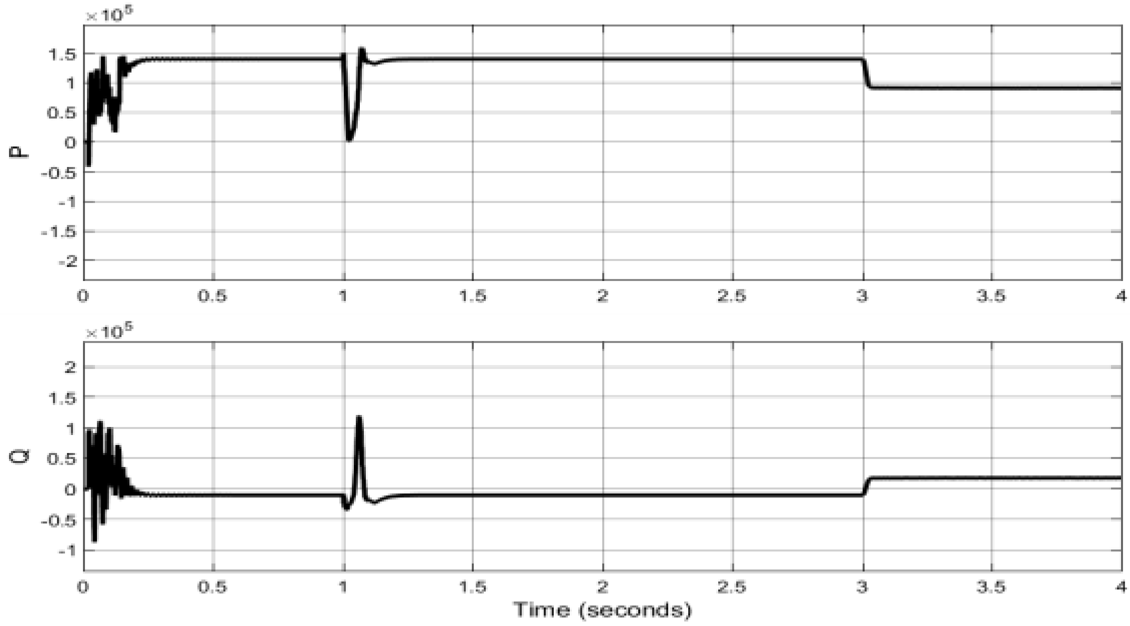

Fig.11. Real and reactive power in abnormal conditions.

At 1s, there is a dramatic decrease in active power to 0 and an increase in reactive power to 125 kvar. During a three-phase fault that occurs at 3 seconds, the active power decreases from 140 kW to 90 kW in figure 11.

3 Advanced neuro fuzzy inference system (anfis):

The ANFIS controller, a neuro-fuzzy system, is implemented in a control unit using Takagi and Sugeno's methods to produce accurate input-output modelling.The adaptive framework acquires knowledge from existing datasets and constructs appropriate fuzzy if-then rules with adequate membership functions. ANFIS produces input-output (I/O) data, where the output is expressed as a linear function. Takagi and Sugeno propose that when a set of inputs is given, two fuzzy (if-then) rules are triggered, resulting in a strong correlation between the input and output. This approach demonstrates efficacy in capturing and leveraging information from the dataset, hence boosting the adaptability and performance of the control system.

Applying the Takagi and Sugeno approach, two fuzzy (if-then) rules are activated based on a particular set of inputs, and can be expressed as follows:

$$f_{i=a_i x+b_i y+c_i} \tag{1}$$

When i is equal to 1 or 2, the variables ai, bi, and ci represent the coefficients, while x and y represent the inputs. The linear transfer function in ANFIS produces an output that accurately reproduces the input. The architecture comprises five levels, as illustrated in the accompanying diagram, which explains the sequential building of the Adaptive Neuro-Fuzzy Inference System (ANFIS).

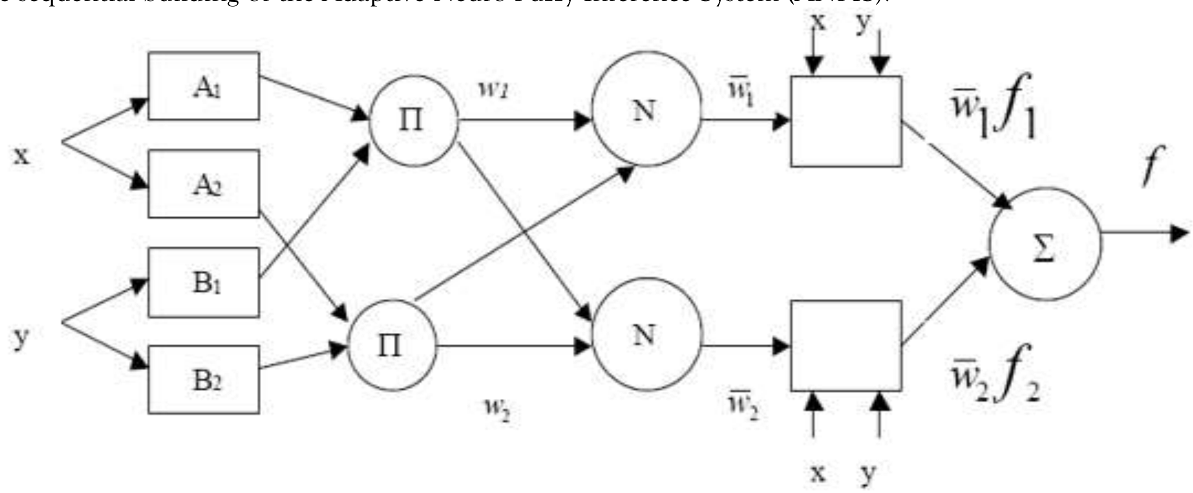

Fig. 12. Basic Architecture of ANFIS

1. **Layer 1 (Input Layer):** Neurones that encode the incoming variables.

The layer's output is determined by using figure 12

$$\text{Output} = f(x,y) \tag{2}$$

Layer 2 (Fuzzification Layer): Every individual neurone calculates the degree of membership for a specific linguistic label that is linked to each input variable.In this case, we assume a triangular membership distribution, where the membership function can be determined as follows:

$$\mu_{tringulaar} = \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \tag{3}$$

Layer 3 (Rule Layer): Neurons here compute the firing strength of each rule, combining the outputs from Layer 2 using the input values and membership grades.

The calculation of the normalized firing strength for each rule is expressed as follows.

$$w_1 = \mu_{Ai}(x) + \mu_{Bi}(y) \tag{4}$$

Layer 4 (Normalization Layer): Normalizes the firing strengths to ensure consistency. The result from this layer is obtained by multiplying the firing strength with the output of the relevant firing rule.

$$\overline{W_1} = \frac{W_1}{W_1+W_2} \tag{5}$$

Layer 5 (Output Layer): Neuron computes the overall output by combining the normalized firing strengths, and it typically employs a linear transfer function.

The comprehensive overall result is obtained by combining the outputs from layer 4 in this manner.

$$O_5, i = \sum \overline{W_i} f_i \tag{6}$$

These layers together create a comprehensive architecture for ANFIS, enabling adaptive fuzzy inference based on the input data.The following figure 13 shows the structure of an ANFIS for 2 input 3 membership functions

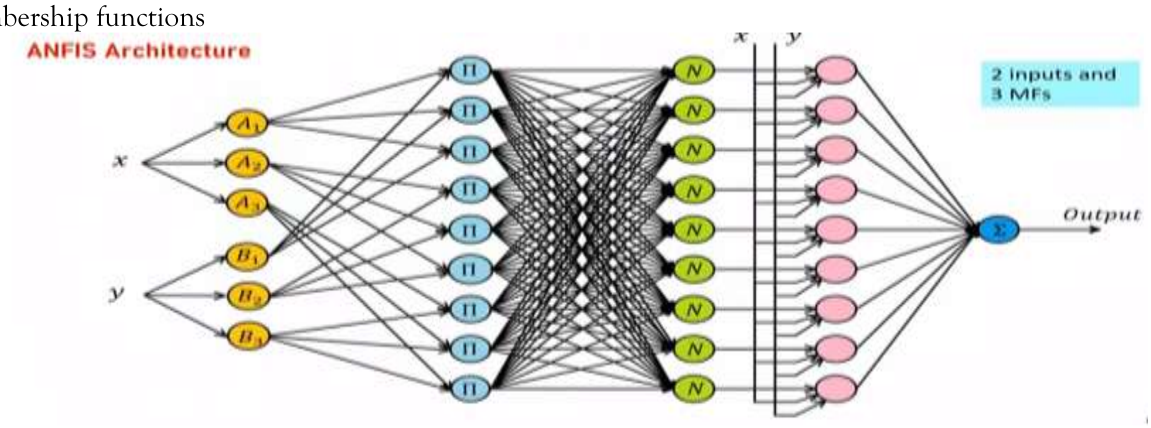

Fig.13 Basic Architecture of ANFIS for 2-input,3-membership functions.

Fuzzy logic is all about providing a range of values for a set of crisp inputs through the process of fuzzification. Fuzzy logic is basically a set of IF and THEN conditions. If a set of conditions are satisfied then a subsequent consequence is generated for that input. Fuzzy logic simplifies a complex computation with a simple IF and THEN rule database. Following the implementation of the above mentioned rule syntax, choice of membership function is essential since it performs the mapping of input points onto a membership value or label. Following the membership mapping function, the rule base is created using the IF and THEN rules. IF denotes the premise while THEN denotes the consequence of the premise.

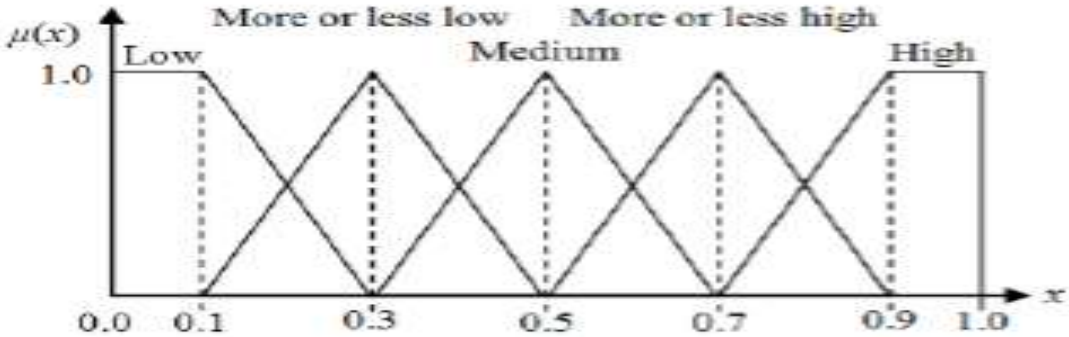

Fig.14. Membership functions of the fuzzy system.

So here the above discussed Sugeno approach is used to calculate the dc voltage by providing Vdc and reference Dc Voltage(Vdc*). ANFIS is trained with 100 Epochs to find the error. Apart from this here a EV charging station is proposed with the help of grid integrate wind and PV systems the membership function of the fuzzificztion as shown in figure 14.

4 Ev charging station based on wind and pv systems connected to grid:

The global surge in the widespread adoption of Electric Vehicles (EVs) in favour of Internal Combustion Engine (ICE) vehicles has prompted numerous countries to shift towards EVs for their transportation needs.India, in particular, has taken substantial steps to promote EV use. Initiatives such as the National Electric Mobility Mission (2012) aimed to deploy 5 to 7 million EVs by 2020. The FAME scheme (2015) focused on reducing EV prices, while significant investments were made in charging infrastructure projects. Moreover, the government declared intentions in 2017 to ban fossil fuel vehicles by 2030. These strategic schemes and targets signify India's strong commitment to accelerating the adoption of EVs, aligning with global trends toward sustainable and eco-friendly transportation.Electric Vehicles (EVs) rely on batteries as their primary power source, necessitating periodic charging. Consequently, the demand for EV charging stations has surged. While the electric grid can support these stations, it faces challenges in managing increased loads and relies predominantly on conventional energy sources. This limitation has spurred the quest for renewable energy alternatives, notably solar power, owing to its renewable and eco-friendly nature. Environmental experts advocate for integrating EV charging stations with renewable energy sources to bolster sustainability.The design of an Electric Vehicle (EV) charging station is formulated to function through the utilization of solar photovoltaic (PV) technology and a battery storage system.In situations where PV generation is not accessible, the station turns to the electric grid or employs a wind mill to fulfil its power needs.This diversified approach ensures continual operation regardless of the availability of renewable sources figure 15.The paper investigates more developments in the field, namely a grid-connected electric vehicle (EV) charging station that incorporates a control method designed to minimise the impact on the grid by minimising load demand and fluctuations. This method enhances the station's integration with the grid, reducing its influence on the overall grid stability during charging procedures. The many methods highlighted emphasise the importance of incorporating renewable energy sources, such as solar power, into electric vehicle charging infrastructure, hence enhancing the sustainability and dependability of transportation networks.

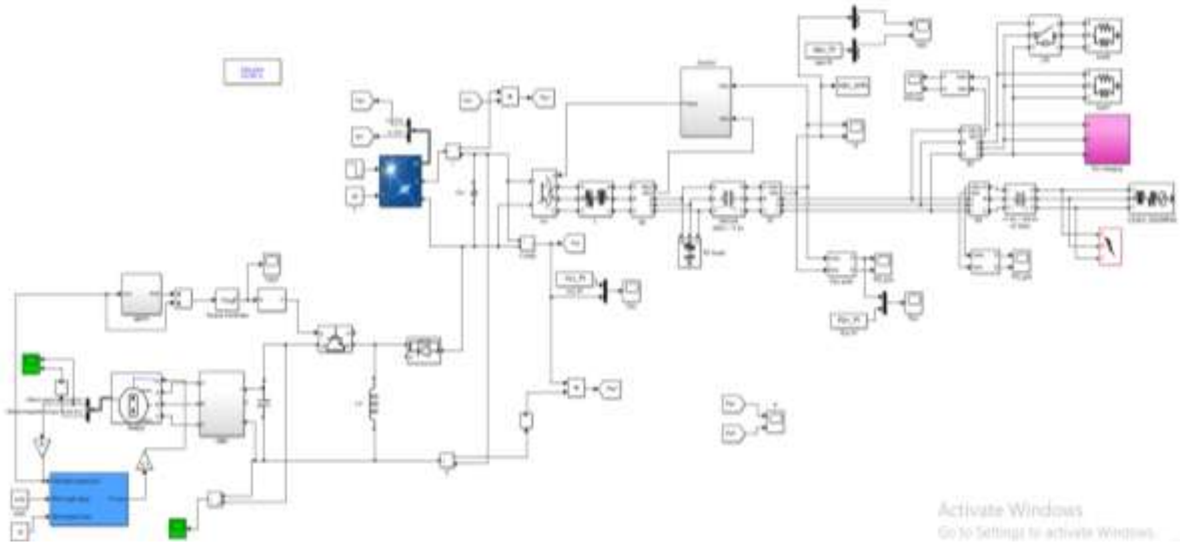

Fig. 15. Simulink diagram of Grid connected PV and Wind with ANFIS controller

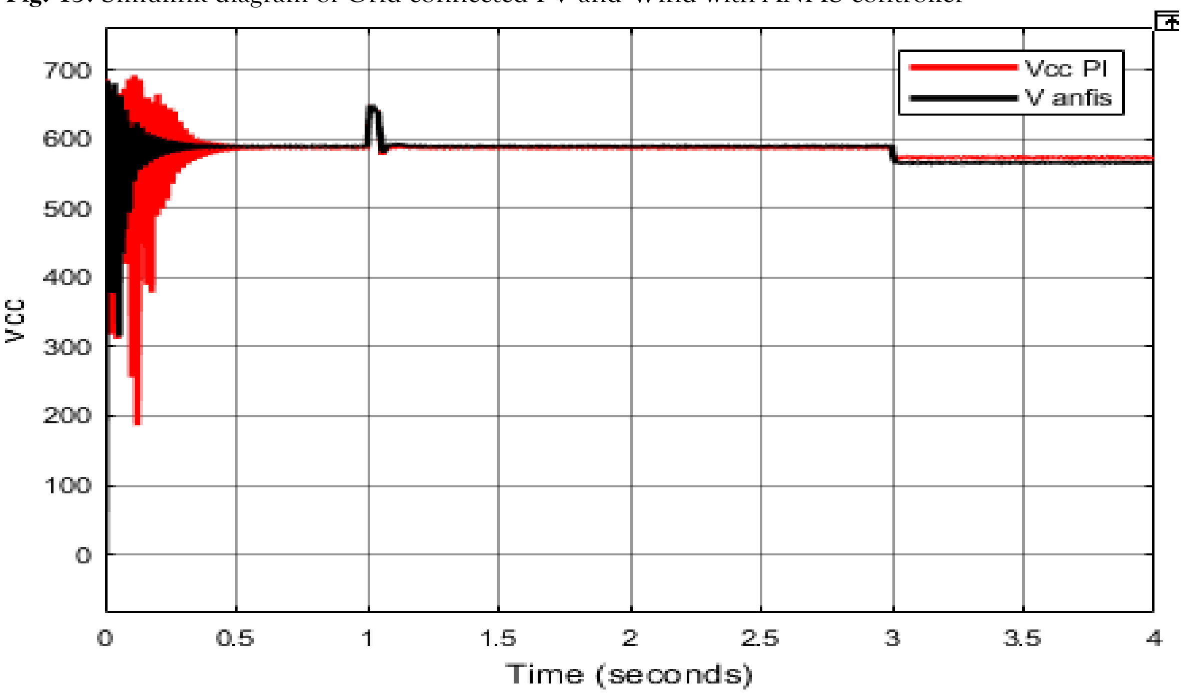

Fig. 16. DC voltage wave form for PI and ANFIS controller.

The DC voltage Vdc is being compared with PI and ANFIS Controllers, respectively. The voltage waveform's ripples are reduced by employing ANFIS by figure 16.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 16s,2025
https://theaspd.com/index.php

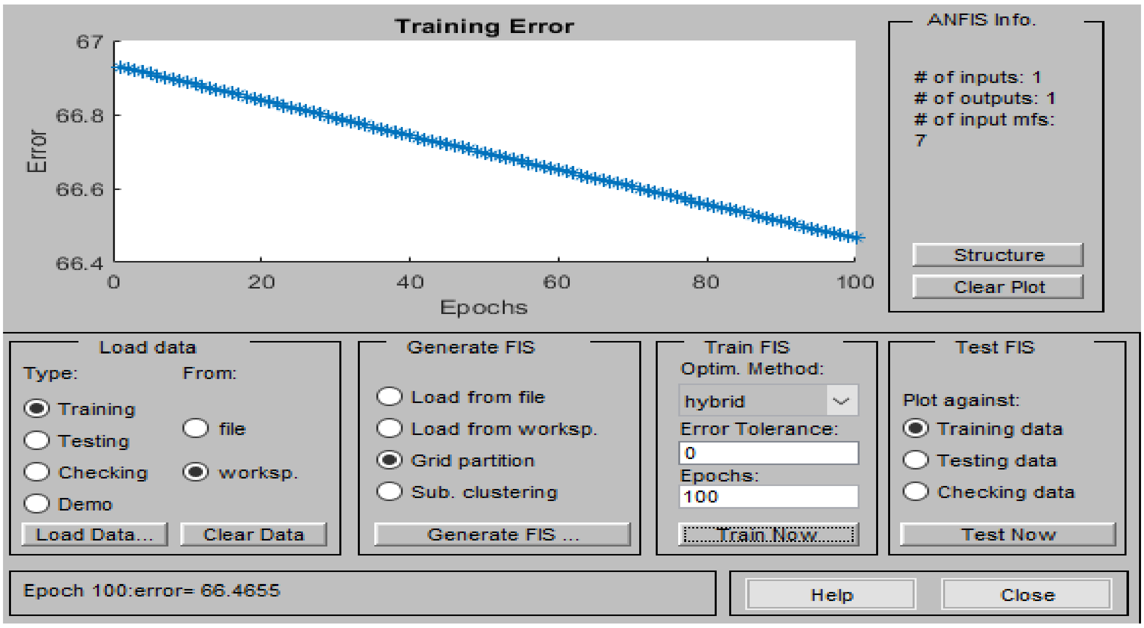

Fig. 17. ANFIS training for 100 EPOCHS

Here the ANFIS trained with 100 EPOCHS to get more accurate values. And the difference in the output before training and after training is shown below figure 17.

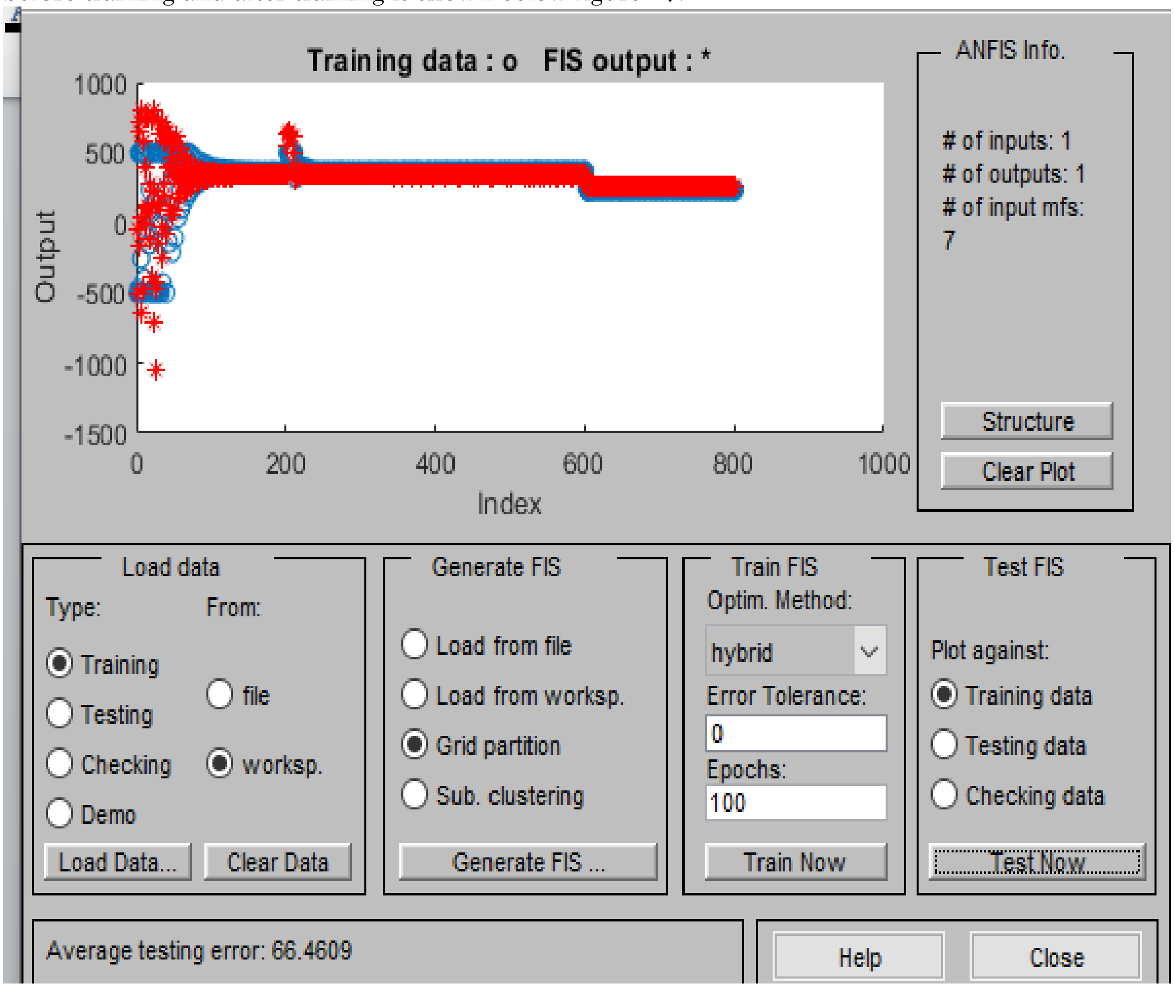

Fig. 18. ANFIS training for error (100 EPOCHS)

As said above the blue colour shows the put before ANFIS is trained and red colour shows the output after training figure 18.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 16s,2025
https://theaspd.com/index.php

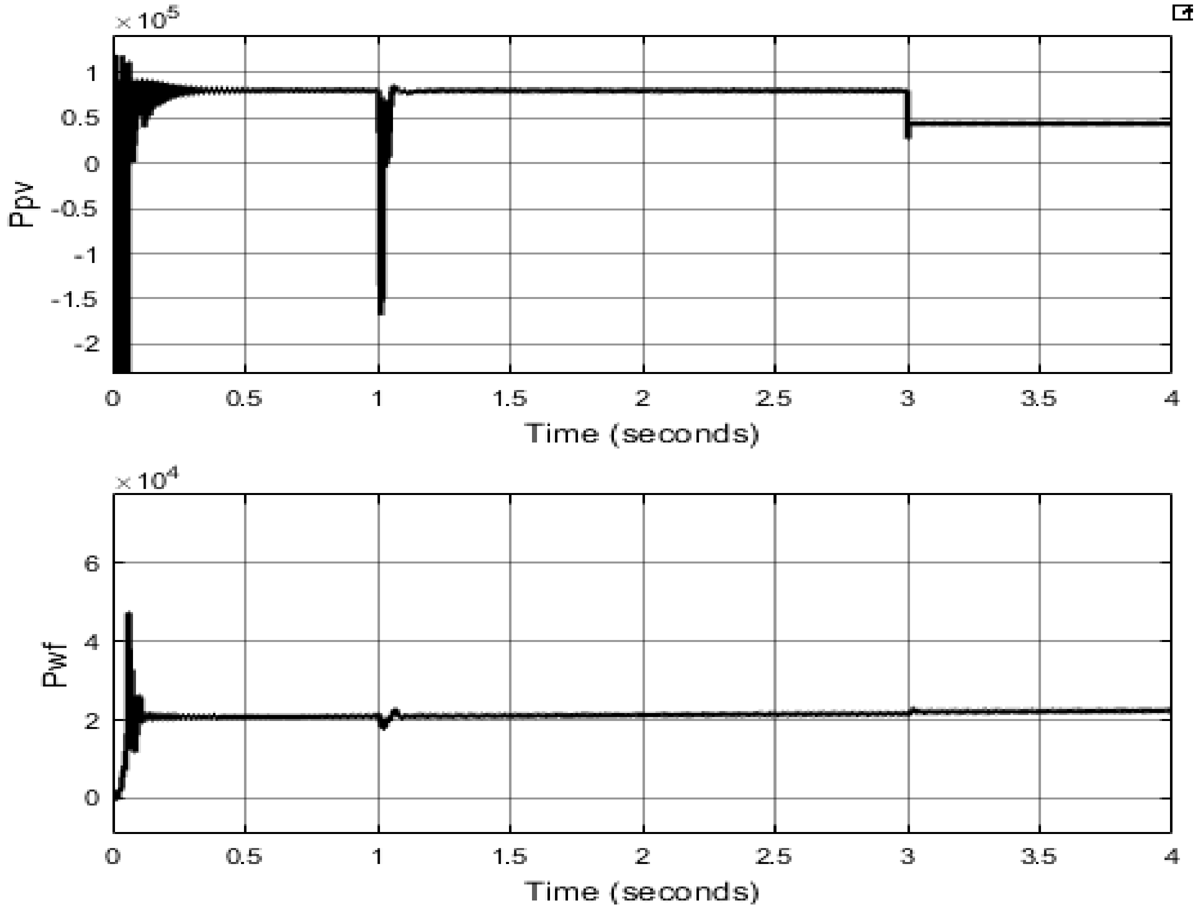

Fig. 19. Real power injected by PV and Wind with ANFIS

The powers that are extracted from the PV and wind farm are shown above. When there is fault at t=1s the power that is extracted by PV module and wind form are getting dipped for a while, during this short period of time the power demand is supplied by grid figure 19.

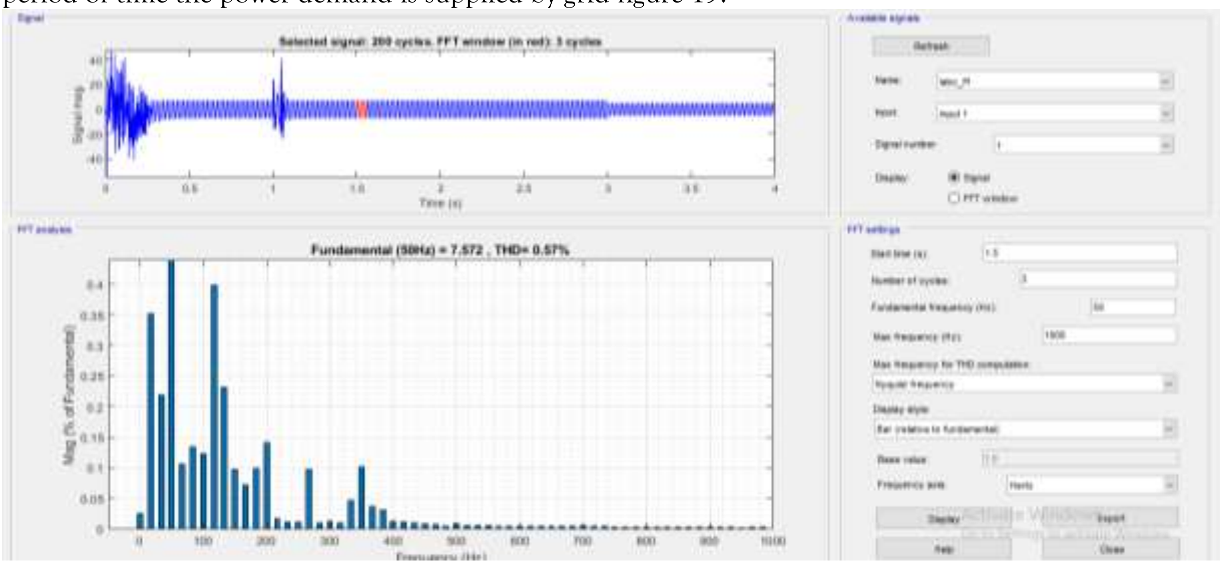

Fig. 20. THD with PI Controller

The figure 20 shows Total Harmonic Distortion with PI controller at t=1 s and is measured for 3 cycles. And it is 0.57%.

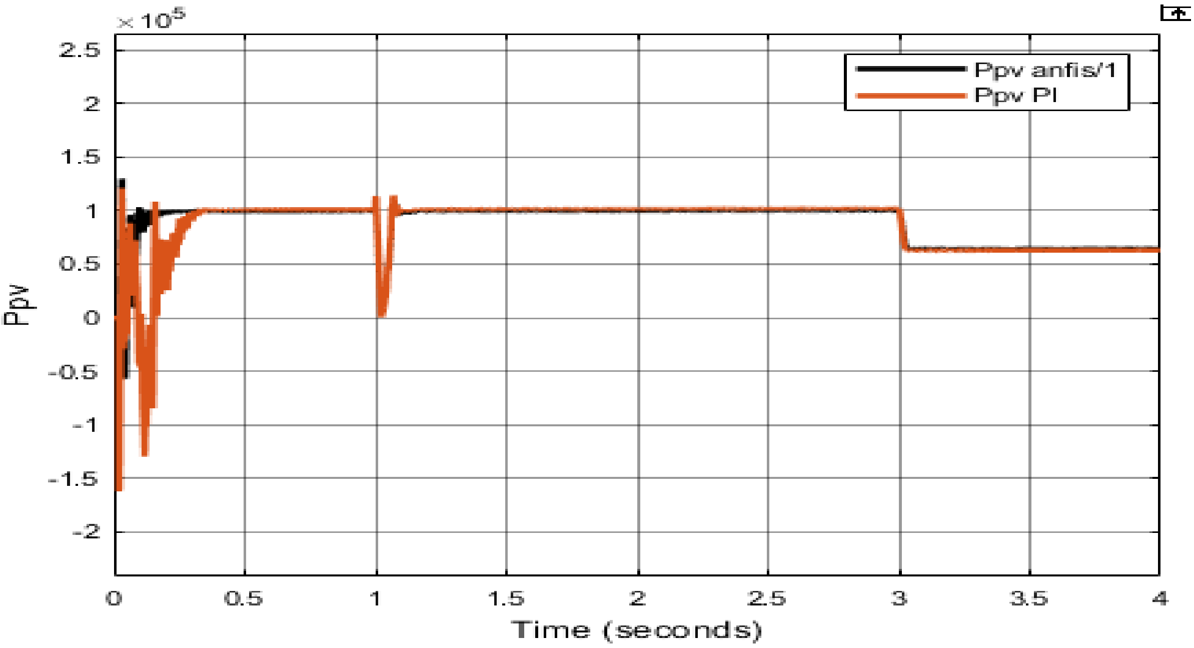

Fig. 21. Real Power inject by PV with PI & ANFIS

In the above figure 21 it is observed that the power injected by PV in to th grid improved with the use of ANFIS when compared to PI controller.

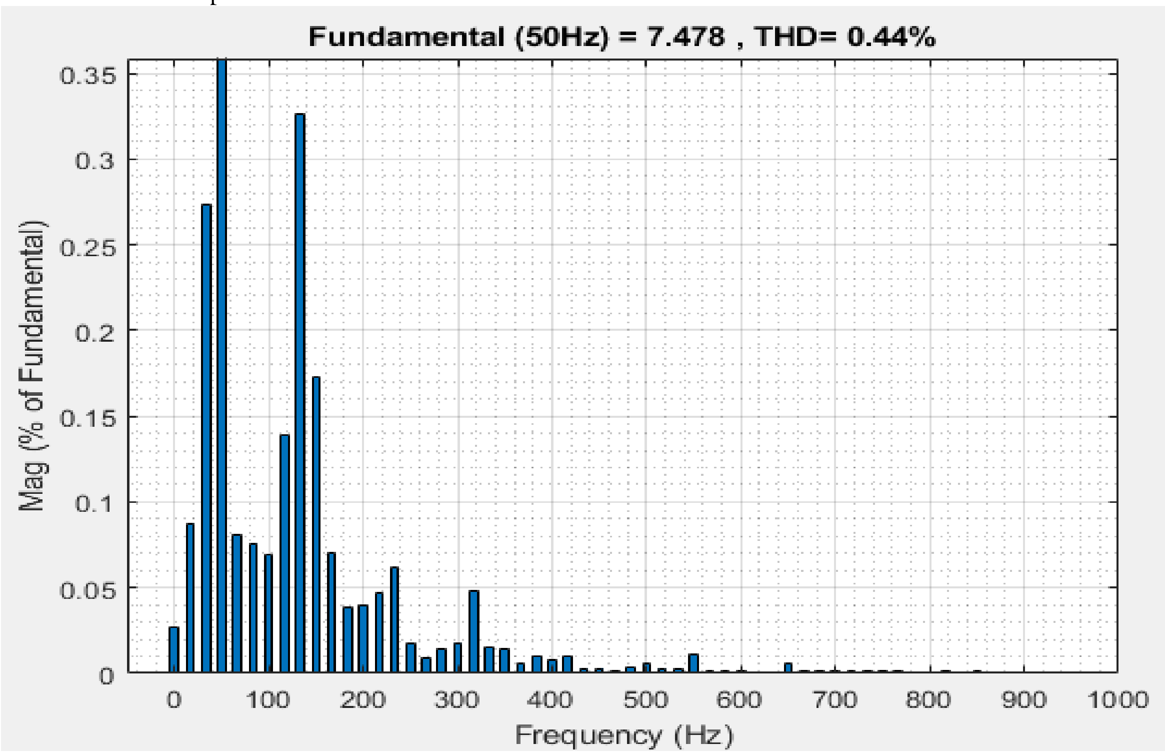

Fig. 22. Total Harmonic Distortion (THD) in conjunction with the ANFIS Controller.

With the use of ANFIS is reduced to 0.44% from 0.57% (PI) this is due to use of the advanced controller like ANFIS figure 22.

5 RESULTS WITH SLIDING MODE CONTROLLER:

Results by updating the Proportional Resonant controller with sliding mode controller are tested and presented s shown below:

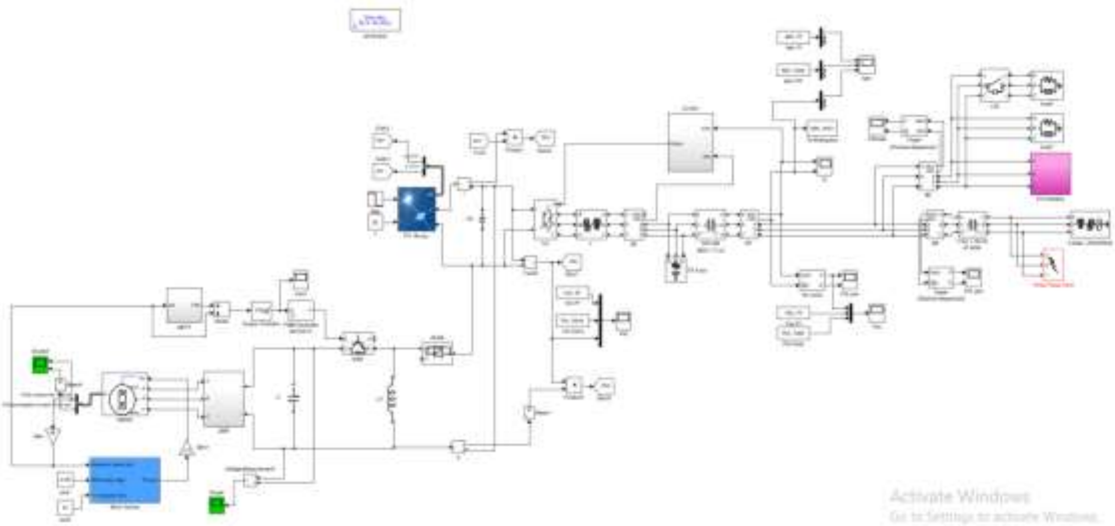

Fig. 23. Simulink diagram of Grid connected PV and Wind with ANFIS controller

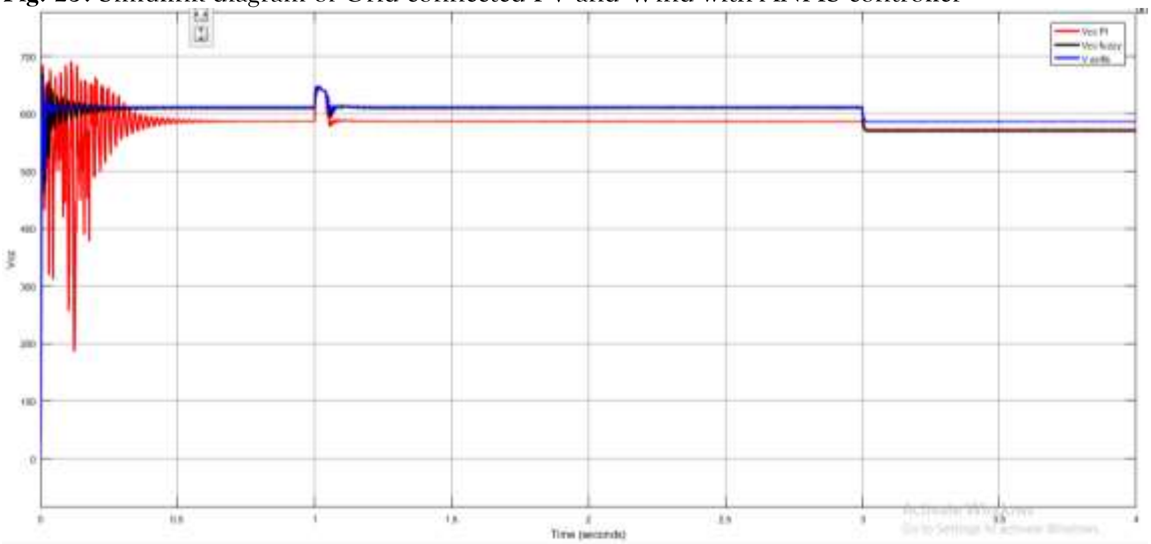

Fig. 24. DC voltage wave form for PI along with sliding mode controller and ANFIS controller.

The DC-voltage of the PV system is evaluated by comparing it with other controllers, such as the PI, Fuzzy, and Adaptive Neuro-Fuzzy Inference System (ANFIS) controllers. This comparison is done by enhancing the Proportional Resonant controller with a sliding mode controller figure 23 and figure 24.

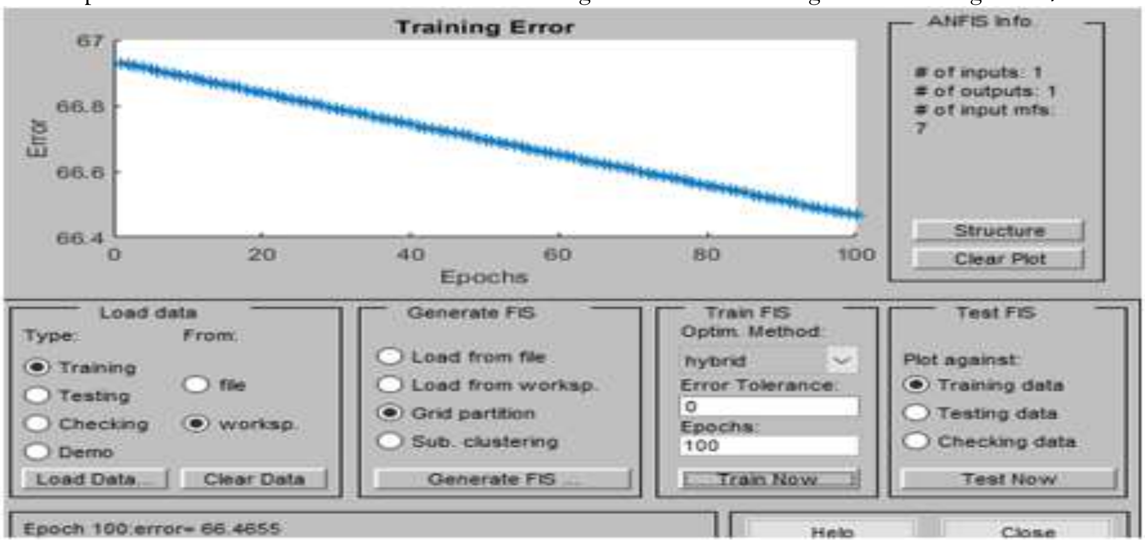

Fig. 25. ANFIS training for 100 EPOCHS with sliding mode controller

In figure 25 it is shown that the ANFIS is trained for 100 EPOCHS for betterment of the output based on the PI controller output. To get the good results the hybrid optimization method is used here.

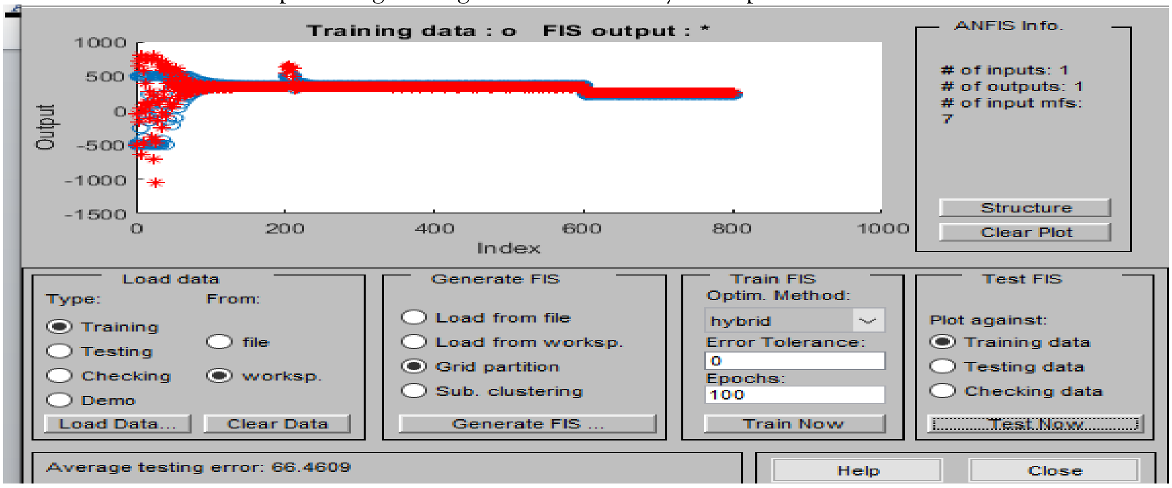

Fig. 26. ANFIS training for error (100 EPOCHS) with sliding mode controller

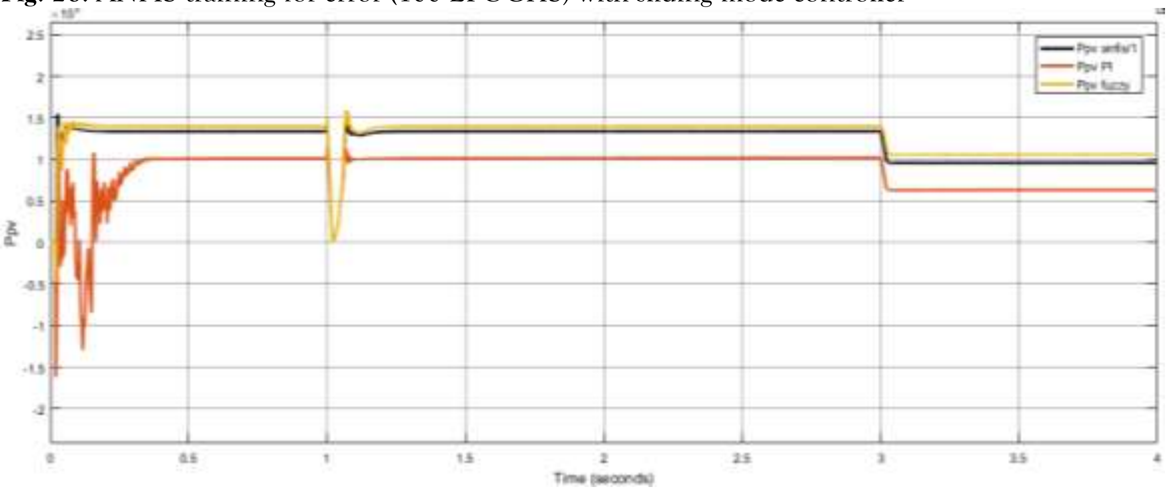

Fig. 27. The actual power generated by a PV system can be enhanced using control techniques such as PI control, Fuzzy logic, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS).

In image above illustrates the actual electricity pumped into the grid by a photovoltaic (PV) system employing a combination of a PI controller, Fuzzy controller, and ANFIS controller figure 26 and figure 27.

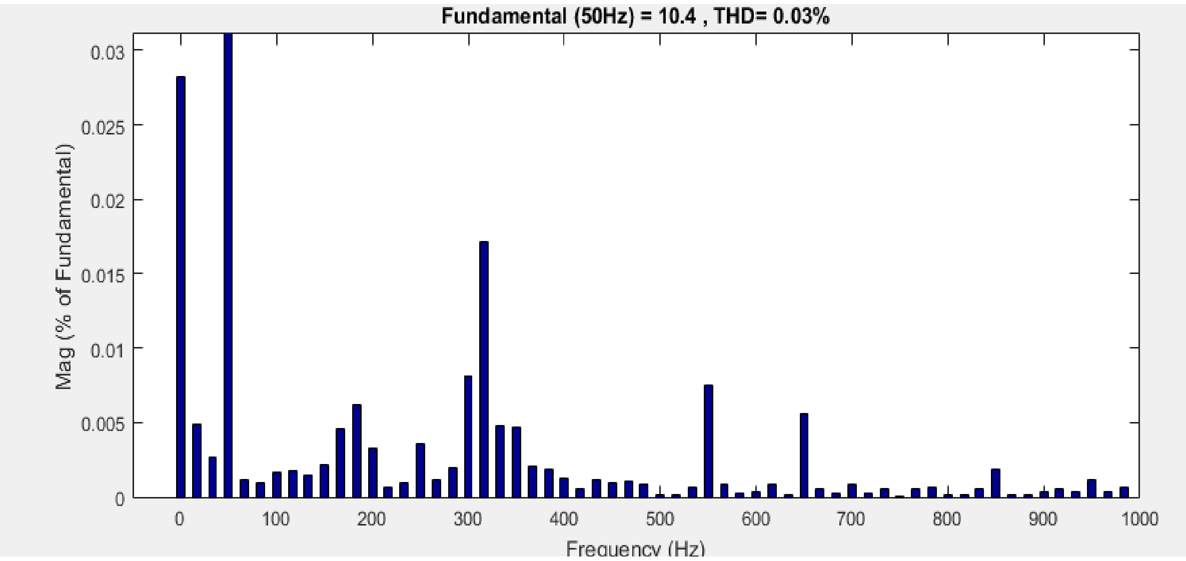

Fig. 28. THD in conjunction with the ANFIS Controller

A Total Harmonic Distortion of the system ANFIS and sliding mode controller is observed as 0.03% which is very low compared with PI controller, Fuzzy controller and ANFIS controller with Proportional Resonant controller and Sliding mode controller figure 28.

Table 1: Complete Description of the Proposed System.

Name of the module	Parameters
Grid	132kV, 50Hz, 2500MVA
PV array	V_{mp}=54.7V, I_{mp}=5.58A, V_{oc}=64.2V, I_{sc}=5.96A, N_s=10, N_s=60, P_{pv} 97kW.
Wind farm	Pwf=35kW, Vdc=560V, Trated=111Nm, Nrated=3000rpm, Rs=0.05ohms, Ls=0.635mH, Phi=0.192V.s, p=4, J=0.011kgm^2. Lbb=1mH, Cin=1000uF, PSF MPPT algorithm. fs=5kHz.
Inverter	Cin=10mF, Ron=0.001ohm, Lf=250uH, Cf=70kVAR.
Control	DSOGI-FLL, wn=314.16rad/s, Incremental conductance MPPT, PR-Kp=0.0211, K1=K2=K3=10, w1c=w5c=w7c=10, wo=314.16rad/s, k=1.41, Ts=1usec, fs=5kHz.
Loads	L1=L2=200kW, 100kVAR. Step change at 2sec, EV load 30A.

- **Availability of data and materials:** Data openly available in a public repository that issues datasets with DOIs.
- **Competing interests:** The author declares no conflict of interest
- **Funding:** No Funding Agency is available
- **Authors' contributions –** Ravi Bukya: Data curation; formal analysis; investigation; methodology. G. Madhu Mohan: Resources; software; validation. M. Sharanya: Visualization; formal analysis, Funding acquisition; supervision. M. Sharanya: Visualization; writing—original draft.
- **Acknowledgements:** This publication was made possible by Malla Reddy Engineering College and Technology, research Grant grant # [13S0108-200028]. The statements made herein are solely the responsibility of the authors. The APC for this paper has been funded by the MRCET R&D, Secundrabad, India.

REFERENCES

1. W. C. Brown, "The History of Power Transmission by Radio Waves," IEEE Trans. Microwave Theory Tech., Vol. 32, pp. 1230-1242, 1984.
2. S. Li and C. Mi, "Wireless Power Transfer for Electric Vehicle Applications" IEEE Journal on Emerging and Selected Topics in Power Electronics, Vol.3. pp. 4-17, 2015.
3. P. Sample, D. A. Meyer, and J. R. Smith, "Analysis, Experimental Results, and Range Adaptation of Magnetically Coupled Resonators for Wireless Power Transfer," IEEE Trans. on Industrial Electronics., Vol. 58, pp. 544-554, 2011.
4. Xiaohui Qu, Yanyan Jing, Hongdou Han, Siu-Chung Wong and Chi K. Tse "Higher Order Compensation for Inductive-Power-Transfer Converters with Constant-Voltage or Constant-Current Output Combating Transformer Parameter Constraints" IEEE Trans. on Power Electronics, Vol.32, pp:394 – 405, 2017.
5. R. Bukya, B. Mangu, A. Jayaprakash and J. Ramesh, "A Study on Current-fed Topology for Wireless Resonant Inductive Power Transfer Battery Charging System of Electric Vehicle," 2020 International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC), Mathura, India, 2020, pp. 415-421.
6. B. Ravi, Vijendar Amgothu," A Robust Noise Reduction Strategy in Magnetic Resonance Images", Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Accepted 08 May 2021.
7. B. Ravi, Vijendar Amgothu," Feature Selection using Multi-Verse Optimization for Brain Tumour Classification", Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 6, 2021, Accepted 08 May 2021.
8. L. Huang, G. Meunier, O. Chadebec, J. M. Guichon, Y. Li and Z. He, "General Integral Formulation of Magnetic Flux Computation and Its Application to Inductive Power Transfer System," in IEEE Transactions on Magnetics, vol. 53, no. 6, pp. 1-4, June 2017.
9. S.I. Babic, F.Sirois and C.Akeyl "Validity Check of Mutual Inductance for Circular Filaments with Lateral and Planar Misalignment"Progress In Electromagnetics Research M, Vol. 8, pp. 15-26, 2009.
10. Adel Moradi, Farzad Tahami, Mohammad Ali Ghazi Moghadam "Wireless Power Transfer Using Selected Harmonic Resonance Mode" IEEE Trans. on Transportation Electrification, Vol.3, pp:508-519, 2017.
11. Sanghoon Cheon, Yong-Hae Kim, Seung-Youl Kang, Myung Lae Lee, Jong-Moo Lee and TaehyoungZyung "Circuit-Model-Based Analysis of A Wireless Energy Transfer System Fvia Coupled Magnetic Resonances," IEEE Trans. on Industrial Electronics, Vol.58, 2906–2914, 2011.
12. Ezhil reena joy, Brijesh kumar, Gautam Rituraj and Praveen Kumar "Impact of Circuit Parameters in Contactless Power Transfer System" IEEE Conference (PEDES), 2014.

13. Roman Boss hard, and Johann W. Kolar "Multi-Objective Optimization of 50 kW/85 kHz IPT System for Public Transport" IEEE Journal of Emerging and Selected Topics in Power Electronics, Vol.4, pp:1370-1382, 2016.
14. P Nayak, Kishan Dharavath, Sathish P " Investigation of mutual inductance between circular spiral coils with misalignments for electric vehicle battery charging" IET Science, Measurement & Technology, DOI: 10.1049/iet-smt.2017.0421.
15. Fei Yang Lin, Claudio Carretero, Grant A. Covic, and John T. Boys "A Reduced Order Model to Determine the Coupling Factor Between Magnetic Pads Used in Wireless Power Transfer" IEEE Trans. on Transportation Electrification, Vol.3, pp:321 – 331, 2017.
16. Sándor Bilicz, Zsolt Badics, Szabolcs Gyimóthy, and József Pávó "Modeling of Dense Windings for Resonant Wireless Power Transfer by an Integral Equation Formulation" IEEE Transactions On Magnetics, Vol. 53, No. 6, 2017.
17. Yang Han and Xiaoping Wang "Calculation of Mutual Inductance Based on 3D Field and Circuit Coupling Analysis for WPT System" International Journal of Control and Automation Vol. 8, pp. 251-266, 2015.
18. J. P. C. Smeets, T. T. Overboom, J. W. Jansen, and E. A. Lomonova, "Inductance calculation nearby conducting material," IEEE Trans. on Magnetics, Vol. 50, 2014.
19. H. V. Alizadeh and B. Boulet, "Analytical calculation of the magnetic vector potential of an axisymmetric solenoid in the presence of iron parts," IEEE Trans. Magnetics, Vol. 52, 2016.
20. M.A.Elgendy,B. Zahawi, and D. J. Atkinson,"Assessment of the Incremental Conductance Maximum Power Point Tracking Algorithm,"IEEE Transactions on Sustainable Energy, vol. 4, no. 1, pp. 108–117, Jan. 2013.doi: 10.1109/TSTE.2012.2202694.
21. S. K. Kollimalla and M. K. Mishra, "A Novel Adaptive P&O MPPT Algorithm Considering Sudden Changes in Irradiance,"IEEE Transactions on Energy Conversion, vol. 29, no. 3, pp. 602–610, Sept. 2014.doi: 10.1109/TEC.2014.2304952.
22. N. M. Kumar and A. A. Kumar, "An Intelligent ANFIS Based Controller for Grid Integrated Wind Energy Conversion System,"IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), 2016.doi: 10.1109/PEDES.2016.7914516.
23. Khare, A. Laxmi, and K. Agnihotri, "Design and Implementation of Fuzzy Logic Controller Based PV-Wind Hybrid Energy System," IEEE International Conference on Power and Energy Systems (ICPS), 2019. doi: 10.1109/ICPS48181.2019.9067663