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Magnify Productivity by Tracking the Solar Maximum Power Point Using Adaptive Neural Fuzzy Interface Technique

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Abstract - **In the current work we dissection the problem arises due to change in environmental condition whilst extracting power from the solar panel. There are some drift problems with solar panel due to the continuously changing temperature and irradiance so to mitigate this challenging task we have to design a system which is capable to adjust along with temperature and irradiance change. While various methods exist, adaptive neural-fuzzy inference system stands out as the most effective for maximum power point tracking, owing to its minimal oscillation and rapid response time. The creation of an effective ANFIS MPPT is hampered by the lack of reliable training data. This study avoids the system from encountering a significant training error by designing an ANFIS MPPT approach based on a big simulation training data. Using a MATLAB simulator for a solar system, the suggested ANFIS MPPT approach is simulated to assess performance. There is a thorough discussion of how temperature and irradiance affect solar panels. To address the drift issue brought on by shifting weather patterns, the ANFIS approach is applied. Results obtained are shown in tables and figures. The results are obtained under two sets of conditions, the first involves maintaining a fluctuating irradiance and constant load, and the second involves maintaining a constant irradiance and varying load, under which temperature remain constant for both conditions. Its showcasing that the suggested approach achieves efficiency of more than 99.3% and precisely matches the optimal maximum power point, according to the data.**

Keywords*: *Artificial Neuro Fuzzy Inference System, Maximum Power Point Tracking, MATLAB (Matrix Laboratory).

I. INTRODUCTION

For the purpose of producing electricity, solar photovoltaic modules rely on temperature and irradiance, however these two variables change when atmospheric conditions such as weather, climate, and seasons change. PV-based power generation is also negatively impacted by other factors such as adjacent trees, buildings, dust, fog, and partial shade from clouds [1-3]. The primary source of energy used today is fossil fuels, which took millions of years to produce and include hard and brown coal, petroleum, and natural gas, petroleum [4]. The escalating exploitation of fossil fuel reserves is expected to render future extraction processes more expensive due to heightened complexity, risks, and technical hurdles [5]. Wind energy, unlike direct solar energy, is derived from indirect solar radiation. It is the temperature differences caused by solar radiation that generate the winds on Earth [6]. Researchers have a shared interest in harnessing photovoltaic energy because it is one of the cleanest and most dependable renewable energy sources [7-8].

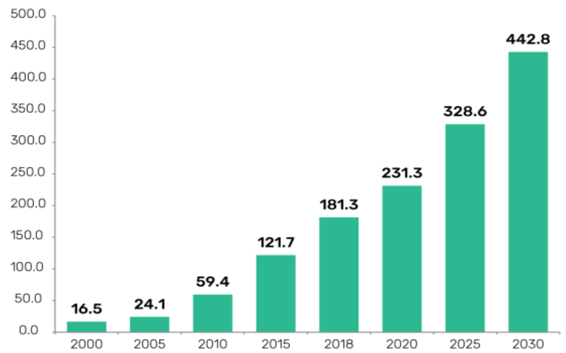

Fig 1: Availability of Green energy (GW) By 2030

Together with other elements that are effective in the operation of PV systems, they include dust accumulation, wind direction, humidity level, and atmospheric pressure. Dust accumulation can diminish the efficiency of PV systems by obstructing sunlight exposure. Conversely, wind

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influences both dust dispersion and PV cell temperature, impacting PV system performance in two ways. While wind can clear dust accumulation, aiding in the cleaning of PV surfaces, it can also increase dust settlement, depending on the wind's direction and velocity [9]. The temperature of the cells decreases with increasing wind speed, improving the PV system's efficiency [10]. Water-vapor droplets' impact on sunlight's irradiance level must be taken into account while analyzing the impact of humidity upon PV system efficiency. Water droplets can reflect, diffract, or refractively absorb light, lowering the amount of direct solar energy that can be received. This results in a decrease in PV system efficiency [10].

The weight of air in Earth's atmosphere, which is related to gravitational force, is known as atmospheric pressure. The latter is negatively correlated with the height at which more solar radiation is directed downward. In order to improve the efficiency of PV systems, this enhances sun intensity [11]. The ability to pinpoint the solar array's ideal operating point, where the most electricity can be extracted for any given load, is a critical component of a photovoltaic system's performance. A typical cell will have a single maximum power point at a given temperature and light level. As a result, in terms of system efficiency, the solar cell's Maximum Power Point Tracking is crucial [12]. Recent works [13-16] introduced MPPT methods with fuzzy logic controllers. While fuzzy-based systems produce better tracking performance than conventional controllers, such as [17], they still lack the adaptability needed to handle changing environments over time. Typically, expert knowledge and experience are taken into consideration while designing a fuzzy logic controller [18–21].

Because of their representational reasoning, adaptability, and explanatory skills—which are helpful in handling complicated systems and strong nonlinearities artificial neural network approaches are being used for photovoltaic applications [22]. Numerous researchers [23–24] have thought about using artificial neural networks (ANN) in solar systems. In [23] Fundamentally, ANFIS combines an adaptive network with a fuzzy inference system. The ANFlS is thus our promising remedy. Still, as far as we are aware, the maximum power tracking issue in photovoltaic-based systems has never been tackled using the ANFIS. The low electric power generation conversion efficiency (9 to 16%) of this system, particularly in low-irradiation situations, is regrettably one of its two main drawbacks. The other is that the amount of electricity produced by the solar array varies constantly with temperature and other meteorological factors. The issue will be addressed by implementing the maximum power point tracking method [24].

Fictitious short circuit current, P&O's, fractional open circuit voltage [25], hill climbing algorithm [26], incremental conductance [27], and MPPT algorithms are among the most frequently used and tested varieties. A PV system's effectiveness can only be increased by improving conventional techniques and relying on other methods that use artificial intelligence (AI). Some algorithms have drawbacks, such as low tracking speed, difficulty of implementation, and overlook of the MPP throughout the partial shading phase. P&O has two drawbacks: oscillation at MPP, which causes output power to oscillate endlessly. Lower energy and efficiency will follow as a result. The second disadvantage is that when abrupt weather circumstances shift, MPP will diverge from it and become less accurate, resulting in energy waste [28]. Researchers have also employed the neuro-fuzzy approach, an intelligent hybrid technique that blends fuzzy logic and artificial neural networks, to determine the global maximum [29-30].

It maps the inputs to the output by utilizing both artificial neural networks and fuzzy logic (FL). The hardest parts of FIS are getting membership functions, distributing membership functions, and creating fuzzy rules. By utilizing the trial-and-error process, these parameters are found. ANFIS modifies these settings via neural networks. ANFIS's ANN component aids in parameter optimization and error reduction. FL is renowned for its organized knowledge representation and for handling uncertainty extremely well. Learning capabilities of ANN are well-known. Thus, FL and ANN benefits are combined in ANFIS. To identify the close to appropriate membership functions alongside the other variables of the relevant fuzzy inference system and finally achieve the required input-output mapping, ANFIS applies an integrated learning method utilizing input-output data sets. This paper's primary goal is to create an intelligent controller that tracks the greatest power point using an adaptive neuro-fuzzy inference system. By doing so, it will maximize energy transfer and boost the efficiency of the PV system as a whole. This innovative method makes it possible to precisely determine the MPP of any type or kind of PV arrangement, even in partially shadowed environments. Furthermore, the neuro-fuzzy network does not need to be re-trained if the PV array layout is altered, for instance, by adding more or less PV modules. Furthermore, there lack many calculations or mathematical equations needed for the suggested method to be straightforward. Unlike the ANN network, the ANFIS network just needs to modify its parameters in the training phase to identify the most ideal structure. Next, a hybrid technique combining the gradient method and the least-squares estimator is used to automatically produce fuzzy rules [31].

System that stores energy in batteries in the MMC-HVDC mechanism is controlled by a DC-DC boost converter that uses ANN based PI. The whole thing is tested in event of a three separate phases ground-level failure close to grids [32]. Utilizing an artificial neural network for state of charge prediction can lower estimate error resulting from physical factors and lower computation costs when utilizing

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embedded component with Internet of Things capabilities. State of charge estimate result demonstrates that the ANN model outperforms the assistance vector processing approach in terms of correctness [33].

II. MODELLING OF PV CELL

The following equations outline the mathematical framework for the photovoltaic generator. The analogous circuit of a photovoltaic cell is shown in Figure 2, which uses one diode in the model to improve quality in PV research.

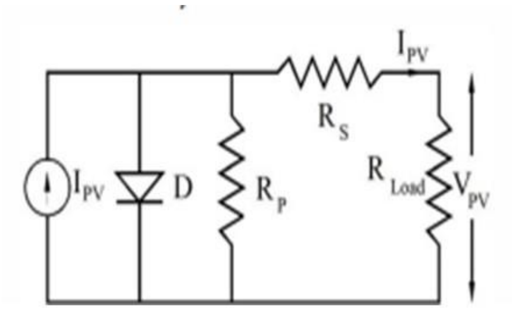

Fig 2: Equivalent Circuit of Photovoltaic Cell

The solar cell's I–V characteristic is represented by the following equations [34].

$$I_{ph} = I_d + I_{Rp} + I_{pv} \quad (1)$$

$$I_d = I_o[e^{(V_{pv}+\frac{I_{PV}R_S}{\alpha V_T})} - 1] \quad (2)$$

$$V_T = \frac{NskT}{q} \quad (3)$$

$$I_{Rp} = \frac{(v_{pv}+(I_{pv}R_S)}{Rp} \quad (4)$$

$$I_{ph} = (\frac{G}{Gn})\,(I_{sc} + (k_i \triangle T)) \quad (5)$$

A photovoltaic (PV) model's generalized current-voltage equation is as follows after combining the aforementioned equations:

$$I_{pv} = I_{ph} - I_o[e^{(V_{pv}+\frac{I_{PV}R_S}{\alpha V_T})} - 1] - (V_{pv} + \frac{I_{pv}R_S}{Rp}) \quad (6)$$

I_{pv} = PV current

I_o = saturation reverse current

V_T = thermal voltage linked to the cell

I_{ph}= fluctuates with temperature changes and has a linear connection with light intensity

I_d = Shockley diode equation

α = The constant referred to as the diode ideality factor

N_s = The quantity of series-connected cells

q = An electron's charge

k = Boltzmann constant

T = Absolute temperature of the p-n junction

I_{sc} = Short circuit current

K_i = The short-circuit current fluctuation coefficient with temperature

G = The amount of light

R_s and R_p = The equivalent resistances of a solar panel in series and parallel configurations are distinct. In parallel configuration, the entire resistance is smaller than the smallest individual resistance; in series, the total resistance is the sum of all of the individual resistances.

$\triangle T = T - T_n$, the temperature variation from the norm

The symbols Rs and Rp, respectively, in the analogous circuit represent the array's analogous series and parallel resistance.

The overall I-V characteristic of a realistic photovoltaic device indicates that the operation in the voltage source zone is primarily influenced by the series resistance (Rs), whereas the operation in the current source region is predominantly affected by the parallel resistance (Rp).

The current through the parallel resistance can be disregarded because the value of the shunt resistance, Rp, is higher than the value of the series resistance, Rs. The photovoltaic cell's light-generating current is directly proportional to solar radiation and temperature [35], which is determined by equation (05).

Figure 3(a) and Figure 3(b) display the I-V as well as the P-V characteristics of the examined PV panel for different irradiance values (G) and a constant temperature of 25°C (T), respectively. As the temperature of the cell rises, the open circuit voltage decreases marginally, but the short circuit current (Isc) depends linearly and directly on the ambient irradiation. With radiation exposure, the open-circuit voltage (Voc) rises, and as cell temperature rises, it slightly falls.

When operating at this Maximum Power Point, the solar array will provide its maximum power output since it is suited to its load. The power output and array voltage unit have an approximately linear connection, as shown in Figs. 3(a) and 3(b), and as a result, the MPP is reached. Power is reduced with every further voltage rise [36].

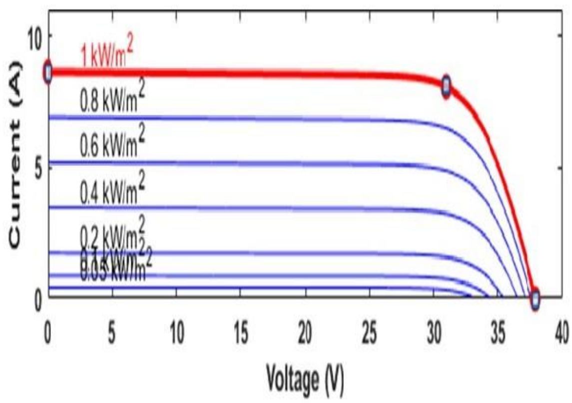

Fig. 3(a) IV array simulated curves at 25°C and variable irradiance

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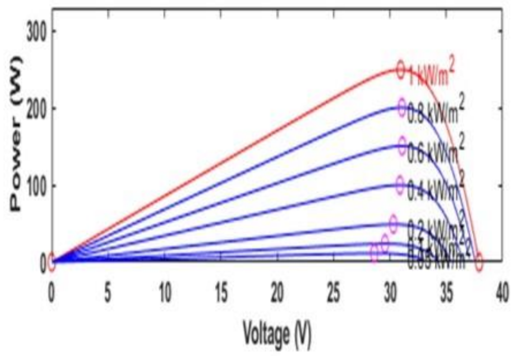

Fig. 3(b) PV array simulated curves at 25℃ and variable irradiance

III. BOOST CONVERTOR

PV array power is fed to the load through a twin stage power electronics system that consists of an inverter and a boost type dc-dc converter. A DC-DC step-up converter is inserted within the photovoltaic array and an inverter in order to keep the load voltage constant. Fig. 4 and Fig. 5 displays the suggested scheme's block diagram.

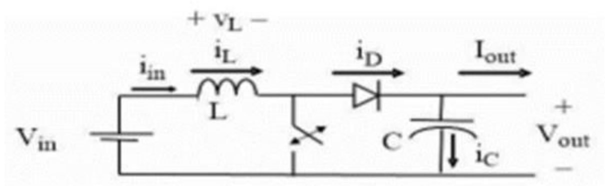

Fig 4: Step Up Chopper or Boost Converter

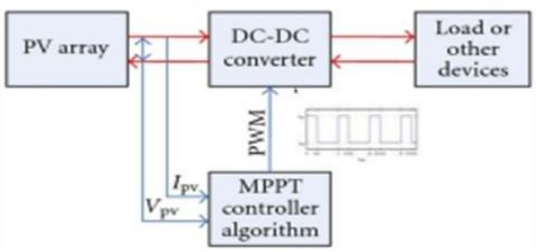

Fig 5: A PV system's MPPT Controller

The output voltage of this converter is always higher than the input voltage. When using continuous conduction mode, the input-output voltage connection is as follows:

$$\frac{Vo}{Vi} = \frac{1}{1 - D} \tag{7}$$

D fluctuates between 0 and 1, as we know. However, as the preceding calculation shows, it is physically impossible for the resulting voltage to input voltage ratio to reach infinity at steady state if D = 1 [37-38].

IV. ANFIS ALGORITHM

Based on fuzzy logic inference and neural network design, the adaptive neuro-fuzzy interference system technology is regarded as a hybrid approach. When creating fuzzy expert systems, the neuro-fuzzy technique is crucial. Regardless, achieving the minimal performance requires careful consideration of the quantity, kind, regulations, and specifications of the fuzzy system Membership Function. The process of reaching the minimal performance involves trial and error. This statement highlights the significance of the settings in fuzzy systems.

One of the adaptive systems' Sugeno networks, ANFIS, aids in training and education. In order to reduce the need for an expert user, this framework harnesses expert knowledge to make models more methodical. To gain a deeper comprehension of the ANFIS architecture, let us examine the fuzzy system below, which is a first-order Sugeno model with two rules and two inputs. Fig. 6 depicts the corresponding ANFIS architecture of a first-order Sugeno fuzzy model with two rules. Each node in a particular layer of the five-layer architecture performs a similar function. fuzzy IF-THEN rule set, where the results are combinations of the inputs in a linear fashion.

Rule 1:

If (x is A1) and (y is B1) then (f1 = p1x + q1 + r1) (8)

Rule 2:

If (x is A2) and (y is B2) then (f2 = p2x + q2 + r2) (9)

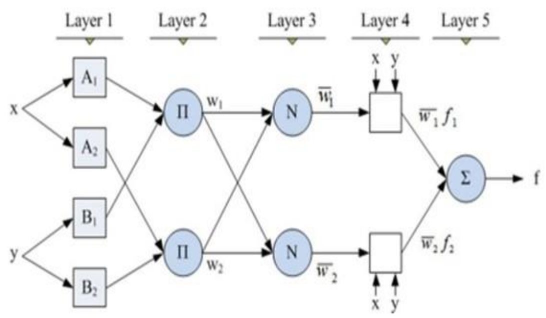

Fig 6: Structure of An ANFIS that is Comparable to a Sugeno Fuzzy Model of First Order with two Inputs and Two Rules

Layer 1: In this layer, each node is adaptive and represents a fuzzy membership function. The output of each node is the degree of membership of the input to the fuzzy membership function it represents. Expressions that may be used to get those results are:

$$O_{1,i} = \mu_{Ai}(x) \quad i=1,2 \tag{10}$$

$$O_{1,i} = \mu_{Bi}(x) \quad i=3,4 \tag{11}$$

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In fuzzy logic, Ai and Bi represent fuzzy sets, typically defined by membership functions (MFs). These sets are often represented in parametric form, which means they're defined by a set of parameters. For example, in the case of trapezoidal-shaped MFs, these parameters define the shape of the trapezoid. $O_{1,I}$ represents the output of a node in the i-th layer of a neural network or a similar computational model.

Layer 2: This type of layer is often referred to as an affine transformation or fully connected layer in neural networks. In such a layer, each node takes in the inputs, multiplies them by a set of fixed weights (parameters), and then passes the result through an activation function. If there's no activation function, then it's just a linear transformation. The notation Π might be used to represent these fixed weights or multipliers. Expression (5) displays the outputs from this node.

$$O_{2,i} = W_i = \mu_{Ai}(x)\mu_{Bi}(y) \text{ i=1,2} \quad (12)$$

Layer 3: The nodes in this layer are referred to as fixed nodes and have a 'N' next to them to indicate that they handle the normalization of the preceding layer's score strength. By guaranteeing that the input to the next layer is within a suitable range, this normalization procedure improves the training process's stability and convergence. This node's output is provided in (13).

$$O_{3,i} = \overline{W} = \frac{w_i}{w_1+w_2} \text{ ; i=1,2} \quad (13)$$

Layer 4: layer of fuzzy logic using adaptable nodes. Adaptive nodes in fuzzy logic modify their parameters in response to input data. Fuzzy logic procedures are usually used to combine inputs to determine the output of each node. Each node's output is determined by multiplying a the first-order polynomial function with the normalized score strength. This means the output of each node can be represented as:

$$O_{4,i} = \overline{W}_i f_i = \overline{W}_i(p_i x + q_i y + r_i) \text{ i=1,2} \quad (14)$$

Layer 5: There is only one node in this layer, denoted by an S, which stands for simple summary.

$$O_{4,i} = \textstyle\sum_i \overline{W}_i f_i = \frac{\sum_i W_i f_i}{\sum_i W_i} \text{ ; i=1,2} \quad (15)$$

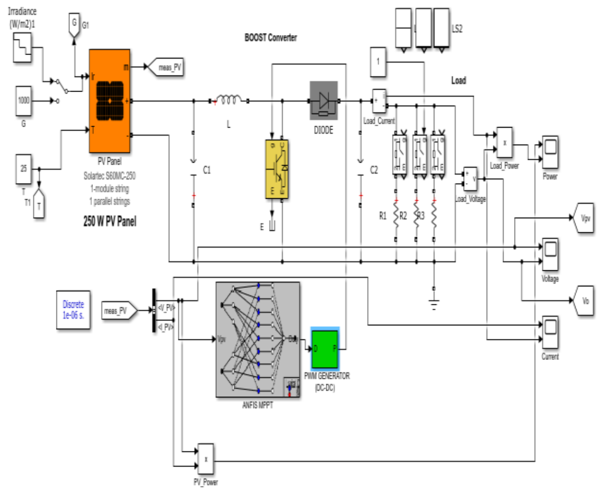

Figure 7: Composite Simulation Model of Proposed ANFIS Based MPPT Technique Under Fixed Load and Sudden Change in Irradiation

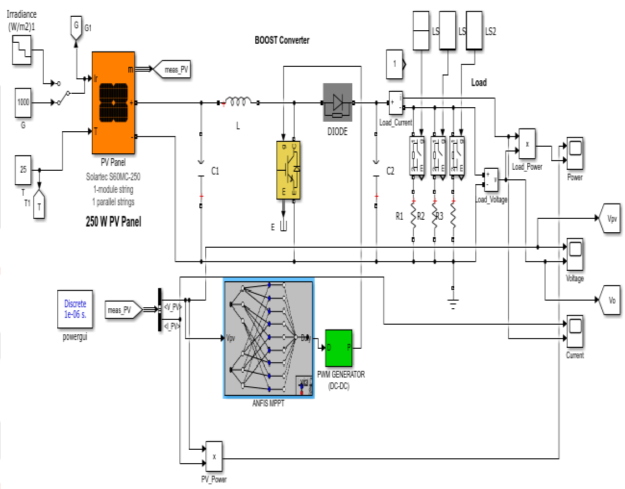

Figure 8: Composite Simulation Model of Proposed ANFIS Based MPPT Technique Under Sudden Change in Load and Fixed Irradiation

Figure 7 depicts a circuit simulation with a set load and immediate fluctuations in irradiance, while Figure 8 shows a circuit simulation with an immediate rise in load and set irradiance. Both scenarios were carried out using the manually operated tap-changing switch to change the position between an anchored and altering illumination level. The conclusion, details, and in-depth data analysis of the figures are summed up in the result and discussion that proceed.

V. RESULT AND DISCUSSION

5.1 ANALYSIS OF OUTPUT WITH FIXED LOAD AND SUDDEN IRRADIATION CHANGE

Figure 9 This figure displays the output voltages under different conditions, comparing the use of the ANFIS method with its absence. The irradiation level, measured in watts per square meter (W/m2), continuously decreases from 1000 to 800 to 600 to 400 to 200 W/m^2. These irradiation levels associated to specific times intervals, from

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0 to 0.2 seconds Irradiation level is 1000 W/m^2, from 0.2 to 0.4 seconds it is 800 W/m^2, from 0.4 to 0.6 seconds it is 600 W/m^2, from 0.6 to 0.8 seconds it is 400 W/m^2, from 0.8 to 1.0 seconds it is 200 W/m^2, the load remains constant throughout these time intervals.

without ANFIS, the voltage reaches 38 volts at 0.002424 seconds, but with ANFIS, it increases to 86.30 volts at 0.197 seconds.

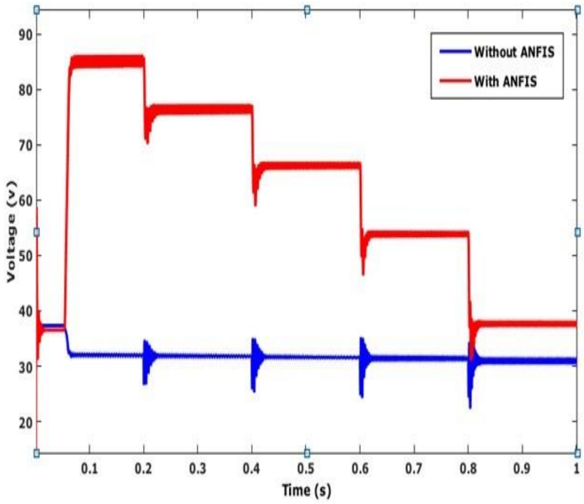

Fig 9: Output voltage of The System with and without ANFIS Under Constant Load Conditions and Different Levels of Solar Irradiation

Fig. 10 displays the current characteristics with and without the ANFIS algorithm. Without ANFIS, the current stands at 8.596 Amperes at 0.0078 seconds, while with ANFIS, it is 2.878 Amperes at 0.197 seconds.

This suggests that the ANFIS algorithm has reduced the current from 8.596 Amperes to 2.878 Amperes and shifted the time to 0.197 seconds.

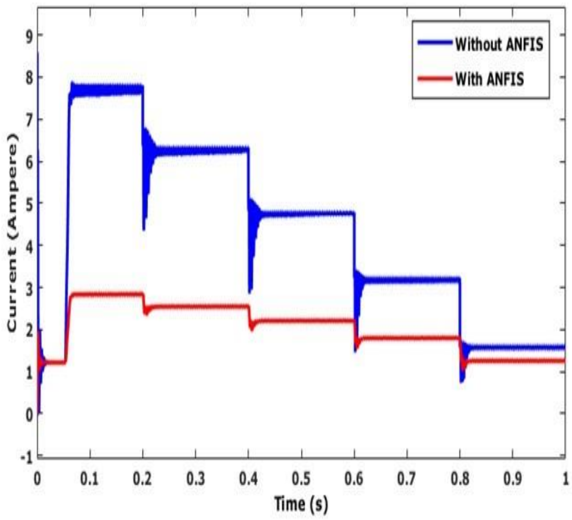

Fig 10: Output Current at Different Irradiation and Constant Load with and without ANFIS

The ANFIS algorithm seems to be doing a great job in maximizing power extraction from the solar PV system, especially under varying irradiation conditions.

Figure 11 depicts the power output without ANFIS is 253.8 Watt at 0.004 seconds, but with ANFIS applied, it increases to 248.4 Watt at 0.197 seconds. This indicates that ANFIS is effectively optimizing the power output, resulting in a slightly lower time delay but higher efficiency.

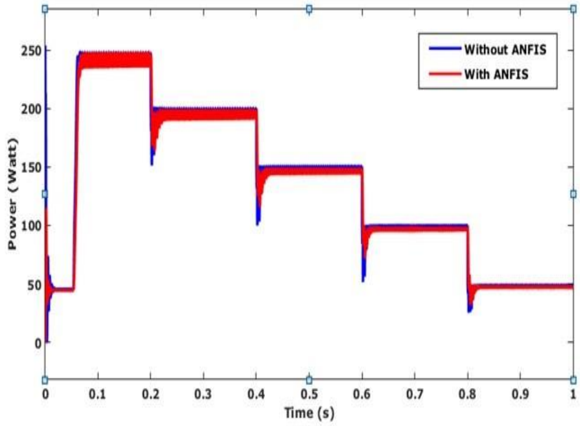

Fig 11: Output Power with a Constant Load and Varying Irradiation with and without ANFIS

5.2 Output Analysis with Sudden Change in Load and Fixed Irradiation

The ANFIS algorithm significantly improves voltage regulation in response to load changes. In figure 12 depicts, Before ANFIS, the voltage response is 37.92 volts at 0.002657 seconds, while with ANFIS, it rises to 99.67 volts at 0.996 seconds. This demonstrates that with ANFIS, the voltage regulation is much better, maintaining a higher voltage level despite the load variations. Figure 13 illustrate the current is significantly reduced when the ANFIS algorithm is applied. This reduction is from 8.596 Amperes at 0.0078 seconds without ANFIS to 3.544 Amperes at 0.161 seconds with ANFIS. This indicates that the ANFIS algorithm is effectively reducing the current in the system, likely resulting in improved performance or efficiency.

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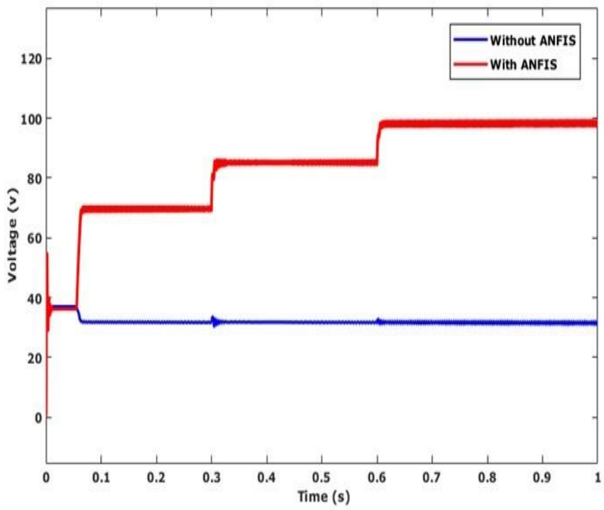

Fig 12: Output Voltage with Sudden Change in Load and Fixed Irradiation with and without ANFIS

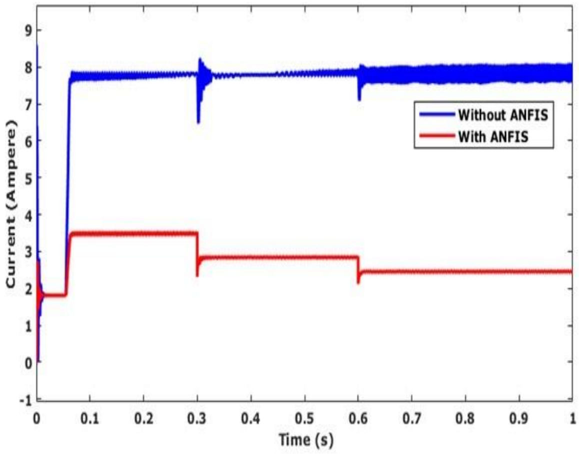

Fig 13: Output Current with Sudden Change in Load and Fixed Irradiation with and without ANFIS

The power characteristics depicted in Figure 14 illustrate the effectiveness of the ANFIS algorithm in maximizing power extraction from the solar PV panel under varying conditions. Initially, without the ANFIS algorithm, the power is measured at 253.8 Watts at 0.00409 seconds. With the ANFIS algorithm, despite the time delay (0.161 seconds), the power is slightly reduced to 251.2 Watts. This reduction is likely due to the computational overhead of the ANFIS algorithm

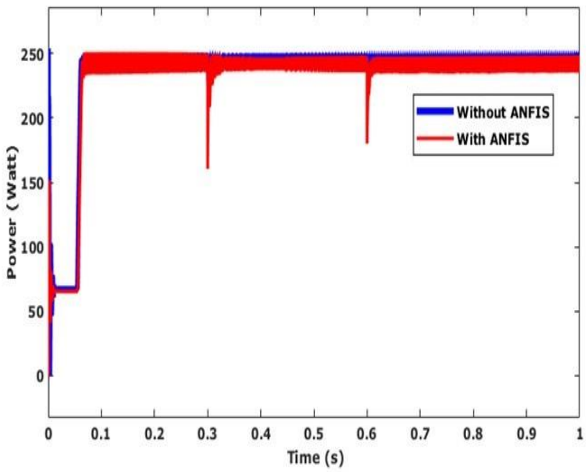

Fig 14: Output Power with Sudden Change in Load and Fixed Irradiation with and without ANFIS

At 0.3 seconds, a load is introduced, causing a disturbance and a decrease in current magnitude. However, the ANFIS algorithm manages to adjust the duty cycle from 0.54 to 0.63 to continue extracting maximum power from the solar PV panel, compensating for the disturbance caused by the load.

Similarly, at 0.6 seconds, another load introduction causes disturbance, but the ANFIS algorithm maintains its efficiency, adjusting the duty cycle from 0.62 to 0.67 to continue maximizing power extraction from the solar PV panel. Overall, these results demonstrate the resilience and effectiveness of the ANFIS algorithm in responding to sudden load changes, ensuring that the solar PV panel operates at maximum power output despite disturbances in the system.

Table 1.1 Comparison of Output Power Under Sudden Changes in Irradiation with a Fixed Load

Irradiation Watt/m^2	Solar panel P_{max} (watt)	ANFIS	
		P_{av}	η_{pv}(%)
200	49.1425	48.48	98.65
400	100.1129	98.58	98.46
600	150.8082	148.6	98.53
800	200.7859	198.3	98.76
1000	249.8472	247.8	99.18
Overall Average η_{pv}(%)			
98.71			

As consequence, the total average efficiency under static load and abrupt irradiance changes is 98.71 %, which is the total aggregate efficiency under various irradiance situations. This is an enhanced findings over the earlier outcome.

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Table 1.2 Comparison of Output Power Under Sudden Change in load with a Fixed Irradiation

Irradiation Watt/m^2	Solar panel P_{max} watt	ANFIS					
		Load 20 Ω	Load 30 Ω	Load 40Ω	η_{1pv} %	η_{2pv} %	η_{3pv} %
		P_{1av}	P_{2av}	P_{3av}			
1000	249.8472	248.6	249.4	249.7	99.50	99.82	99.94
Overall Average η_{pv}(%)							
99.75							

Considering that the load raises suddenly, and the irradiance remains constant, the total average efficiency which represents the aggregate efficiency of the rapid growth in load is 99.75 %. This is a far better finding than the previous result, and it is almost exactly what was desired. The hypotheses and the results fit rather well.

VI. Conclusion

ANFIS-based MPPT controllers offer superior efficiency, faster convergence times, and better performance compared to traditional methods and other advanced control techniques like ANN and FLC. Their ability to adapt to varying conditions makes them a highly effective solution for optimizing the performance of solar PV systems.

The study utilized MATLAB along with Simulink for simulation experiments and compared the results with conventional PV panel outputs. The ANFIS MPPT algorithm showed consistency in performance despite sudden load changes, varying irradiation, and different environmental conditions. This robustness was demonstrated across both variable and steady irradiation conditions. The voltage, current, and power curves exhibited by the ANFIS-based system illustrated its superior performance, efficiency, and robustness. The efficiency of the ANFIS algorithm surpassed 99.75%, which is quite impressive. Furthermore, the ANFIS algorithm accurately tracked the optimal maximum power point, ensuring efficient power extraction from the solar panels. Comparative studies with previous experiments and simulations showed that the proposed ANFIS algorithm outperformed conventional methods in terms of reliability and efficiency. These findings indicate that ANFIS-based MPPT algorithms can significantly enhance the performance of photovoltaic systems, making them more reliable and efficient across diverse climatic conditions.

ANFIS, nevertheless is legitimate for three inputs. If this number rises, ANFIS model becomes more complicated and has more rules, which is undesirable and results in poorer output. This drives up calculations and lowers the effectiveness of model. In issues involving large databases, it may impede effective implementation of ANFIS.

Although ANFIS-PSO may be simply updated to add hybridization enhancements, it offers the highest promise to advance its capabilities over time. As a result, PSO may be paired with ANFIS to create a variation. Researchers have also suggested using PSO's accelerated processing future capability to expand ANFIS's potential.

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