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Comparative Analysis of FLC and ANN Techniques for Efficient MPPT in Changing Conditions in Jordan

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Abstract:- This paper describes a study focused on enhancing the solar PV efficiency schemes utilising the MPPT algorithm. The study shows the FLC and ANN methods for MPPT in addition compares their performance. It highlights the increasing interest in solar power and Jordan's efforts to adopt renewable energy resources. The goal of the study is to develop a cost-effective MPPT algorithm accomplished by adapting to varying conditions. The paper describes the methodology, counting the design of the PV scheme and simulation parameters. Also, it describes the buck converter design and offers specifications for the PV system, buck converter, and NN construction. Simulink models for the FLC control-based MPPT, and ANN-based MPPT are obtainable, along with rules of fuzzy and training process details, respectively. The ultimate aim is to develop scheme efficiency by using these algorithms. Accordingly, it can be declared that the ANN-based MPPT approach trades off the FLC-based MPPT technique in regards to accuracy, responsiveness, and total power extraction efficiency based on the thorough research performed in this work. These results show the possibility of using ANN in MPPT algorithms to develop solar system performance and energy harvesting capacities. Insightful information was obtained by contrasting the reliability of the FLC-based MPPT technique with the ANN-based MPPT strategy in maximising power extraction from solar systems.

Keywords:- *Photovoltaic, Maximum Power Point Tracking, Fuzzy Logic Control, Artificial Neural Network, Perturb and Observe Algorithm, Fuzzy Sets, Membership Functions, Fuzzy Rules, Error Histogram, Regression Plot.*

I. INTRODUCTION

Solar energy has recently emerged as a very appealing alternative to traditional energy sources. The rising emphasis on solar energy technologies is a result of their effective developments and the escalating acceptance of solar energy schemes in countries with plenty of sunlight. This pattern highlights solar energy's substantial promise as an environmentally friendly and renewable source of energy [1].

Moreover, the appeal of solar energy schemes derived from their several benefits. Solar energy provides an eco-friendly and green energy solution, decreasing reliance on fossil fuels and limiting the emission of greenhouse gases. Additionally, solar energy schemes deliver decentralised strategies to energy generation, empowering businesses and communities with advanced energy resilience and independence. The solar power scalability installations, ranging from small applications such as residential setups to large applications such as solar farms, develops their suitability and versatility across various environments. Photovoltaic (PV) schemes can function independently or be integrated with power grids [2].

Despite its heavy dependence on oil imported from other countries to meet energy needs, Jordan is taking steps to minimise this reliance by adopting solar power and other resources of renewable energy. The country is implementing actively pursuing and supportive policies for the solar energy project development, aiming to foster sustainability, develop the security of energy resources, and capitalise on the environmental and economic renewable energy advantages [3]. Jordan possesses substantial solar energy, with certain regions experiencing up to sunshine 300 days annually [4].

These characteristic positions the country as a favourable location for using solar power [5], [6], and [2]. Over the past twenty years, Jordan has encountered considerable challenges in light of rising energy costs, compounded by the limited economic sources of the country. In response, Jordan has embarked on a comprehensive restructuring and transformation of its country's energy and economic strategy. This energy strategy aim is to develop the non-governmental sector's involvement in electricity generation as well as distribution, develop establishment, and competition an autonomous controlling entity aimed at the power field [7, 8].

The country has funded initiatives aiming at the advancement of solar energy in accordance with this approach. The evaluation process has contained implementation and systematic monitoring of suitable technologies, as well as pilot and demonstration projects [9]. The possibility for using PV systems in Jordan is considerable, particularly in isolated and remote areas that are distant from the power grid as well as unlikely to be linked in the near future. The power generated amount by a PV system relies on factors such as connected load, solar irradiance, and operating temperature. Environmental factors like irradiance and temperature impact the PV system performance, but the operating point can control by using the power electronics devices through the application of the Maximum power point tracking (MPPT) method. These methods allow the PV scheme to work at its best power output [10].

As solar irradiance fluctuates, the PV system MPP also changes. Therefore, it becomes significant to apply MPPT method to ensure constant tracking and keep the power output at the maximum point of the system [11], and [12].

MPPT represents an electronic device utilised in PV systems to develop the power transmission between the utility grid or battery and the PV panels. Its role is to aid in changing the voltage level, in the form of a DC-DC converter, it converts the relatively high DC voltage generated by the PV panels to a low DC voltage appropriate for the batteries' charging, vice versa. The overall PV plant efficiency relies on several factors, such as the inverter efficiency, the MPPT algorithm effectiveness, and the PV model's efficiency. The PV panel's effectiveness is influenced by the fabrication of solar cells, which typically does not surpass 22.5% [13].

Improving the inverter's and PV panel's efficiency poses challenges because of cost considerations and technological limitations. However, improving the algorithms utilised in MPPT is a cost-effective solution that can be applied to existing Photovoltaic scheme [14], and [15].

Although there are several MPPT techniques, each has its own drawbacks and trade-offs. The difficulty is in developing an MPPT algorithm that is capable of handling sudden alterations in circumstances while requiring the fewest possible extra parts. It is difficult to create an efficient MPPT algorithm because it not just must balance accuracy and complexity but also being able to adapt to sudden alterations in the environment. To maintain the system's cost-effectiveness, the algorithm should be able to rapidly adapt to changing conditions like cloud cover and shade while using the fewest number of new components possible. The system can intelligently identify the maximum power point, optimse power extraction, and ensure dependable performance across a range of operating situations by using intelligent methods like Fuzzy logic controller (FLC) and Artificial Neural network (ANN).

This study aims at developing an effective MPPT algorithm offering a strategy can cope with unexpected shifts in circumstances. The focus is on reducing the number of components need, thereby decreasing costs and improving system performance. The study provides the application of FLC and ANN techniques to achieve these aims. Another goal is to compare the performance of these methods and determine their effectiveness in tracking MPP.

The outline for the project includes an introduction that highlights the significance of MPPT algorithms and their role in optimising power extraction from PV panels. The literature review section provides an overview of existing MPPT methods and their limitations. The methodology section is divided into four parts: PV panel design, buck converter design, ANN for MPPT design, and FLC for MPPT design. These sections discuss the design and implementation of each component in detail. The results discussion and analysis section present the simulation results for the ANN-based and FLC-based MPPT techniques, analysing their performance based on three metrics: produced power behaviour, computation time, and complexity. Finally, the project concludes by summarising the findings and highlighting the most effective MPPT technique based on the evaluation metrics.

II. LITERATURE REVIEW

The literature highlights how ineffectively popular MPPT methods, including the (P&O) method, Incremental conductance IC approach, FOCV, and FSCC, tr Perturb and observe algorithm ack the MPPT in a variety of weather scenarios. Researchers have looked into applying FLC, combining P&O with adaptive control, and using ANN to find solutions around these constraints. By offering more accuracy, simplicity, and flexibility, FLC and ANN-based techniques have showed promise in enhancing MPPT performance. ANN models have also been used to predict solar radiation with effectiveness. These developments in solar radiation forecasting and MPPT algorithms help to develop the overall efficiency of photovoltaic systems.

A commonly employed method for MPPT is P&O technique. The method intermittently regulates the output voltage value of PV panels towards tracking the MPP. Nevertheless, the P&O technique faces a compromise between the oscillation amplitude and tracking rapidity around MPP. When the voltage step size is minor, oscillations are minimised, and then the tracking speed is reduced. Instead, a higher voltage step size develops tracking rapidity nonetheless amplifies the oscillations [16], and [17].

In order to overcome the P&O method limitations, the IC known as incremental conductance, the IC MPPT technique, was developed. The fact of the power/voltage curve slope at the MPP is still zero is exploited by this approach. The MPP value may be properly tracked by comparing the instantaneous conductance voltage with the IC voltage. Despite the fact that each of the P&O and IC approaches are simple to use, they can encounter difficulties maintaining MPP tracking during hastily varying weather situations [18].

The FOCV refers to fractional-open-circuit-voltage; the method is another straightforward MPPT approach that presumes a linear relationship between the voltage at the MPP with the voltage at the open circuit connections. However, determining the optimal voltage factor for this technique is challenging and relies on specific operating conditions, which can result in probable power losses. Correspondingly, the FSCC refers to fractional-short-circuit-current; a method undertakes a linear relation between the MPP current and a technique that establishes a linear relationship among MPP current and fractional short-circuit current value at the short circuit terminals, but it faces comparable limitations [19].

In recent times, there has been a rise in the utilisation of Fuzzy logic (FL) theory in the MPPT method with the purpose of improving tracking performance, especially in cases characterised by frequent weather variations. Nevertheless, FL-based methods heavily rely on the experience and expertise of the user, as they necessitate the adjustment of several parameters through a process of error and trial [20].

A different method to develop MPPT performance in the face of fast-changing weather situations involves integrating the P&O mathematical method with an adaptive-integral-derivative-sliding-mode-control. This integration allows for better optimisation of the MPPT process, taking into account the rapid change in weather [21].

While this integration slightly develops performance related to the conventional P&O method, it also introduces additional complexity to the design of control. To further develop the dynamic MPPT performance, it can employ distributed sensors of voltage thru bypass diodes [22].

Nevertheless, this approach brings about increased expenses and elevated complexity within the system. In general, despite the existence of many MPPT methods proposed in the literature, each one comes with its own set of limitations. The creation of an effective MPPT algorithm that can effectively handle sudden changes in conditions while reducing the need for components continues to pose a large problem.

Altas and Sharaf [23] developed a configuration comprising a PV system linked to an electric load combination. They implemented FLC to identify and track MPP by taking into account variations in load and temperature within the scheme. The simulation of the scheme was performed utilising the MATLAB, the Simulink interface software. Two control parts were utilised to control the DC voltage at the load and the speed at the DC motor output of permanent magnet material through the utilise of DC-DC choppers. Evaluating various MPP points led to a reduction in errors.

Alata et al. [24] created the tracking of sun scheme that employed FLC. The control scheme was modelled using a Sugeno fuzzy suggestion system, which incorporated fuzzy IF-Then instructions for output and input. To accurately simulate the system's behaviour, the three-dimensional virtual realism simulator was utilised. Realistic values for the parameters of the simulation were employed, and the scheme was tested to guarantee precise tracking of the sun's movement, at an average of 4 minutes.

Iqdour. R and Zeroual [25] suggest the FLC forecast solar radiance per day in Morocco country. Sugeno fuzzy suggestion scheme was utilised for the purpose of designing the daily irradiation. The suggested system outdid two other systems founded on higher-order statistics regarding reliability and accuracy.

Takun et al. [26] compared an FLC along with one of the common traditional P&O technique for MPPT in a PV scheme. FLC demonstrated better accuracy, simplicity, and performance. The proposed scheme involved defuzzification, rule-based operations, and fuzzification. Simulation utilising MATLAB Simulink show the FLC scheme's superiority under variable insulation conditions.

Alam et al. [27] utilised FLC to implement a PV system. The fuzzy logic rule system resulted from actual experiments, and the scheme was intended to have the capability of self-learning for instruction creation. The structure of the controller consisted of defuzzification, rule-based operations, and fuzzification. The scheme was constructed, evaluated, and simulated, utilising software and artificial light sources indoors rather than relying on direct sunlight.

Several models, including semi-empirical, empirical, artificial intelligence, and physical systems, have been utilised to estimate the radiation of solar. Multiple models' integration is suggested for precise predictions.

Hamdan A et al. [28] utilised three different types of ANNs to forecast the hourly radiation of solar in the city of Amman. By employing the NARX, Elman NN, and FFNN models, they were able to achieve an in elevated level of accuracy in predicting the solar radiation. The models were trained to utilise 10 years of climatological data.

Badran A and Dwaykat [29] employed linear regression analysis to forecast the average amount of global irradiation received per day on a monthly basis for various kinds of weather in Jordan. The coefficients used in the regression model range from 0.7-0.8.

Al-Sbou A and Alawasa [30] used a NARX prototype with seven various architectures to predict the average amount of global radiation received per day within the confines of Mutah City. Inputs involved daily weather situations, humidity, and wind speed. The NARX prototype verified the capability to predict solar radiation precisely.

Mohammed B et al. [31] utilised the NARX prototype to forecast hourly solar irradiation within the confines of Amman City. Obtaining promising findings. They suggested the utilise of the NARX prototype for hourly solar irradiation forecast in Jordan.

Alomari H et al. [32] deliberate the association between solar irradiation and the power of solar PV. They used meteorological data and ANN to forecast power production, the significance of the power prediction importance for enhancing the solar PV system integration in Jordan.

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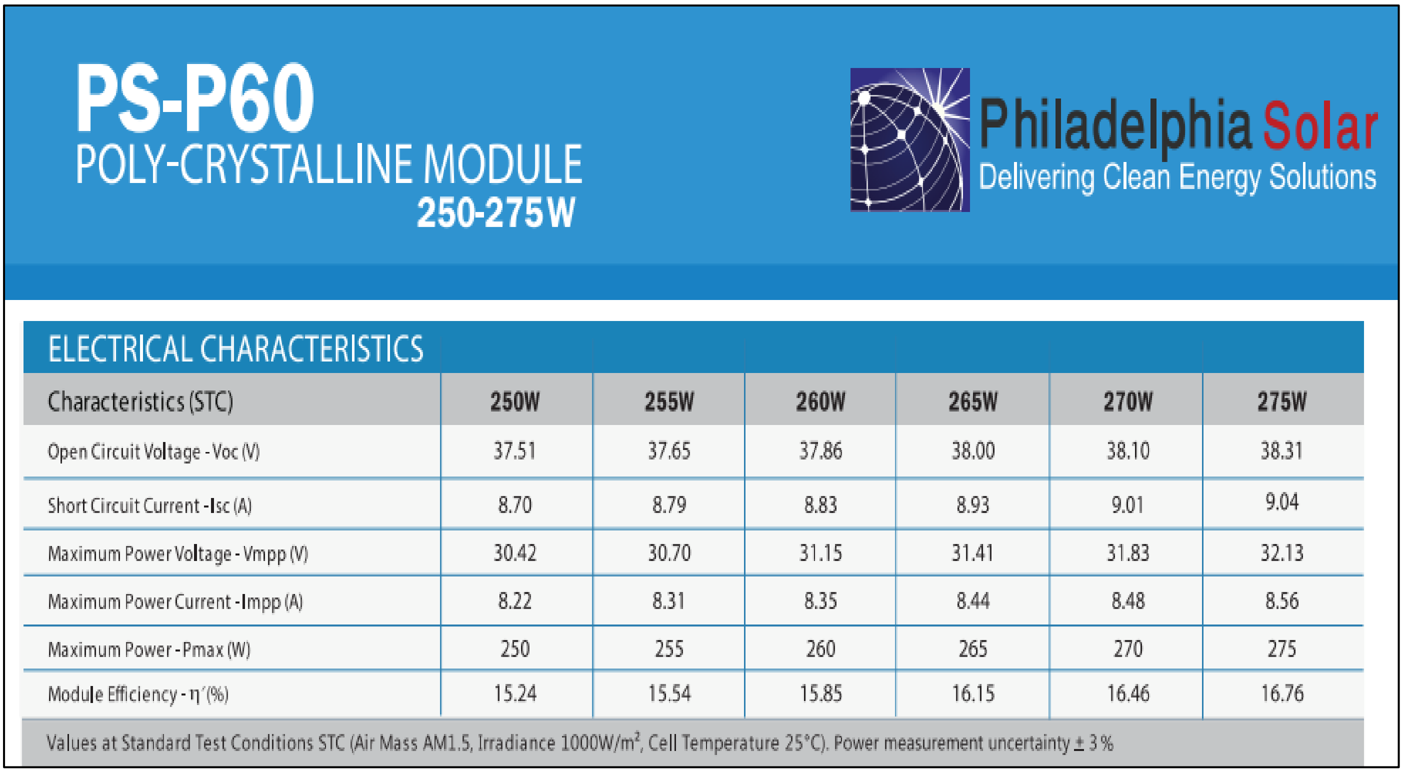
These studies validate the implementation of ANN and FLC for effective solar power schemes and solar irradiation forecasts in different locations. The table provided in the Appendix describes a summary of recent studies focusing on different aspects of photovoltaic systems, including MPPT techniques, control strategies, and solar radiation prediction models.

III. METHODOLOGY

Enhancing the algorithm for MPPT integrating PV panels in a solar energy system is the primary goal of this research. In order to correctly track the MPP and minimise oscillation, FLC and ANN approaches were compared. The research takes into account Jordan's desert climate and takes into account the typical temperatures for particular months. Electricity generated from the solar panels is transferred to the load using a buck power DC-DC converter. A produced dataset is used to train the ANN for MPPT, which is created in Simulink with certain parameters. By establishing linguistic parameters including fuzzy rules, the Fuzzy Logic Designer toolbox using MATLAB Simulink is used to develop the FLC for MPPT. Based on the values provided from the buck converter, Simulink models are created to manipulate the control impulses of the converter.

➤ *PV Panel Design*

The primary goal of this study is to develop an MPPT algorithm capable of handling sudden changes in conditions. a PV solar power scheme converts solar form of energy into electrical form of energy. Temperature and irradiance are the inputs to a PV panel. Temperature and irradiance have an impact on MPP. MPP may be tracked using a number of various MPP techniques. Furthermore, the PV panel brand used in the simulation was Polycrystalline Philadelphia, with specifications shown in Figure 1 of 250 W.


PS-P60
POLY-CRYSTALLINE MODULE
250-275W
Philadelphia Solar
Delivering Clean Energy Solutions

ELECTRICAL CHARACTERISTICS

Characteristics (STC)	250W	255W	260W	265W	270W	275W
Open Circuit Voltage - Voc (V)	37.51	37.65	37.86	38.00	38.10	38.31
Short Circuit Current - Isc (A)	8.70	8.79	8.83	8.93	9.01	9.04
Maximum Power Voltage - Vmpp (V)	30.42	30.70	31.15	31.41	31.83	32.13
Maximum Power Current - Impp (A)	8.22	8.31	8.35	8.44	8.48	8.56
Maximum Power - Pmax (W)	250	255	260	265	270	275
Module Efficiency - η´(%)	15.24	15.54	15.85	16.15	16.46	16.76

Values at Standard Test Conditions STC (Air Mass AM1.5, Irradiance 1000W/m², Cell Temperature 25°C). Power measurement uncertainty ± 3%

Fig 1 PV Module Specifications

➤ *Table 1 Contains Information on the PV Array used in this System.*

Table 1 PV Panel Parameters.

Parameter	Value
Maximum Power	250.0524 W
Voltage at MPP	30.42 V
Current at MPP	8.22 A
Open Circuit Voltage	37.51 V
Short Circuit Current	8.7 A
Temperature Coefficient of Isc (%)	0.10 ± 0.05 %/°C
Temperature Coefficient of Voc (%)	-(0.383 ± 0.01) %/°C

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The figure provided below represents the ideal IV (Current vs Voltage) and PV (Power vs Voltage) curve characteristics of a solar panel array for the maximum power point (MPP) at changed irradiance levels. This figure will be used to conduct a comparison between two techniques: FLC and ANN, both applied to the MPPT (Maximum Power Point Tracking) process.

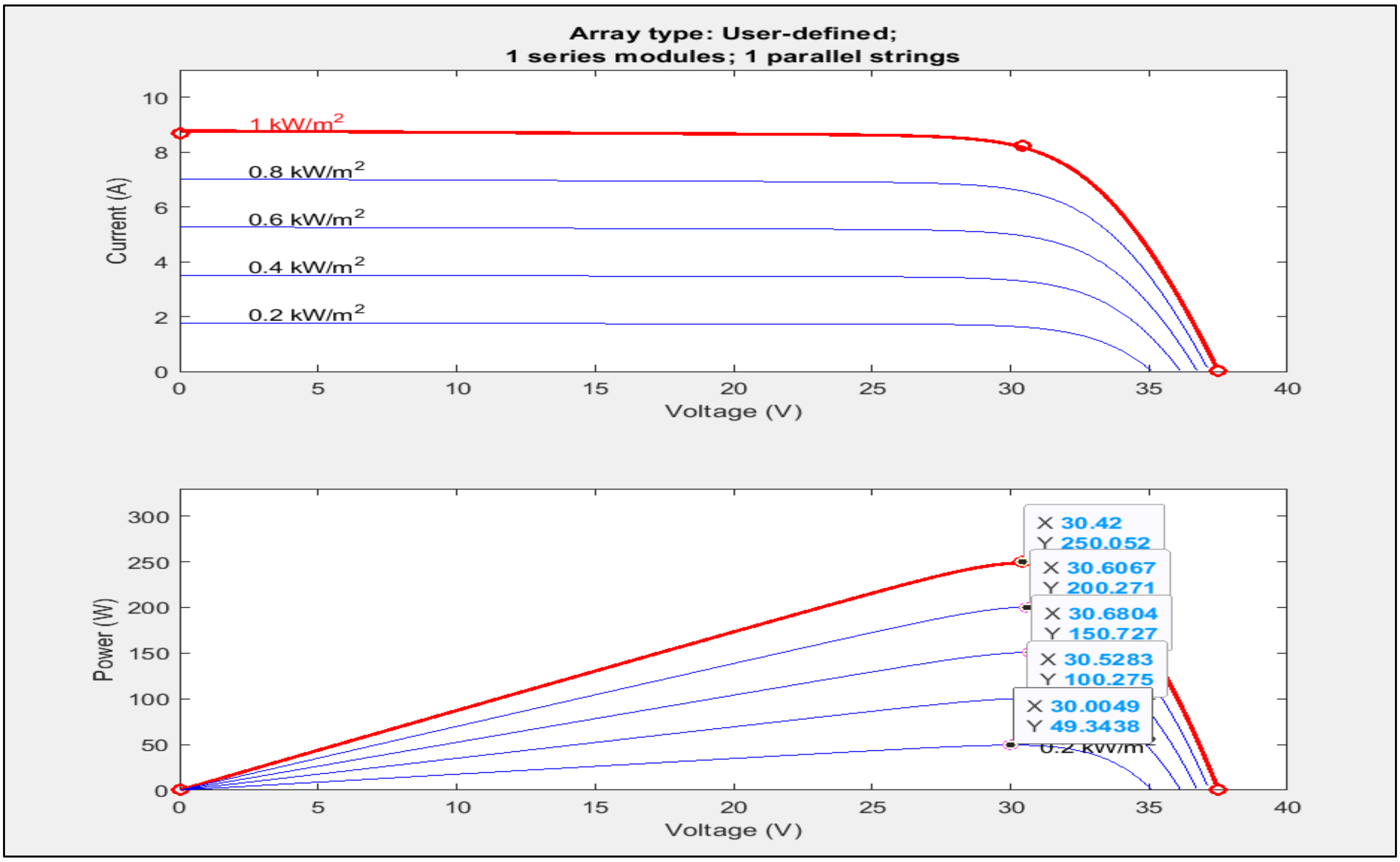

Fig 2 MPP at Different Irradiance Levels

The purpose of this comparison is to analyse and evaluate which technique, FLC or ANN, provides the closest power production to the ideal MPP with less oscillation. Jordan has a desert environment with warm summers and cold winters. According to the region and the season, average temperatures may vary. The following graph indicates that the most agreeable average temperatures take place throughout the warmest months of the year; the June, May, July, September, November and October. The "hot season" additionally encompasses the hottest months, August, September, in addition October.

The simulation utilised the average minimum and maximum temperatures in Irbid, Jordan, spanning from 11°C to 35°C [33] while considering input irradiance values set between 200-1000 W/m².

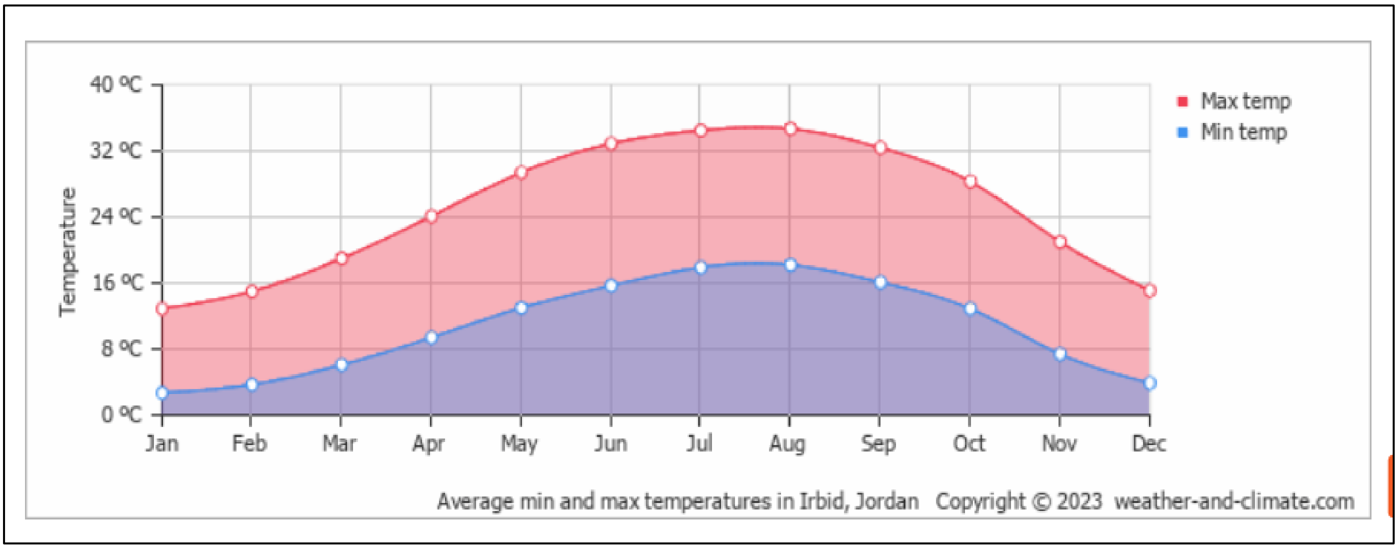

Fig 3 Average Min and Max Temperatures in Irbid

➢ *Buck Converter Design*

To transport the electricity from the solar modules towards the load, the scheme uses a buck power DC-DC converter. Through the simulation development, the PV panel is then linked to model the appropriate blocks describing the buck converter's components, including resistors, capacitors, along with inductors, which must be included in order to model the buck in Simulink in MATLAB. Based on the above table, the corresponding values for the capacitance (C1, C2), resistance (R), and inductance of the (L) are given. The components are linked in accordance with the design of the buck converter circuit and the control method. The following table displays the parameters for the buck converter.

Table 2 Buck Converter Parameters.

Parameter	Value
Capacitance (C1)	0.0158 F
Capacitance (C2)	0.33 F
Resistance (R)	10 Ω
Inductance (L)	3.4 mH

➢ *ANN for MPPT Design*

Various phases are involved in setting up the ANN used for MPPT in Simulink, which is part of MATLAB. In Simulink, a ANN structure is first generated. The activation function of the input layer is then adjusted to "tansig" to map inputs between -1 and 1, and the input layer is programmed using two neurons reflecting solar temperature and irradiance. The activation functions of the hidden layers are designed in accordance with the number of hidden layers that are discovered through a procedure of trial and error. One neuron indicating the desired value of duty cycle for gate triggering in the buck converter is set up in the output layer. The temperature range is adjusted to 25°C as in the STC, long with an irradiance range from 200 W/m2 incrementing by 200 reaching 1000 W/m2. The following table illustrates the applied ANN for MPPT parameters:

Table 3 ANN for MPPT Parameters

Parameter	Value
Number of Hidden Layers	Trial and Error Method
Training Data Points	1000
Temperature Range	25°C
Number of Samples	1000
Number of Hidden Neurons	10
Number of Epochs	1000
Irradiance Range	200 W/m² to 1000 W/m²

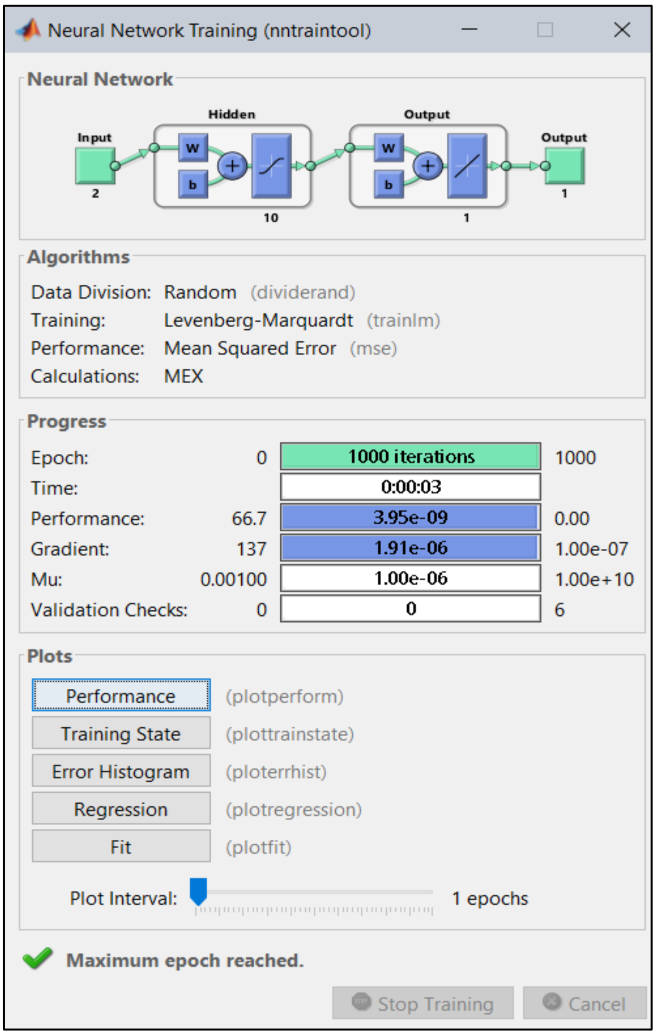

Fig 4 Traning Setting for NN

A code was utilised for the training dataset of the NN. It randomly generates temperature and irradiance values within specified ranges and calculates the corresponding current, voltage, and power values for the solar panel. The code starts by defining the given parameters, shown in the PV panel spfication table. Then, in order to produce 1000 data points, it enters a loop that executes 1000 times. It randomly chooses a temperature (T) and an irradiance (G) for each iteration, both of which must fall within the predetermined ranges (Tmin to Tmax). Next, it calculates the (IMP) using the formula:

$$\mathrm{IMP(i)} = \mathrm{IMPS} * (\mathrm{G/Gs}) * \big(1 + \big(\mathrm{alpha} * (\mathrm{T} - \mathrm{Ts})\big)\big) \ldots\ldots \quad (Eq.1)$$

Similarly, it calculates the voltage at the MPP using the formula:

$$\mathrm{VMP(i)} = \mathrm{VMPS} + (\mathrm{beta} * (\mathrm{T} - \mathrm{Ts})) \ldots\ldots \qquad (Eq.2)$$

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Finally, it multiplies the current and voltage values to determine the power value at the MPP. It saves the input values (temperature and irradiance intensity) in the array's "input" and the output values (voltage) in the array's "output" for each iteration. Additionally, it calculates the current at MPP (output1) and power at the maximum power point (output2) to have a comprehensive dataset. Overall, this MATLAB code effectively generates the required dataset for training then testing ANN or FLC in the subsequent steps of the project.

A ANN's training process demonstrates how effectively it adapts and develops over time. Metrics like validation loss and accuracy, including validation accuracy, are frequently included in the following figure. The objective is to reduce the loss and boost accuracy, showing that the network produces more precise predictions. The learning curve depicts the performance of the network's trend and convergence. Monitoring these parameters enables evaluation of the network's data adaptability and directs changes to develop performance.

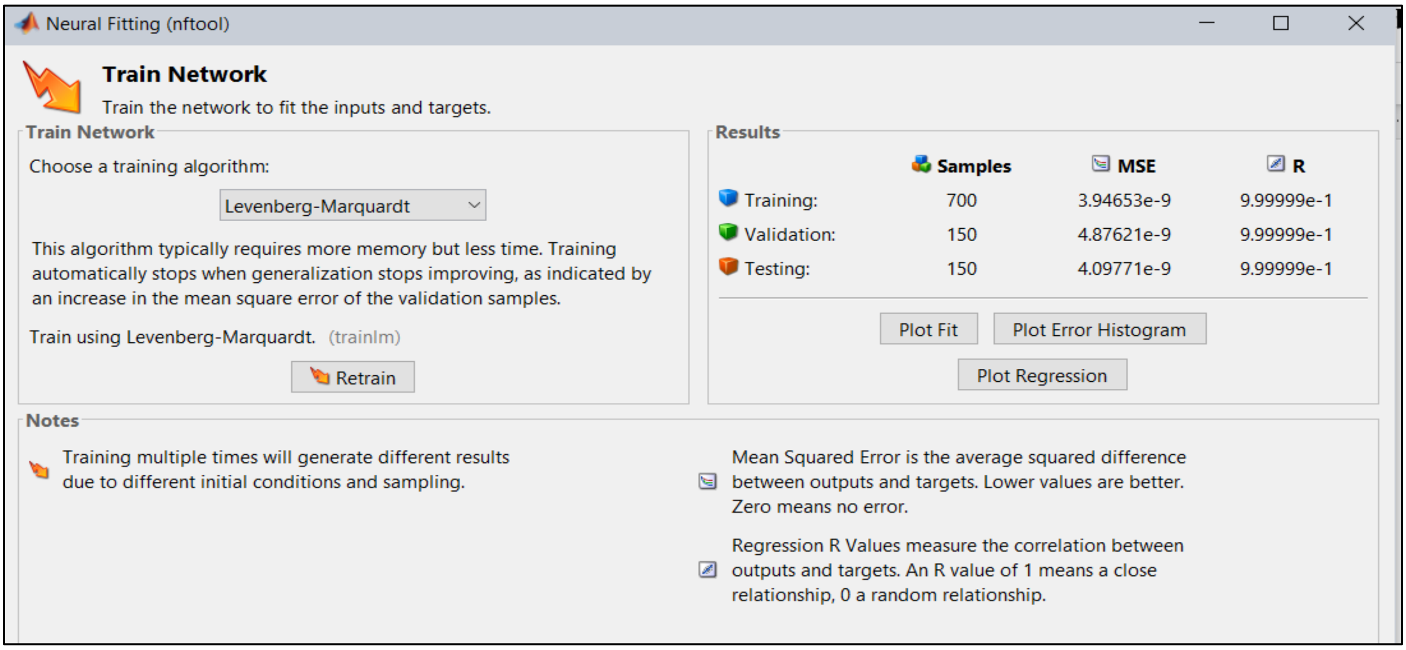

Fig 5 Neural Fitting Window

The Simulink model that provides a visual representation of the NN-MPPT algorithm and allows for simulation and analysis of the PV system's behaviour underneath diverse circumstances is shown below:

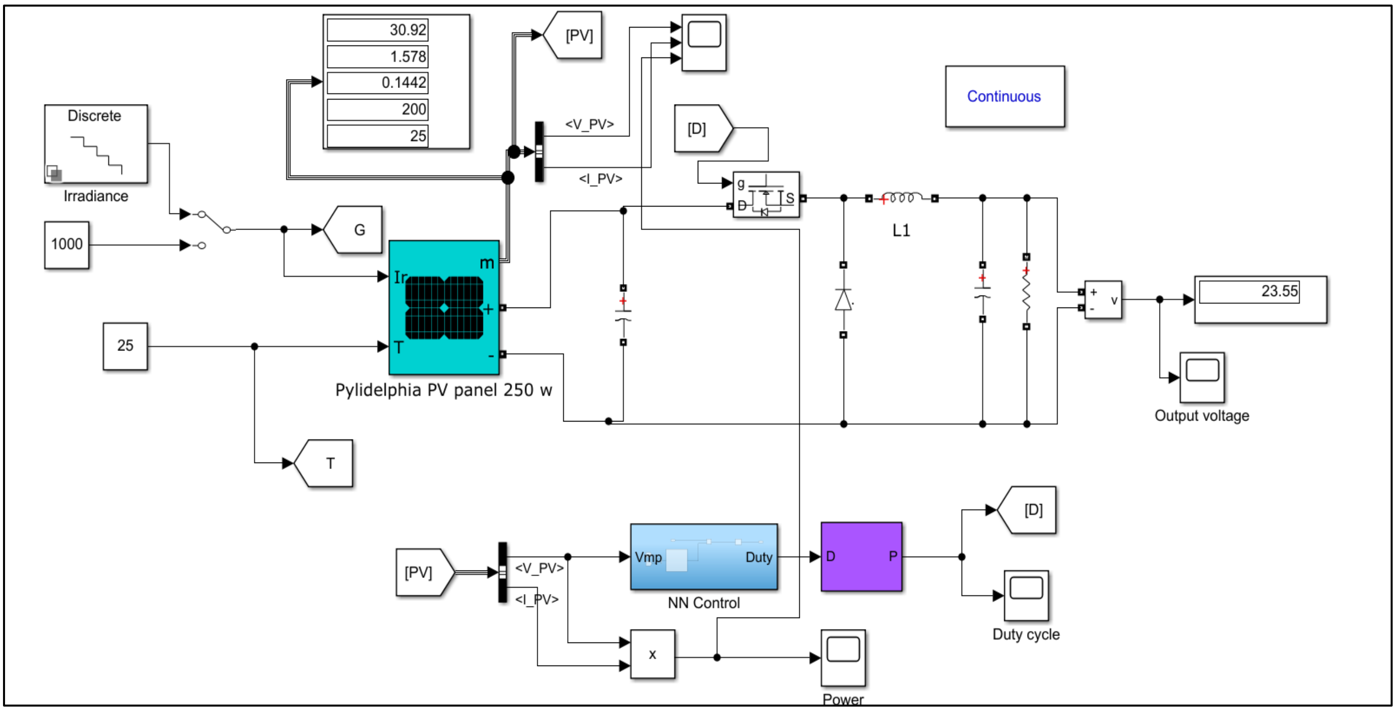

Fig 6 PV Simulink Model-based NN-MPPT

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➢ *FLC for MPPT Design*

The Fuzzy Logic Designer toolbox was used in conjunction with the Fuzzy Converter approach in MATLAB Simulink. Membership functions were used to define linguistic parameters for the variables that were input (Error and Variance of Error) in a new model. The model was expanded to include FL blocks like Fuzzify, Rule Base, and Defuzzify to make it easier to convert numerical inputs into language variables, establish rules, and derive numerical output values. For the outcome of the variable (Duty Cycle), the language variables and functions of membership were set up appropriately. To ensure adequate data flow inside the system, the blocks were linked. The Fuzzy Converter was successfully constructed in MATLAB Simulink by utilising the FL Designer toolbox, connecting it with other system elements, including the buck converter.

PV Simulink model-based FLC-MPPT requires precise parameters, including fuzzy sets, membership functions, rules, as well as input-output ranges, in order to describe the fuzzy converter properly. The proper FL blocks must be built, and the fuzzy converter's behaviour must be defined using these specifics. Two inputs are used by the FLC to determine the MPP position: the gradient of the P-V curve's tangent line (dP/dV) and the operational point's displacement direction (d2P/dV2). The following equations represent these inputs:

$$E(k) = \frac{(P(k) - P(k-1))}{(V(k) - V(k-1))} \ldots \ldots \qquad (Eq. 3)$$

$$CE = E(k) - E(k-1) \ldots \ldots \qquad (Eq. 4)$$

By dividing the difference in voltage (V) between two adjacent locations (k and k-1) taking place at the P-V curve by the difference in power (P), Equation 3 determines the slope of the tangential line.

CE, which stands for the operating point's displacement direction, is calculated by deducting the current slope value (E(k)) from the slope value that came before it (E(k-1)). These equations aid in calculating the MPP location in the FLC-MPPT algorithm by analysing the change in slope and displacement of the operational point analysing the P-V curve.

Through membership functions, these input values are transformed into linguistic variables. Figures 7, 8, and 9 display the membership functions for the research's input and output values. For linguistic variables, there are seven categories that have been established: PS, PM, PB, NS, NM, and NB; where the letter N refers to negative, P refers to positive, M refers to medium, B refers to big, and S refers to small linguistic variables.

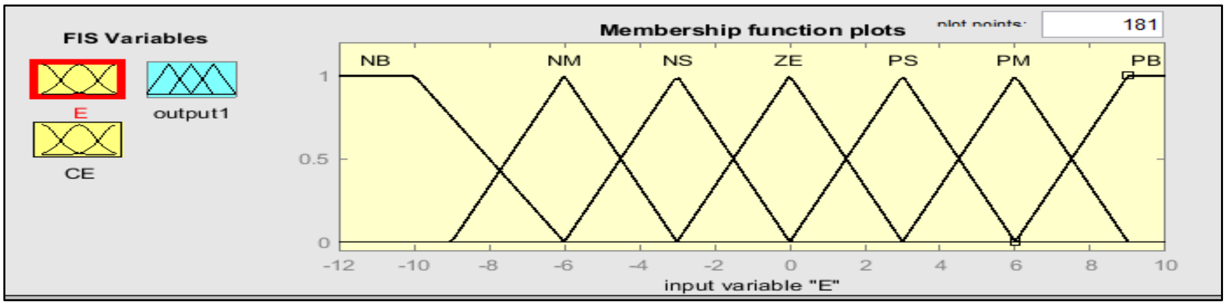

Fig 7 Error MF Input

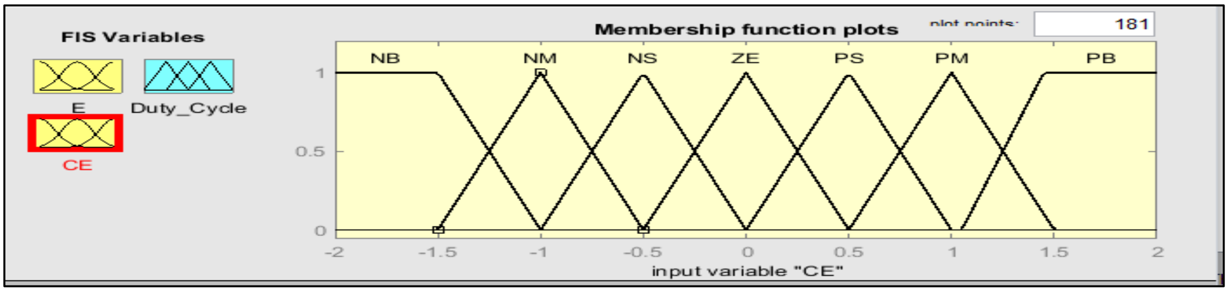

Fig 8 CE MF Input

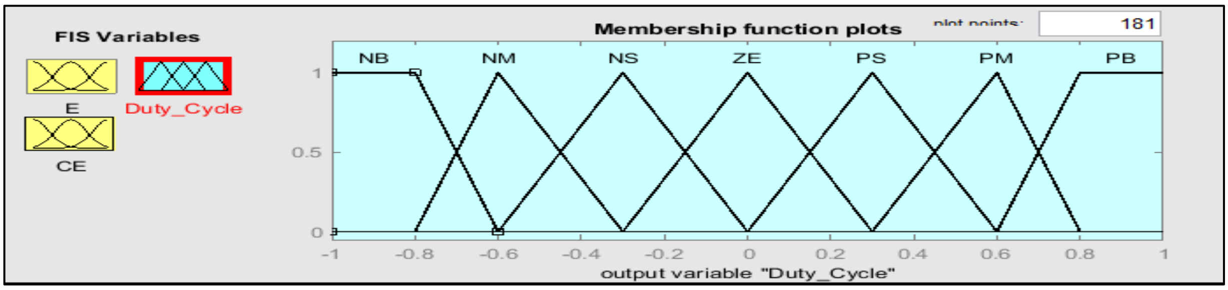

Fig 9 Duty Cycle MF

The fuzzy rules used to model and regulate a system are represented by a rule matrix for a fuzzy system. Fuzzy rules specify the connections between input and output variables in a FLC using linguistic expressions and fuzzy sets. The fuzzy rule used in this research study is displayed in Table 4.

Table 4 FLC Rules

E/CE	PB	PM	PS	ZE	NS	NM	NB
PB	ZE	ZE	ZE	NB	NB	NB	NB
PM	ZE	ZE	ZE	NM	NM	NM	NM
PS	ZE	ZE	ZE	NS	NS	NM	NM
ZE	NS	NS	ZE	ZE	ZE	PS	PS
NS	PM	PM	PS	NS	ZE	PS	ZE
NM	PM	PM	PM	PB	ZE	ZE	NS
NB	PB	PM	PM	PB	ZE	ZE	ZE

It can be noticed from the following figure that illustrates the PV Simulink model-based FLC-MPPT that the FLC Block uses the current values and voltage output values from the PV solar panel as input and applies FL rules to identify the proper control actions. The MPPT Block then modifies the control signals of the Buck Converter Block using the output from the FLC Block. The Buck DC-DC Converter Block regulates the output current and voltage to transfer energy through the solar panel to the load.

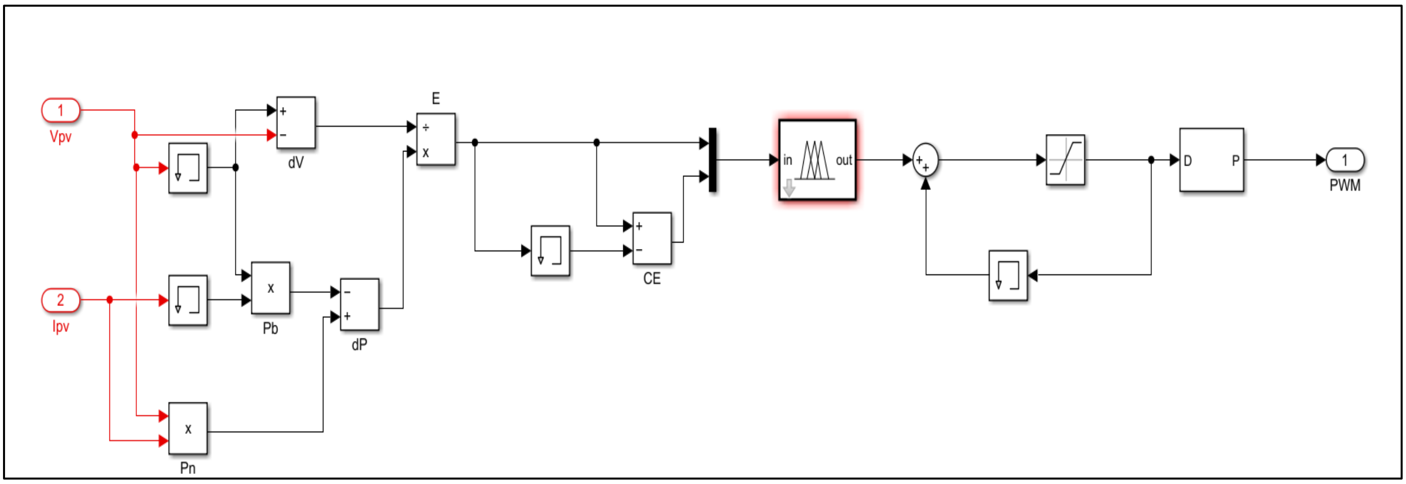

Fig 10 FLC_MPPT Simulink Subsystem

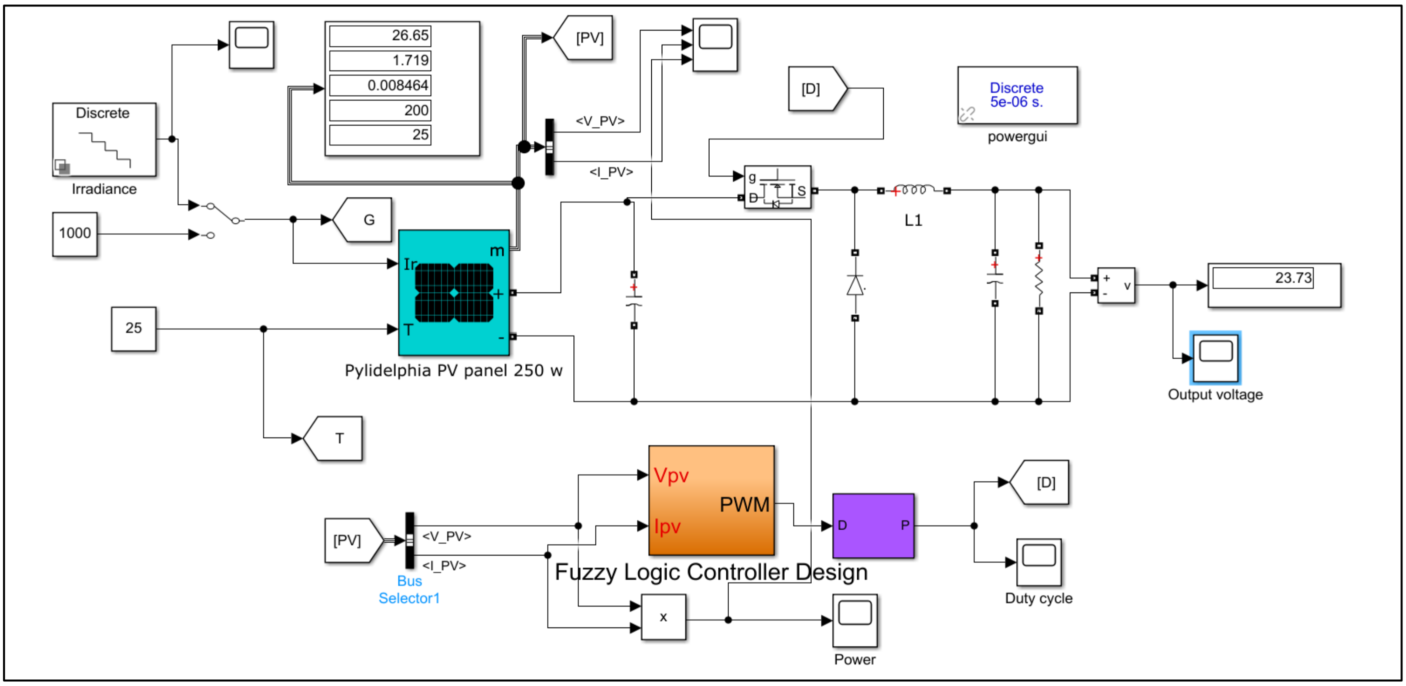

Fig 11 PV Simulink model-based FLC-MPPT

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IV. RESULTS DISCUSSION AND ANALYSIS

The Results, Discussion, and Analysis section of this study provides a comprehensive evaluation and comparison of two distinct MPPT techniques: the ANN-based approach and the FLC-based approach. This section presents the simulation results, discusses their implications, and analyses the performance of each technique based on various metrics. By examining the power estimation accuracy, computation time, and complexity, a thorough understanding of the strengths and limitations of each approach is gained. The obtained results are presented and discussed below.

➢ *ANN-based MPPT Simulation Results*

The regression curve of the NN-based MPPT approach is shown in Figure 12. It illustrates the relationship between the expected and actual power production. A strong linear connection shows how well the ANN model works.

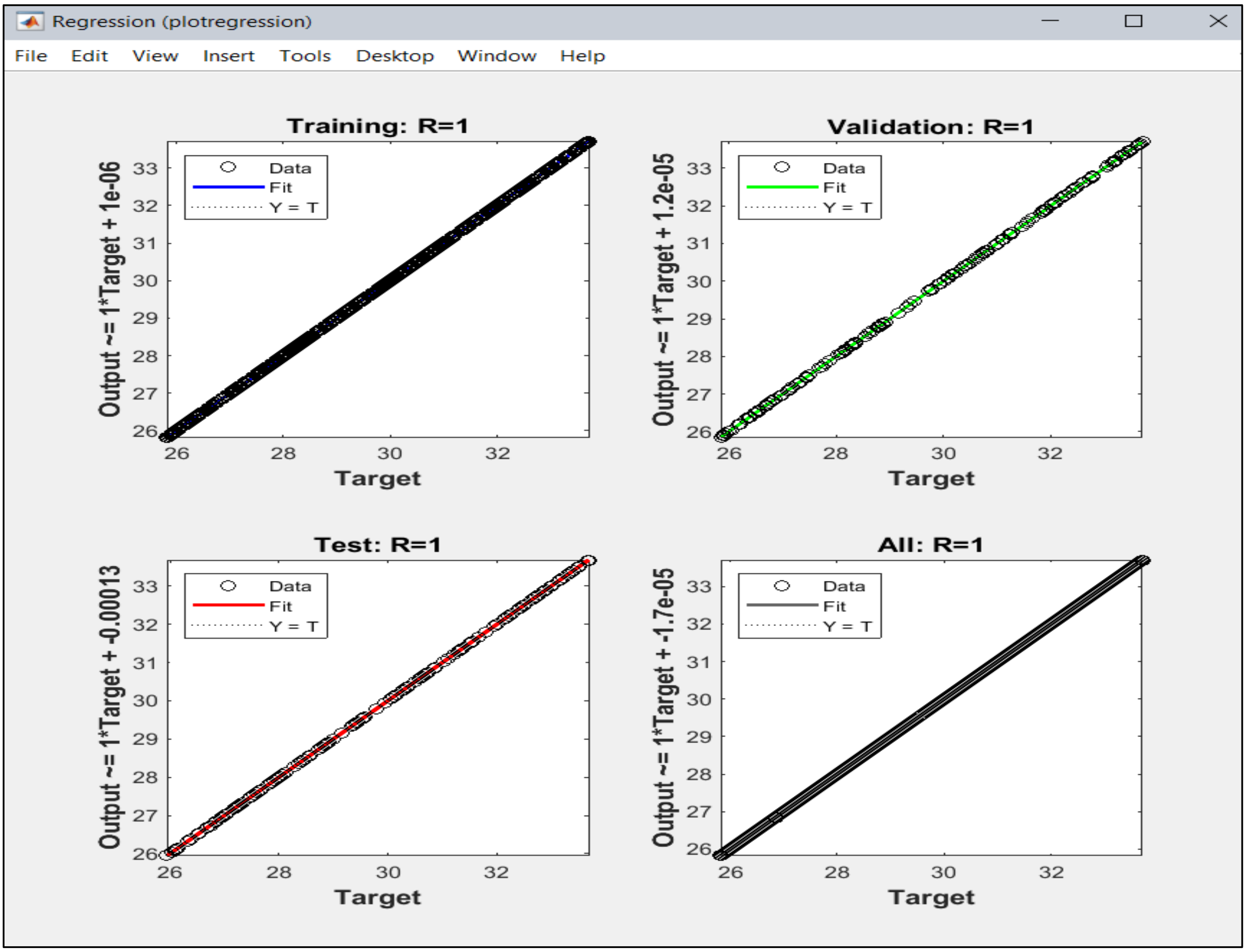

Fig 12 ANN Regression Plot

As can be observed from the ANN regression plot, the test, validation, and training regression values are all 1, demonstrating a great correlation and ideal fit to the anticipated and actual output values. This shows that the ANN model for MPPT utilised in the research is quite accurate and successfully identifies the fundamental correlations and patterns in the data. The constant regression results of 1 across several datasets show that the model can generalise effectively to unknown test and validation results without either under or overfitting the data. This indicates a solid and trustworthy ANN model for precise power output forecasting in MPPT under varying circumstances.

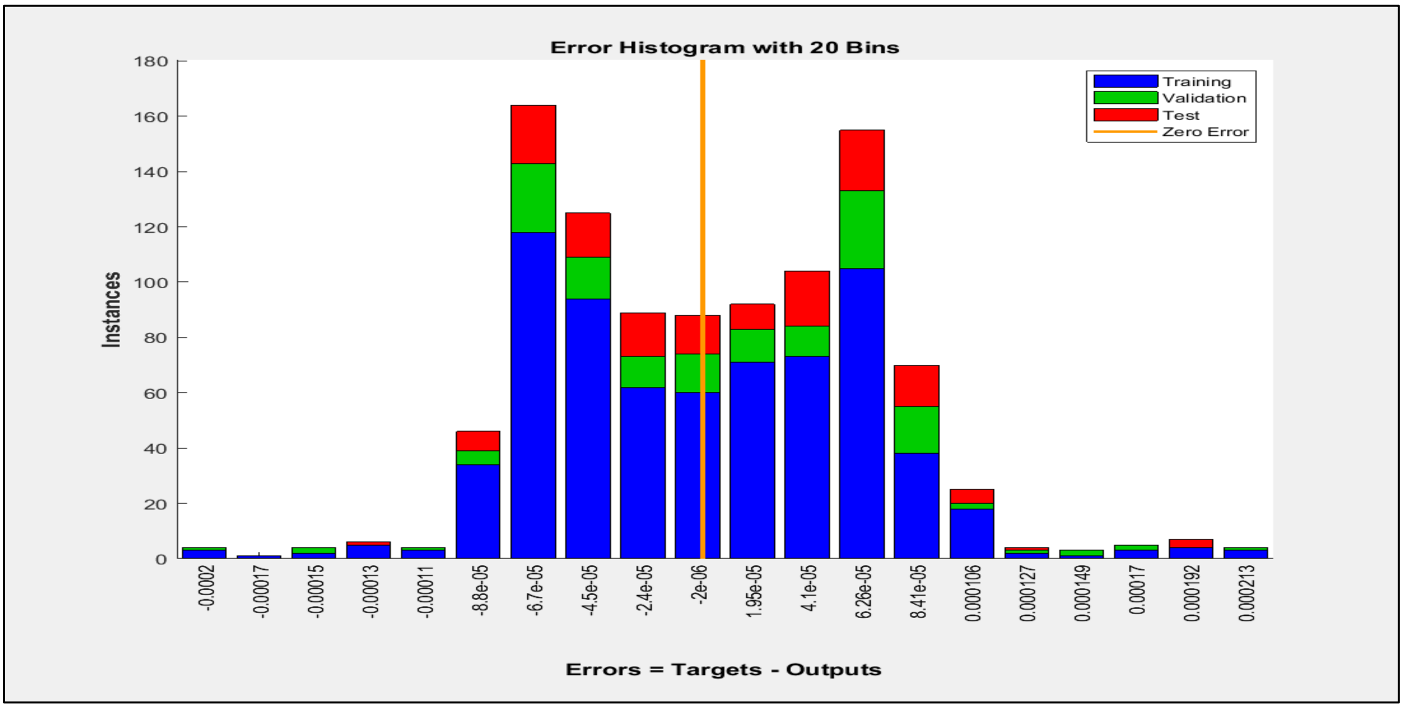

Fig 13 Error Histogram

The error histogram, shown in Figure 13, shows how errors between the expected and real power are distributed, which shows a tight and symmetrical distribution centred on zero, showing that the ANN made correct predictions. Figure 14 displays the MPPT performance of the ANN-based approach at various levels of irradiance.

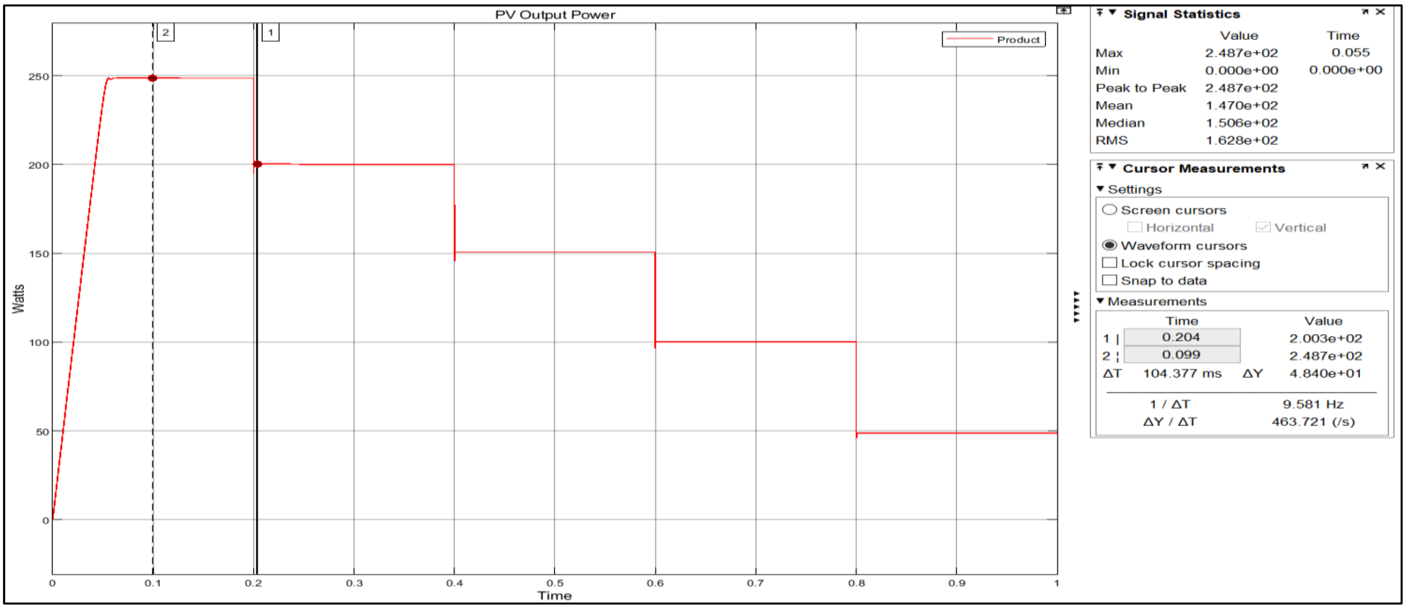

Fig 14 PV Output Power

The MPP of the ANN-based approach demonstrates a high degree of accuracy when tracked throughout a range of irradiance circumstances, according to an investigation of its MPPT performance at various irradiance levels. The anticipated power values at PV characteristics nearly match the actual power values, demonstrating the efficiency of the ANN-based MPPT approach. Results show how well projected and real power outputs at various irradiance levels correspond. For instance, the anticipated power production of 248.7 W at an irradiation level of 250 W/m2 is almost exact to the actual power figure of 250 W. The projected power values match the real values well at other irradiation levels.

These results demonstrate that even under fluctuating irradiance circumstances, the NN-based approach can effectively track the MPP and provide efficient power extraction from the PV system. The close agreement between anticipated and real power values highlights the ANN model used in the MPPT process's adaptation and optimisation skills.

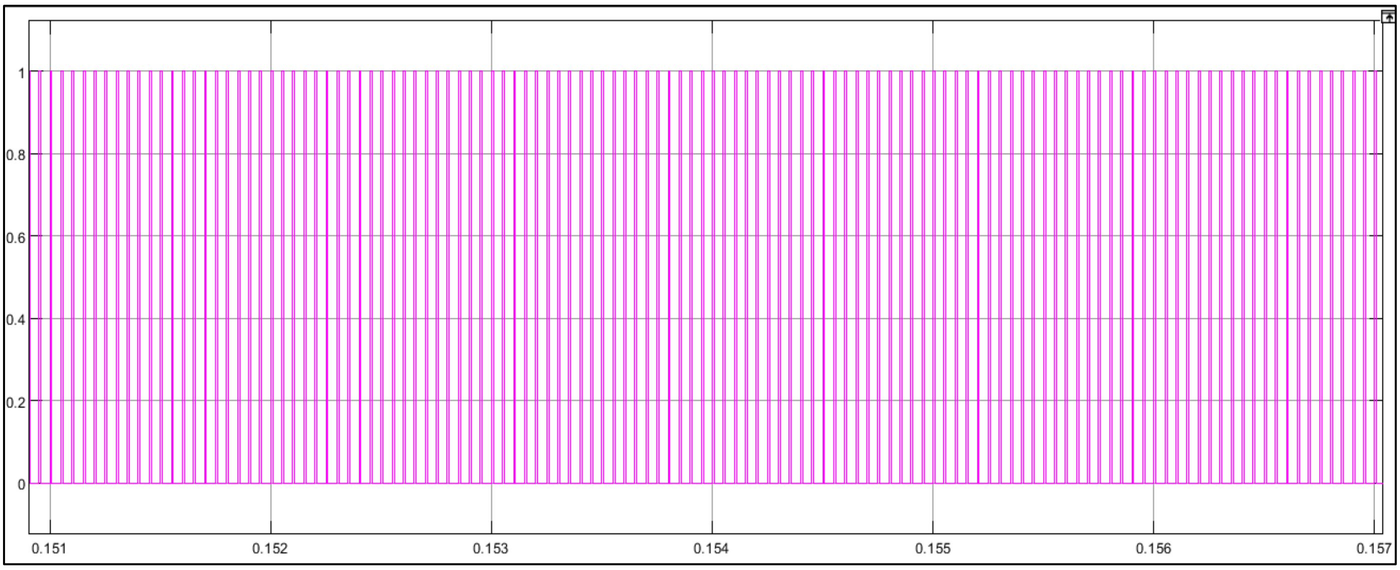

Fig 15 Duty Cycle Wave form of ANN

The duty cycle waveform of the ANN is depicted in Figure 15, which shows the control signal generated by the MPPT algorithm. The smooth and precise waveform demonstrates the ability of the ANN to adjust the duty cycle accurately for optimal power extraction. The following figure shows the PV characteristics of the ANN produced under various irradiance intensities:

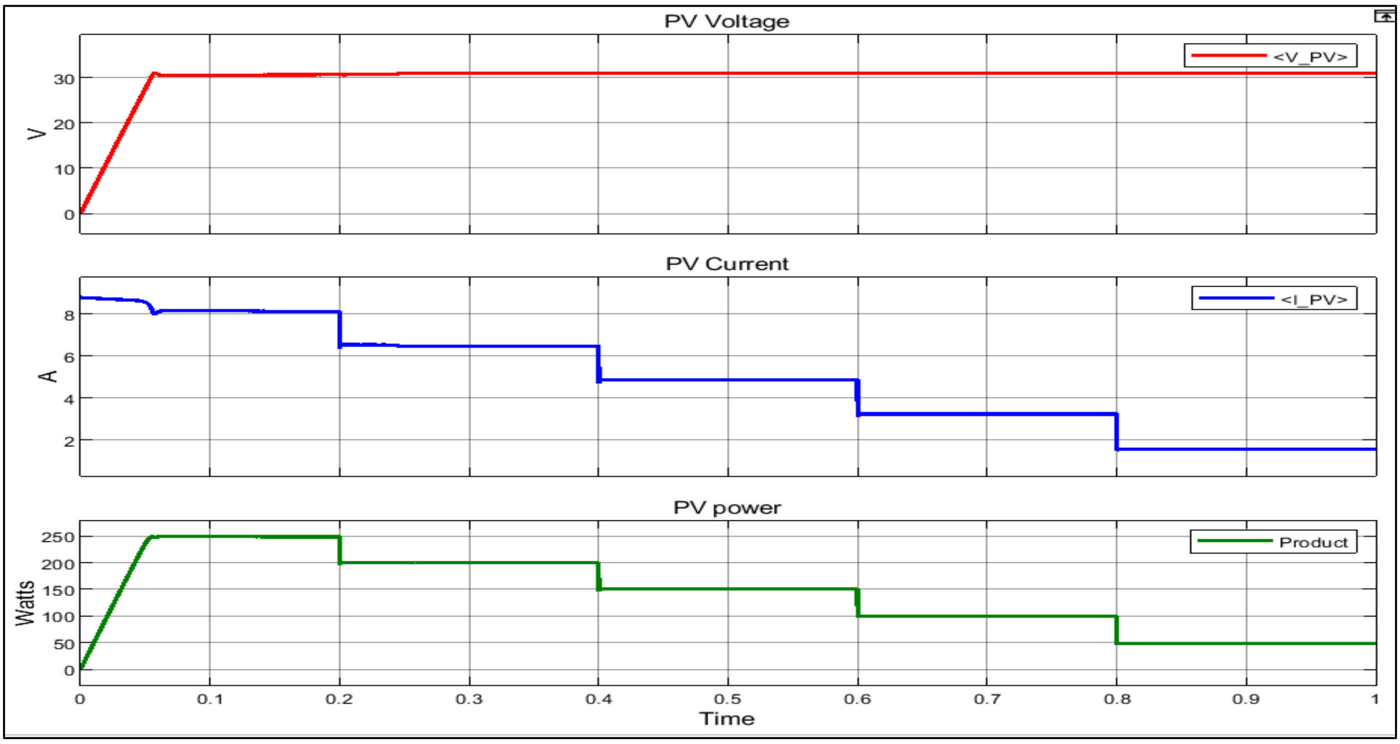

Fig 16 PV Measurements

When examining the PV characteristics for the ANN produced under various irradiance intensities, it can be found that increasing irradiance intensity often results in an increase in PV voltage because more electron-hole pairs are generated. The ANN model's accuracy in forecasting PV voltage is high and closely matches the anticipated trend. Similarly, when the intensity of the irradiance increases, the PV current tends to grow as more photons are absorbed by the PV cells, producing more current. The ANN model generates results consistent with the anticipated trend because it properly depicts the link between irradiance and PV current. Both factors have an impact on and are reliant on power output, which is the result of PV voltage and PV current. Accordingly, it fluctuates, with rising irradiance levels causing increased power output and lower levels leading to a decrease in power.

➢ *FLC-based MPPT Simulation Results*

The surface viewer in Figure 18 is used to demonstrate the efficacy of the FLC-based MPPT strategy. It illustrates the FLC's surface plot and explains how it may change with the environment.

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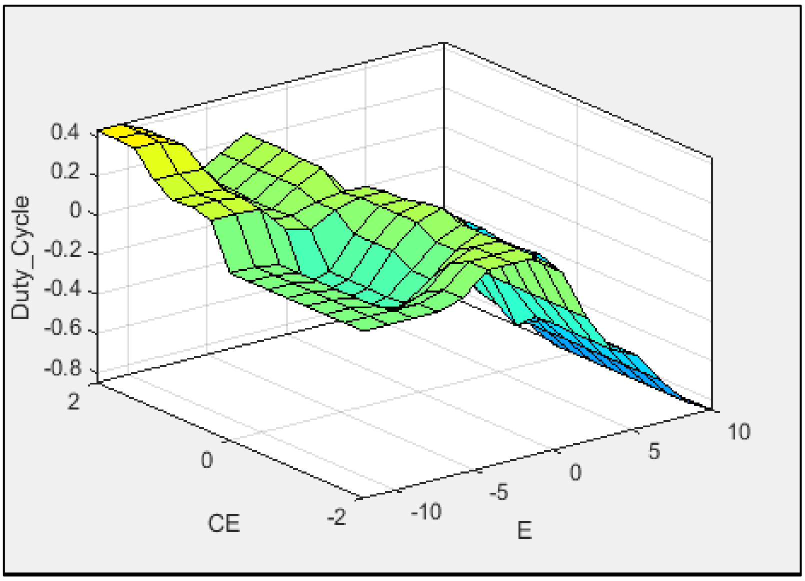

Fig 17 The Surface Viewer

The FLC-based MPPT system's behaviour with regard to various input parameters and their combinations may be seen using the surface viewer. It shows how the inputs like irradiance level and duty cycle relate to the output, which is generally the power production of the PV panel scheme. The PV output power produced utilising the FLC-based MPPT approach is shown in Figure 18.

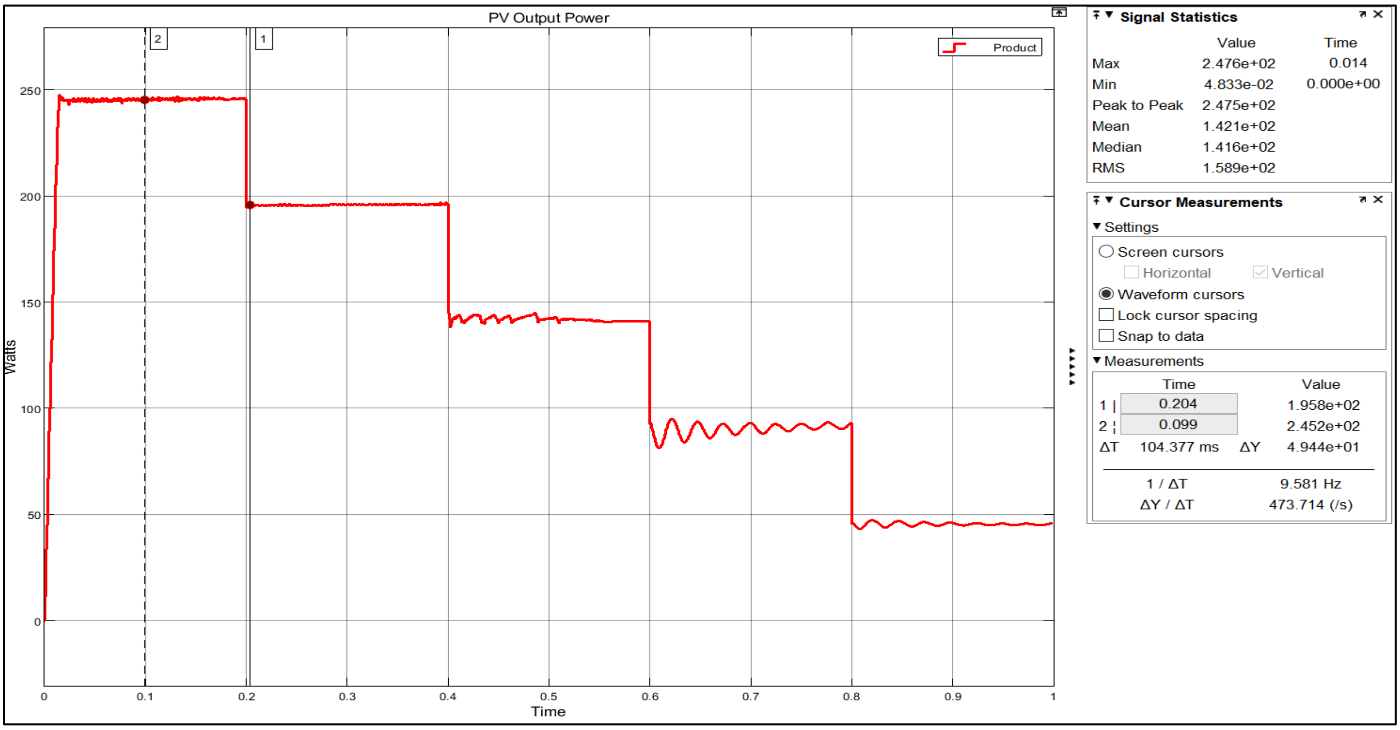

Fig 18 PV Output Power of FLC

As observed, the power output achieved using the FLC-based MPPT approach differs based on the PV's power's characteristics. The actual power levels produced utilising the FLC and the predicted power values differ. The power curve's oscillations imply that the FLC-based MPPT technique would have difficulty maintaining constant and reliable power production. These variations may be a result of the FLC's fundamental properties, which depend on membership functions and language rules for decision-making. FL's inherent uncertainty and imprecision may lead to less accurate power tracking and fluctuating power output.

It is crucial to remember that even though the FLC-based MPPT technique might not accomplish reliable power tracking, it still offers a different strategy for maximising the energy extracted from the PV system. Although the FLC is adaptable and can change the duty cycle dependent on the environment, it might not be able to give a steady and smooth power output.

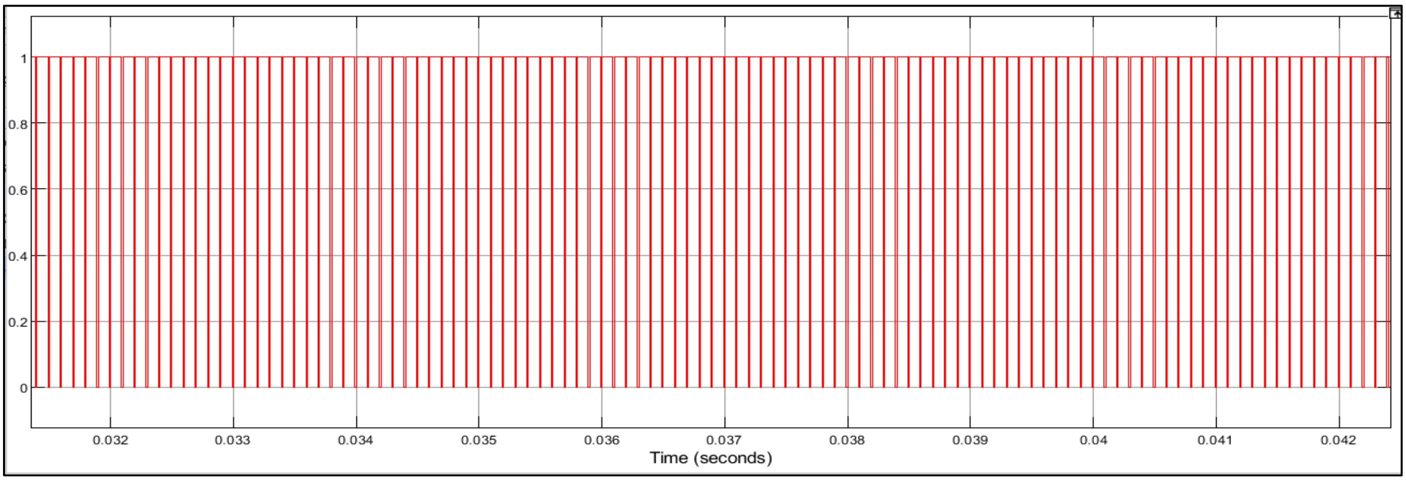

Fig 19 Duty Cycle Wave form of FLC

Figure 19 demonstrates the control signal that results from the MPPT algorithm as well as the FLC's duty cycle waveform. The waveform's smoothness and accuracy show that the FLC can precisely alter the duty cycle for maximum power extraction.

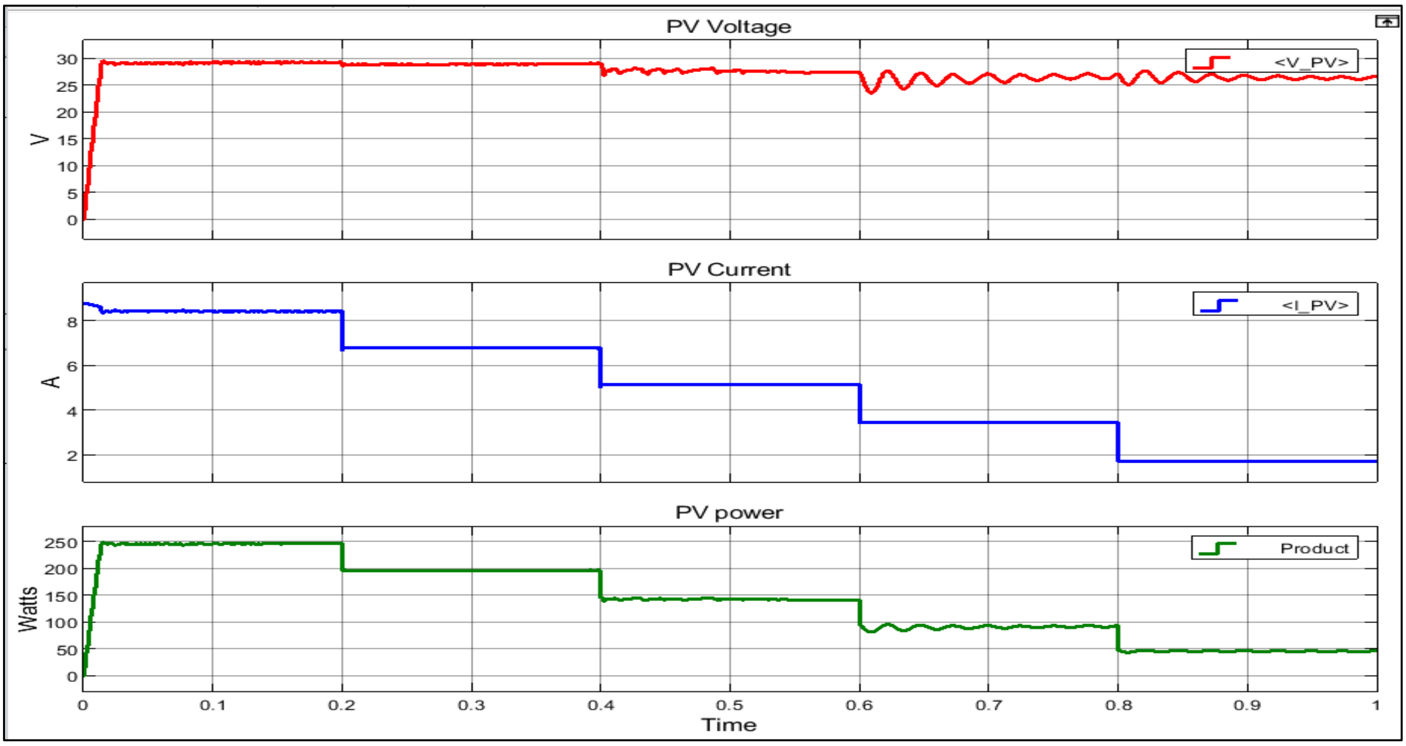

Fig 20 PV Measurements Output of FLC

With some obvious oscillations, the PV measurement waveforms produced from the FLC exhibit behaviour comparable to that of the ANN (regrading to PV voltage and power. The intrinsic qualities and constraints of the employed control algorithms might be blamed for these oscillations. In the FLC control algorithms, oscillations can be observed in the PV voltage due to the dynamic nature of the algorithms and the time required to adapt to varying environmental conditions. These fluctuations are within an acceptable range and do not significantly impact system performance. The oscillations in voltage directly affect the power output since power. Therefore, the oscillations in the PV voltage waveform can propagate into the power waveform.

➢ *MPPT Techniques Analysis and Comparison*

In the analysis and comparison of MPPT techniques, several metrics are considered to evaluate their performance and practical viability. This analysis focuses on three key metrics: produced power behaviour, computation time, and complexity.

- *Metric1: Produced Power Behaviour*

When analysing the power behaviour of both the ANN and FLC-based MPPT techniques, it can be observed that both approaches produce power outputs values that are adjacent to the real power values. The power outputs obtained from both techniques align well with the expected power values at different irradiance intensity levels.

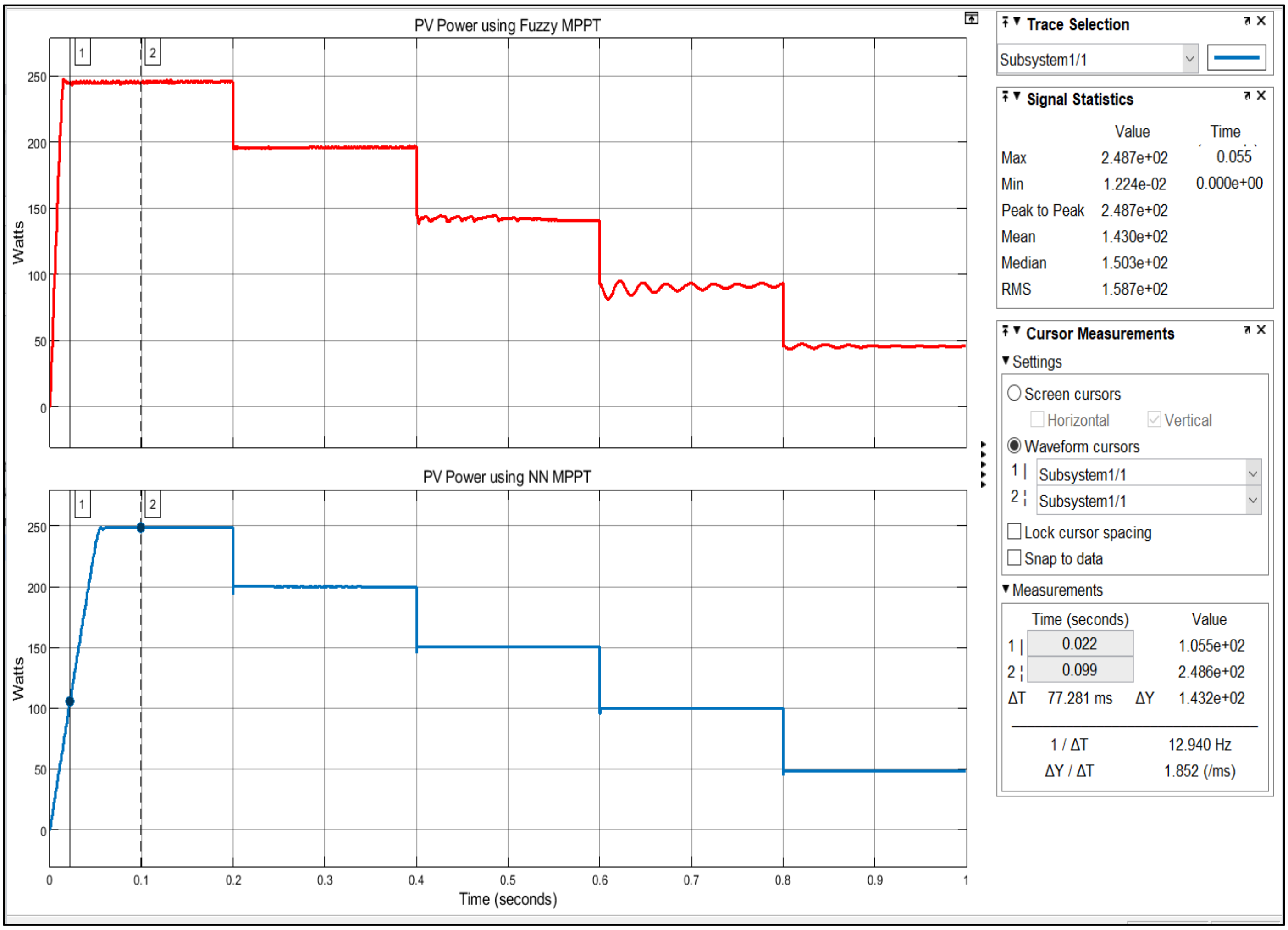

Fig 21 Power Output Curves for Evaluation of ANN and FLC-based MPPT Approaches.

With few deviations from the real power levels, the ANN-based MPPT approach exhibits high accuracy in tracking the power output. Like the ANN approach, the FLC-based MPPT technique generates power outputs that roughly resemble the predicted values but with slightly larger fluctuations. Although the power outputs of the two strategies may differ somewhat, both show the capacity to maximise power extraction from the solar energy system under varying conditions. This shows that for tracking the MPP and attaining efficient power generation, both ANN and FLC-based approaches are useful.

A comparison of the NN-based and FLC-based MPPT methods is shown in Table 5, regarding to the produced power at different irradiance levels. The table demonstrates that the NN-based technique consistently outperforms the FLC-based technique, with higher power outputs at each irradiance level.

Table 5 Comparison between ANN and FLC-based Output Power

Irradiance intensity (W/m^2)	Power at PV Characteristics (W)	Power at ANN (W)	Power at Fuzzy (W)
1000	250	248.7	245.2
800	200	200	195.8
600	150	150.6	141.6
400	100	100.1	93
200	50	48.8	44.9

From Table 5, it can be observed that both the ANN and FLC techniques yield power outputs that are generally close to the power at PV characteristics. The projected power numbers and the actual power values, however, differ just slightly. For instance, the FLC-based MPPT approach predicts a power output of 245.2 W at an irradiance intensity of 1000 W/m2, whereas the ANN-based MPPT technique predicts 248.7 W. The power outputs of the two approaches also exhibit modest variances at various irradiance levels.

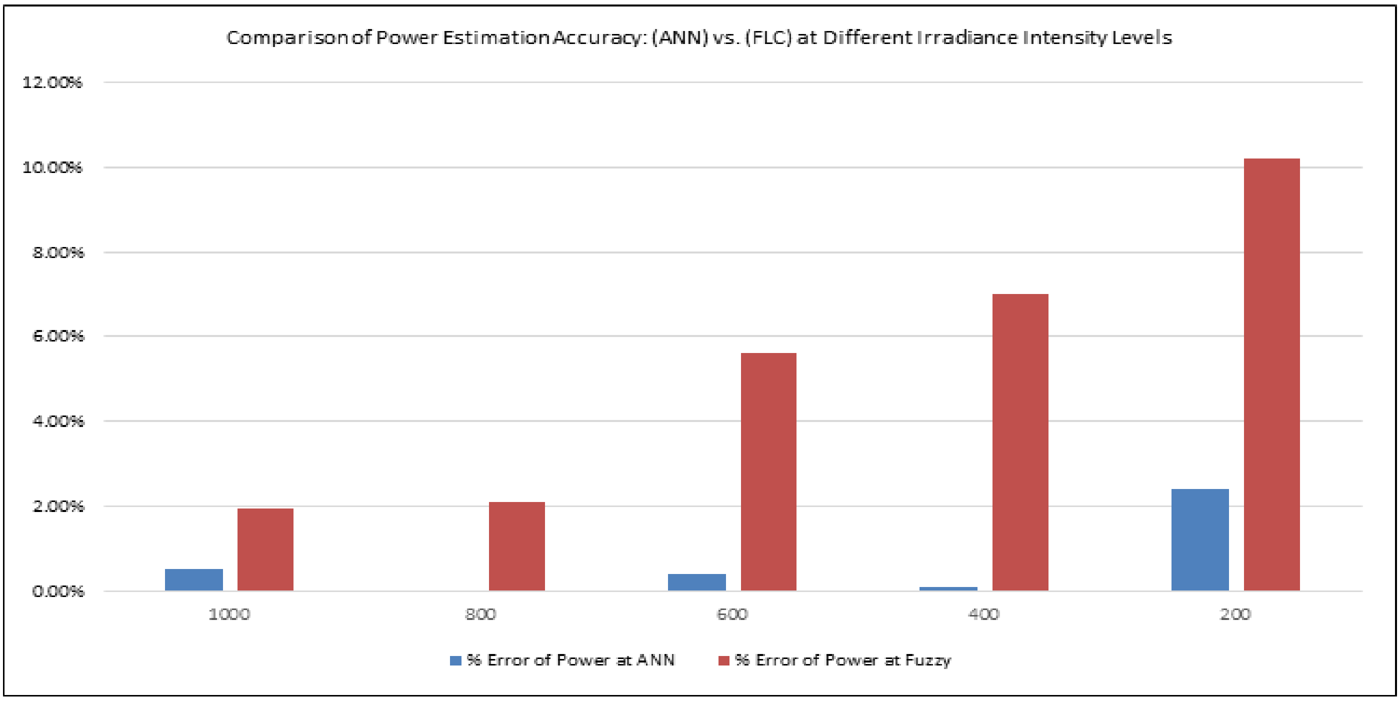

Fig 22 Comparison of Power Estimation Accuracy: ANN vs FLC at Different Irradiance Intensity Levels

The provided chart presents the % error of power estimation for an ANN and FLC across different levels of irradiance intensity. The chart facilitates analysis by providing a clear visual representation of the performance comparison between the two methods. It shows that the ANN generally exhibits lower % errors in power estimation compared to the FLC. As the irradiance intensity decreases, the % errors vary for the ANN and FLC, with the ANN consistently maintaining lower % errors overall. This chart serves as a valuable instrument for evaluating and understanding the relative outcomes of these two methods in power estimation based on varying irradiance intensity levels. Table 6 provides the error percentages for both techniques, indicating the deviation of the forecast power values as of the actual power values.

Table 6 Error Percentage of ANN and FLC MPPT Techniques

Irradiance intensity (W/m^2)	% Error of Power at ANN	% Error of Power at Fuzzy
1000	0.52%	1.92%
800	0%	2.1%
600	0.4%	5.6%
400	0.099%	7%
200	2.4%	10.2

Although the ANN and FLC procedures have usually low error rates, while the FLC methodology has a little greater error % than the ANN technique. For instance, the FLC approach yields an error percentage that is 1.92% at a radiation intensity of 1000 W/m2, compared to the ANN technique's 0.52% mistake rate.

Accordingly, the analysis of the produced power behaviour suggests that both the ANN and FLC-based MPPT Techniques can provide power outputs that are quite close to the real power levels. The ANN technique generally exhibits lower error percentages, indicating a slightly higher accuracy in power prediction compared to the FLC technique. However, the differences between the techniques are relatively small, suggesting that both approaches can effectively optimise PV system power extraction under varying irradiation circumstances.

- *Metric 2: Computation Time*

When evaluating any MPPT technique's performance and practical viability, calculation time is a crucial component to take into account. According to the information recorded, the FLC-based MPPT approach runs the simulation in around 3.33 minutes compared to the ANN-based MPPT technique, about 30 seconds. The computation time required by the MPPT techniques is a crucial consideration for their practical implementation.

The ANN-based technique offers a shorter computation time of 30 seconds, allowing for faster decision-making and real-time adjustments in dynamic environments. In contrast, the FLC-based technique has a longer computation time of approximately 3.33 minutes, which may limit its suitability for applications requiring rapid response. However, the FLC-based technique may offer stability, adaptability, and power generation efficiency advantages. Therefore, the selection of the appropriate MPPT technique should consider the trade-off between computation time and performance accuracy, ensuring a balance between feasibility and effectiveness in the specific application. The chart below illustrates the computation time required by two MPPT techniques: FLC and ANN.

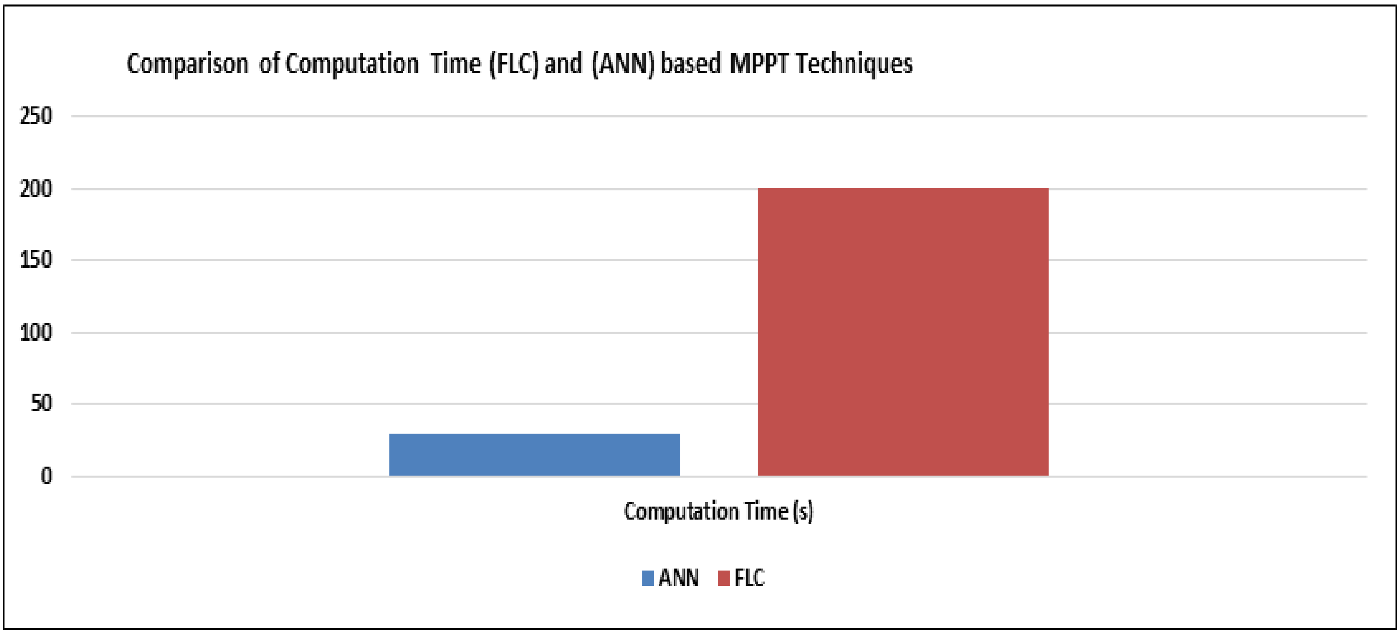

Fig 23 Comparison of Computation Time for FLC and ANN based MPPT Techniques

Consistent with the data recorded, the FLC-based approach takes approximately 3.33 minutes (199 seconds) to complete the simulation, whereas the ANN-based technique only requires about 30 seconds. The shorter computation time of the ANN-based technique allows for faster decision-making and real-time adjustments in dynamic environments.

- *Metric 3: Complexity*

Several considerations may be taken into account when comparing the complexity of the NN-based and FLC-based MPPT approaches in a Simulink design:

✓ *Number of Parameters:*

FLC often necessitates creating and fine-tuning membership functions, rule sets, and linguistic variables. The quantity of input and output variables, as well as the level of detail in the membership functions, determine how sophisticated FLC is. (Number of components)

The complexity profile of the ANN: ANN is distinct. The design and configuration of the ANN, including the number of layers, nodes, and activation functions, determine how many parameters are used in an ANN-based MPPT approach. With the size and complexity of the network, the complexity rises.

✓ *Training Requirements:*

- FLC: This approach does not need formal training because it uses heuristics or expert knowledge. The control settings might need to be adjusted to reach the finest performance.

- ANN: The link between the input (irradiance, temperature, etc.) and output (voltage, current, power) data must be learned through training for ANN. During training, a dataset is fed into the network, and weights and biases are modified using methods like backpropagation or optimisation algorithms. Even for huge networks, the training procedure might take a while

✓ *Implementation Complexity:*

- FLC: Designing and setting membership functions, outlining rules, and putting the inference mechanism into action are all steps in the implementation of FLC in a Simulink design. Simulink's basic blocks can be used to create FLC. However, when creating an efficient FLC system, human rule tweaking and domain knowledge may be necessary.

- ANN: Using the required blocks or unique MATLAB functions, one must design the ANN architecture before implementing an ANN-based MPPT approach in Simulink. It takes some understanding of ANN and data preparation techniques to configure the network and train it using the supplied data.

V. CONCLUSION

This study's objective was to find out how FLC and ANN techniques may be utilised to monitor a photovoltaic system's MPP under a variety of different environmental factors. Cost savings, a reduction in the number of components required, and developed system performance were the objectives. A PV panel with predetermined characteristics and a buck converter architecture were used for the simulation.

Based on the evaluation metrics and simulation results, the NN-based MPPT approach demonstrated superior performance compared to the FLC-based MPPT approach. The ANN model exhibited high accuracy, as indicated by the strong linear relationship between the expected and actual power production, resulting in precise power output forecasting under various conditions.

Additionally, the ANN-based MPPT technique showcased better response time and tracking efficiency, allowing for faster and more accurate adjustments to changes in solar irradiance and temperature. This capability contributes to developd power extraction and overall system performance. On the other hand, the FLC-based MPPT technique performed reasonably well but exhibited limitations in terms of accuracy and responsiveness. The FLC struggled to accurately capture complex relationships and adapt to varying environmental conditions, resulting in suboptimal power extraction in certain scenarios.

Therefore, it can be said that the ANN-based MPPT approach beats the FLC-based MPPT technique regarding the accuracy, responsiveness, and total power extraction efficiency based on the thorough research carried out in this work. These results show that ANN may be used in MPPT algorithms to increase the efficiency and energy-harvesting capacity of solar systems. Conclusion: Comparing the effectiveness of the NN-based MPPT approach with the FLC-based MPPT technique in improving power extraction from solar systems provided insightful information.

For the comparison of ANN and FLC based MPPT approaches, two potential future research avenues are as follows. First, investigating cutting-edge ANN topologies like CNNs, RNNs, or DNNs, as well as methods like transfer learning or ensemble learning, can develop the MPPT algorithm's accuracy and resilience.

Second, by combining the advantages of both methods, hybrid systems that mix ANN-based and FLC-based techniques may result in a more precise and flexible MPPT algorithm. These potential future avenues for study can aid in the creation of smarter, more efficient methods for maximising power extraction from solar systems.

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VI. APPENDIX

➢ *Evaluation of Different Control Strategies for Photovoltaic Systems*

Table 7 Comparative Analysis of Photovoltaic System Control Strategies

Study	Configuration	MPPT Technique	Target of Control	Description	Ref
Atlas and Sharaf	The photovoltaic system connected to the hybrid electric load	Fuzzy logic control	Voltage and speed regulation at the DC load and DC motor using chopper converters	Design of the scheme utilising FLC to sense and track MPP taking into account load changes and temperature. Simulated in Matlab Simulink	[23]
Alata et al.	Sun tracking scheme	FL control (Sugeno fuzzy inference system)	Sun tracking	Develop of the sun tracking scheme utilising a virtual simulator. FLC is applied based on actual values.	[24]
Iqdour and Zeroual	Forecast of daily solar irradiation	Fuzzy logic control	Daily solar radiation prediction	Proposal of the fuzzy logic system to forecast daily solar irradiation. Contrast with other systems show superior results.	[25]
Takun et al.	Photovoltaic system	Fuzzy logic control	Current control obtained from photovoltaic	Comparison of the FLC with the P&O method in order to MPP tracking. Then, simulated in Matlab	[26]

				Simulink.	
Alam, et al.	Photovoltaic system	Fuzzy logic control	System control based on real experiments	Applying of FLC based on actual experiments as well as self-learning scheme. Verified by using light sources indoors.	[27]
Hamdan et al.	Hourly solar irradiation forecast	Artificial neural networks (FFNN, Elman NN, NARX)	Hourly solar irradiation forecast	Utilisation of ANN for precise hourly solar irradiation prediction utilising meteorological data.	[28]
Badran and Dwaykat	The average value prediction of solar irradiation for month	Linear regression	The average value prediction of solar irradiation for month	Forecast of the average amount of global radiation received per day on a monthly basis utilising linear regression system.	[29]
Al-Sbou et al.	Daily global solar radiation prediction	NARX models	Global solar irradiation per day prediction	Prediction of global solar irradiation on a day using different NARX systems based on climatological data.	[30]
Mohammed et al.	Solar radiation per hour prediction	NARX models	Hourly solar radiation prediction	Use of NARX system for precise hourly solar irradiation forecast in an exact location.	[31]
Alomari et al.	Solar radiation and solar PV power correlation	Artificial neural networks	Power prediction from solar radiation	Study of the association between PV power and solar radiation using ANN for power forecast.	[32]