Power Tracking Capability Enhancement of a Grid-Tied Partially Shaded Photovoltaic System Through MPC Based Maximum Power Point Technique

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Abstract- Multiple studies in recent years have suggested various strategies for Maximum Power Point Tracking (MPPT) of the photovoltaic based distributed generation systems. When local shadowing occurs, the output–voltage–power curves of photovoltaic (PV) arrays display complicated multi-peak patterns. Because photovoltaic (PV) array characteristic curves have several local maxima, most standard tracking algorithms fail to detect maximum power point under partially shadowed situations. So numerous authors have discussed various MPPT methods to track the maximum power available during partial shading conditions. In this regard, this research article proposes a novel Model Predictive Controller (MPC) technique to track maximum power during non-uniform illumination conditions. The MPC technique is simple in method and easy in implementation. Further, the proposed approach features a quicker dynamic reaction and a better steady-state response. The proposed model is designed in Matlab/Simulink environment under partial shading conditions. For justifying the efficiency of the proposed controller, the proposed MPC controller characteristics have been compared with traditional methods such as Artificial Neural Network (ANN) and Fuzzy Logic Controller (FLC). A detailed comparison of the voltage, current and power values obtained from the MPC, ANN and FLC controller characteristics has been tabulated. The values obtained confers that the proposed controller is more efficient and the system dynamics are better in comparison to ANN and FLC methods thus justifying the real-time implementation of the proposed controller.

Keywords Maximum Power Point Tracking (MPPT), Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Model Predictive Controller (MPC), photovoltaic system, partial shading.

1. Introduction

In recent times, there has been a greater emphasis on generating electricity from sustainable and renewable sources, owing primarily to enhanced electricity consumption, as well as the global appeal to reduce the economic and ecological effects due to electricity generation from non-renewable power sources, such as fossil fuels. As a result, the generation of electrical energy from renewable energy sources such as hydropower, biomass, wind, sea, sun, and others has expanded significantly [1].

Solar energy from all renewable sources of energy has the best chance for power generation, which is why it is frequently employed. Solar energy is a zero-emission natural resource. Due to the growth in power consumption, it is critical to the transition to renewable sources of energy that are environmentally friendly and abundant in nature. The MPPT controller increases the efficiency of the photovoltaic system. Perturb & Observe (P&O) and Incremental Conductance (INC) are two commonly utilized MPPT methods [2].

Grid-connected photovoltaic systems are typically constructed of photovoltaic arrays, with one or two energy conversion stages acting as an interconnection between both the photovoltaic array and the voltage regulation [3]. Usually, the power supplied at the solar array's endpoints is insufficient to allow the photovoltaic array's energy to be transferred to the grid through a single DC–AC (Direct Current) (Alternating Current) converter [4]. In this situation, the first converter stage is required to step up the PV array power through DC-DC converters [5]. As a result, series linkages may be used to lower the boosting ratios necessary to attain a voltage output at the first DC-DC conversion stage. As a result, every DC-DC conversion contributes to the overall output power, necessitating lower boosting ratios [6].

Numerous conversions and techniques have been developed and recommended to determine the Maximum Power Point (MPP) [7]. Certain approaches, like the short circuit current and accessible voltage techniques, take advantage of the link between the solar cell characteristics and the photovoltaic system's operational range. These approaches need distinct arrays for monitoring the system's short circuit current and open-circuit voltage. Several techniques are based on the notion of a photovoltaic system [8]. Other systems, such as fuzzy logic and neural network control schemes, depend on intelligent control. These approaches make use of the solar array's nonlinear features and achieve a high position in maximum point tracking [9].

Yin et al. [10] suggested a multi predictive control approach for depth models based on strategies for monitoring the Maximum PowerPoint. The multi-step depth model predictive control technique improves control performance by combining deep neural networks with model predictive control. Deep neural networks are capable of increasing prediction accuracy by reducing steady-state oscillations. The model predictive control approach has the potential to significantly increase the tracking speed and dynamic performance of solar power systems.

Eltamaly et al. [11] suggested a unique rapid Adaptive Particle Swarm Optimization (APSO) technique. The issue of extended cluster formation was overcome by modifying the control signal of the DC-DC boost converter's initial values to match the projected peaks. This modification reduces the time required for converging and avoids premature divergence. Because of the recorded Global Peak (GP) in-memory problem, the PSO will be unable to collect the current GP if it is less than the recorded one.

Dehghani et al. [12] explained that a Fuzzy Logic Controller (FLC) optimization using a mixture of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is built to achieve the Maximum Power Point (MPP). The recommended FLC takes as inputs the proportion of power fluctuations to voltage variations and the derivatives of power changes to voltage variations and outputs the duty cycle. The PSO-GA optimizes the range of changes in fuzzy membership functions and fuzzy rules as an optimization process.

Divyasharon et al. [13] suggest a framework way for monitoring the highest power point of a partly shaded total cross-connected (TCT) solar array using a fuzzy logic controller. The suggested solution makes use of an MPPT-based fuzzy logic controller with two inputs from a voltage and current sensor. Additionally, the solar array employs a total cross-connected topology (TCT), which outperforms conventional configurations such as serial (S), parallel (P), and serial-parallel (SP).

Bounabi et al. [14] developed a novel controlling technique for grid-connected Photo-Voltaic (PV) systems using two multilayer three-phase multilevel inverters. This controlling approach employs the Space Vector Pulse Wide Modulation (SVPWM) technology to regulate the Diode Clamped Inverter (DCI) and cascade converter topology, as well as the Particle Swarm Optimization (PSO) method to run the PV system at the Maximum Power Point (MPP). To tackle the challenge of MPP tracking under partial shade circumstances, a Field-Programmable Gate Array (FPGA) implementation of PSO-based Maximum Power Point Tracking (MPPT) is suggested.

Authors in [15] have discussed the FFT analysis of a Photovoltaic based grid connected transformer less three-phase cascaded diode-clamped multilevel inverter with reduced leakage current.

In [16], authors have discussed about the benefits that the Auburn University received from roof tops solar arrays and have suggested arrays that can account for nearly 21.07% of annual electricity requirement by buildings which is equivalent to 14.43% of total campus electricity for all operations.

Table 1 depicts the summary of the literature review discussed above concerning various MPPT methods adopted by different researchers. Further, an exhaustive literature survey has been carried out and presented in Table 2 highlighting the comparative study based on the performance index of all available MPPT techniques adopted by numerous authors in the literature and the proposed MPC method.

The entire research article is categorized into the following sections. In Section 2 detailed mathematical modelling of the PV system has been projected. In Section 3 the conventional ANN and FLC technique along with the proposed MPC techniques has been discussed in detail. Section 4 discusses the Simulink model and the analysis of the simulation results obtained. Section 5 presents the future scope of the present study undertaken. Finally, in Section 6 the conclusion from the entire study has been projected.

Table 1. Summarized table of the reviewed literature

Author	Techniques	Outcomes
Yin et al. [10] (2021)	Algorithm for multi-step predictive control of depth models using deep neural networks.	Enhance the solar power system's tracking system and dynamic performance.
Eltamaly et al.	Metaheuristic techniques such as MPPT and	Reduces the time required for convergence and

[11] (2020)	PSO	prevents premature convergence. Also, prevent the PSO from capturing the current global peak.
Dehghani et al. [12] (2020)	Fuzzy logic controller with combining of PSO and GA.	Faster response rate and higher accuracy compared to other controllers.
Divyasharon et al. [13] (2019)	MPPT using ANN	Performance is compared for homogeneous and non-uniform climates.
Bounabi et al. [14] (2018)	Space vector pulse wide modulation and Cascade Inverter Topologies along with PSO	The FPGA/Simulink-based Hardware in the Loop technique was produced with the fewest limitations.
Niazi et al. [15] (2018)	Improved bypass technique with an SMD and MOSFET	Minimizes the power loss and reduces the reverse voltage across the shaded cell.
Dube et al. [16] (2018)	Module Tilt Angle (MTA) and Optimum Module Placement (OMP)	The area needs have been lowered while maintaining the same dimensions and number of modules.

Table 2. Comparative study of various MPPT techniques

MPPT Methods → **Performance Index ↓**	**PSO**	**APSO**	**GA**	**FLC**	**ANN**	**Proposed MPC**
MPPT Accuracy at Steady State	Low	Medium	Low	Medium	Medium	High
Level of complexity in implementation	Medium	Medium	Medium	High	High	Medium
PV array dependence	Low	Low	Low	High	High	Low
The capability of tuning parameter	Medium	Medium	Medium	High	High	High
The necessity of periodic tuning	Medium	Low	Medium	High	High	Low
Response at Transient Condition	Medium	Medium	Medium	Medium	Medium	High
Parameters that can be tuned	Voltage, Current	Voltage, Current	Voltage, Current	Varies	Varies	Varies
Speed of convergence	Low	Medium	Low	Medium	Medium	High
The ability to adapt to changes in irradiance levels	Medium	Medium	Medium	Medium	Medium	High

2. Mathematical Modelling of Photovoltaic System

The photovoltaic is a pn-junction semiconductor that converts solar energy directly into electrical energy by this phenomenon is sometimes referred to as the photovoltaic cell. Additionally, photovoltaics is influenced by environmental factors such as temperature and sun irradiance. Solar's analogous circuit is seen in Fig. 1 [13].

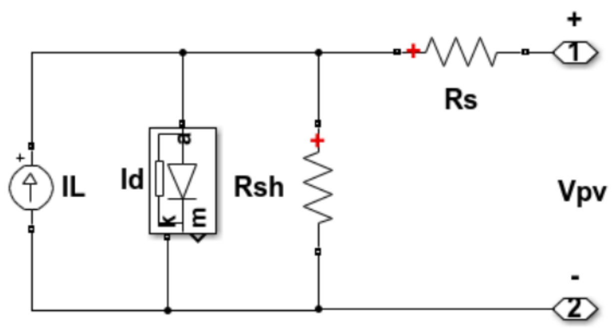

Fig. 1. Circuit of solar cell [17].

The output current of the solar module is as follows:

$$I_{pv} = I_L - I_o\left[\exp\left(\frac{q\left(V_{pv} + I_{pv}R_s\right)}{kTAN_s}\right) - 1\right] - \frac{\left(V_{pv} + I_{pv}R_s\right)}{R_{sh}} \quad (1)$$

Where I_{pv} is the output current of the solar array, V_{pv} is the output voltage of the solar array, I_L is the light-induced current, R_{sh} and R_s are shunt and series resistance respectively, k is the Boltzmann constant (1.38x 10^{-23} J/K), q is the charge of the electron (1.602x 10^{-19} C), A is the p-n junction ideality factor and T is the cell temperature, I_o is the open-circuit current. N_s are photovoltaic cells in series.

The open-circuit current I_o is given by

$$I_o = I_{oref}\left[\frac{T}{T_r}\right]^3 \exp\left[\frac{qE_g}{kqA}\left(\frac{1}{T_r} - \frac{1}{T}\right)\right] \quad (2)$$

Where T_r is the temperature of the reference cell and E_g is the bandgap energy of the semiconductor. I_{oref} is reverse saturation current.

The photocurrent I_{ph} is determined by cell temperature and solar irradiance as in (3):

$$I_{ph} = [I_{sc} + k_c(T - T_r)]\frac{G}{1000} \quad (3)$$

Where I_{sc} is the short circuit current, G is the solar irradiance, k_c temperature coefficient of the short circuit current.

The PV array power is given by

$$P_{pv} = I_{pv}V_{pv} \quad (4)$$

I_{pv} is the output current of the photovoltaic panel, Meanwhile, V_{pv} is the terminal voltage of the module and P_{pv} is the peak of photovoltaic current.

3. Control Techniques

Control techniques used for the PV MPPT are discussed below.

3.1. Conventional techniques

In this section, Artificial Neural Network and Fuzzy Logic Controller techniques are discussed.

3.1.1. Artificial Neural Network

Mechanical design plays a vital role in components adjustment fittings and customer's choice for an efficient vehicle. All electrical and mechanical components will only work if adjusted adequately against appropriate dimensions. A 250W monocrystalline PV panel can be installed on the car's roof using Very High Bond (VHB) double-sided instant bonding tape for a smooth and clean visual appearance. The back trunk of the car can be used as a battery bank in which a Machine Learning feature selection is critical since employing irrelevant qualities in the training phase of different prediction algorithms can increase the system's cost and run time [17].

In a broader sense, a data-driven learning challenge might be characterized as:

Considering a set of labelled data samples $(x_1, y_1), \ldots, (x_l, y_l)$, where $x_i \in \mathrm{R}^n$ and $y_i \in \mathrm{R}$ $(or\ y_i \in \{\pm 1\}$ in the case of classification problems), which achieves the lowest error in the prediction of the variable y_i.

Deep learning (DL) is a multi-layered neural network that is capable of learning complicated data patterns at a high level of abstraction. There are two types of models in DL. One kind is called Feed-Forward Networks (FFNs), in which information flows from input to output, while the other is called recurrence networks (RNs), in which information from previous inputs influences the current input using feedback connections. Ensemble approaches for categorization include approaches other than Support Vector Machine (SVM), Artificial Neural Network (ANN), and DL [17].

ANN as shown in Fig. 2 is a kind of data processing system that is capable of deriving significance from complicated data and detecting trends and patterns in data that is too complicated to classify using human or computer approaches. ANNs are regarded as feasible computational models capable of being used for a wide range of challenging issues. ANNs are crucial in solving issues including predictions, classifications, complex system prediction and regression [18].

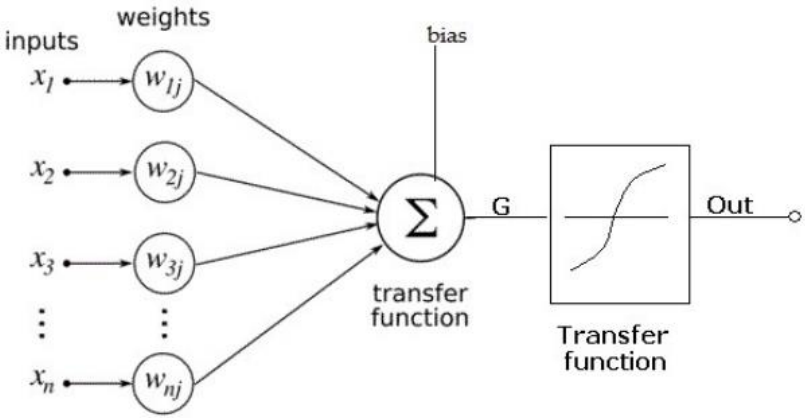

Fig. 2. Model of an artificial neuron network [18]

A single neuron model is shown in Fig. 2 with a sigmoid transfer function at the output.

The transfer function is:

$$G_j = \sum_i x_i * W_{ij} + Bias \quad (5)$$

The output of the neuron is given to the sigmoid function is given as:

$$Out = sigm(G) \quad (6)$$

$$Sigm\ (G) = \frac{2}{1 + e^{-2G}} - 1 \quad (7)$$

For a hidden layer neuron, output = G which is the same as the sum of all the inputs to the neuron. W_{ij} denotes the parameter (or weight) associated with the connection between unit j in layer l, and the unit i in layer l +1, Bias is the additional set of weights. G_j defines the output layer.

The connections, patterns, or structures that an ANN contains are referred to as design. Architecture refers to the organizing of neurons into structures known as levels [19].

For simple models, three layers are recognized the input layer, the hidden layer, or layers, and ultimately the output layer. The input layer is where information is received, and this may be accomplished by the use of sensors that detect signals in the surroundings. The output layer is the reaction to all synaptic activities inside the networking, and in the case of a robotic system, it may act as an effector. The hidden layer is responsible for performing the activities (calculations, adjustments) necessary to model the surroundings [20].

In MPPT controllers, ANN is used to anticipate the voltage (V) or power (P) output at any moment. To estimate the load cycle, the computed value is then compared to the immediate data acquired. The first layer of the network's input parameters will be significant variables such as temperature (T) and Irradiance (G) [21].

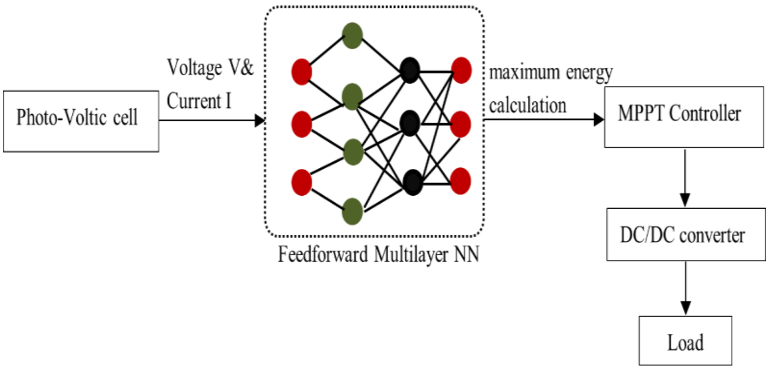

Fig. 3. Block diagram of an ANN [12]

In PV systems, ANN MPPT control has received a lot of attention. ANN can execute MPPT under both uniform and changing atmospheric conditions. Fig. 3 depicts a generic schematic of its functioning [21].

The photovoltaic cell transforms the electric energy in the form of current I and voltage V to the ANN architecture, which determines the maximum amount of power that can be used and transmits it to the MPPT controller, which checks the atmospheric conditions and then converts it to the DC [22].

3.1.2. Fuzzy Logic Controller for MPPT calculation

FLC is a subset of multivariable logic in which the corresponding values may be any real integer between 0 and 1. It discusses the notion of half-truths or partial truths, whose real worth is somewhere between wholly true and utterly incorrect [23].

FLC is predicated on the premise that humans make inaccurate judgments without access to numerical data. The term fuzzy model refers to a strategy for representing vagueness or erroneous data. This sort of model is capable of recognizing and using particular data and information [24]. It has been applied in a variety of domains, including artificial intelligence and control theory.

Fig. 4 shows the process involved in fuzzy systems, which are often utilized in fuzzy logic controllers and signal conditioning applications. An FLC converts sharp inputs into sharp outputs. It is made up of four parts: rules, fuzzifier, inference engine, and defuzzifier. Once the rules are set, an FLC may be considered as a mapping from inputs to outputs, which can be stated quantitatively as y = f.(x) [25].

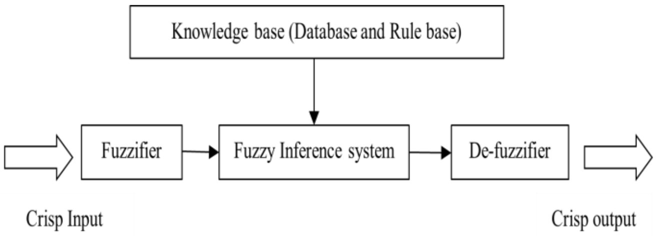

Fig. 4. Process of fuzzy system

Fuzzy logic controllers are a subset of artificial intelligence that does not need sophisticated mathematical concepts such as Boolean algebra. The goal of fuzzy logic is to replicate the human capacity to transform if-then statements into mathematical models. Fuzzy logic has three primary components: fuzzification, level of knowledge (which includes both data and rules), and defuzzification [26].

The fuzzification method may be utilized to transform natural language into crisp input. However, the knowledge base processes the crisp input using both a database and a rule base to produce proper results. A fuzzy controller has two inputs, one for voltage and one for current. The duty cycle produced by fuzzy logic is utilized as the input to the Pulse Width Modulation (PWM) as shown in Fig. 5.

Table 3 below depicts the advantages and disadvantages of techniques used i.e., ANN and FLC.

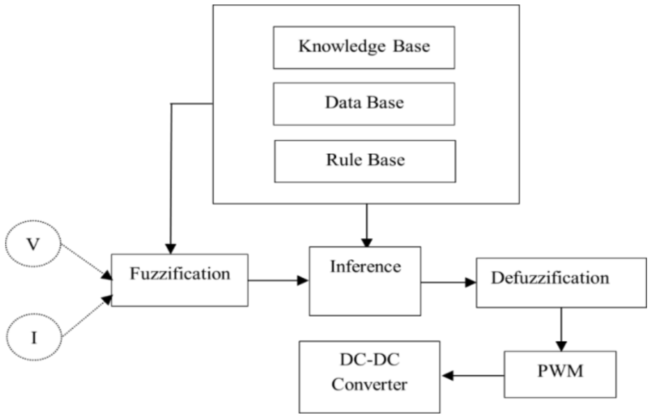

Fig. 5. Block diagram of Fuzzy logic controller [26]

Table 3. Advantages and disadvantages of ANN and FLC techniques

Technique	Disadvantages
Artificial Neural Network (ANN)	• Reduces the trust in the network. • Their structure necessitates the use of processors with parallel processing capacity. • No specific rule for determining the structure of ANN.
Fuzzy Logic Controller (FLC)	• Lack of real-time response. • Input variables can only be used a certain number of times. • More fuzzy grades are needed to grow the rule significantly to get more accurate outcomes.

3.2. Proposed Model Predictive Controller (MPC) Technique

MPC has been used in low switching frequency power electronics since the 1980s for high voltage applications. Due to the MPC algorithm's high switching frequency, broad implementation was not practical at the time [27].

MPC's primary property is its ability to forecast the future behaviour of desired control variables up to a specified time point in the horizon. The anticipated control variables are utilized to minimize a cost function to find the ideal switching state. A system model may be used to represent the time-varying model of the control variables needed for prediction. Voltage and current waveforms are estimated using the system model, and the optimal set point is determined using a cost function [28].

The MPC approach provides a more rapid dynamic reaction and a more stable steady-state response. However, the dynamic and steady-state responses are dependent on the step size that is used to generate the reference current in the MPC approach [29].

The photovoltaic system, a Cuk converter, and the max power controller are shown in Fig. 6. For the DC-DC converter, a Cuk topology was used. The reference current was computed using the P&O approach and compared to the expected current. Based on the cost optimization, the error predicted in the next sampling time and switching mode was calculated [29].

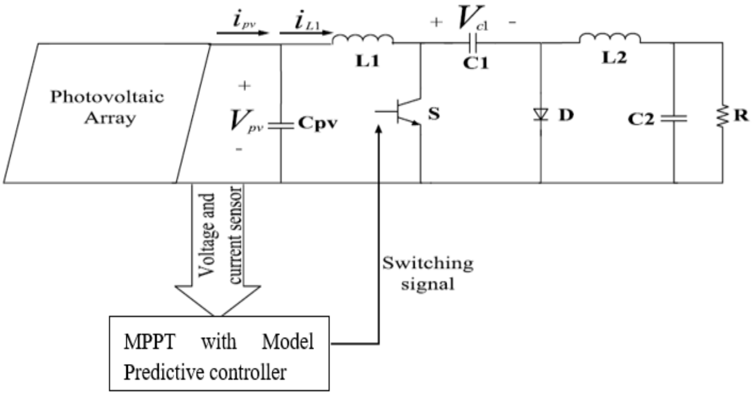

Fig. 6. Block diagram of MPC [12]

3.2.1. Advantages of MPC

The advantages of MPC are explained below.

- Most widely used control algorithm in material and chemical processing industries.
- Enhanced uniformity in the quality of discharges and reduced items that did not meet specifications during grade transition. Bandwidth has been increased by keeping operating costs low while adhering to restrictions for optimization, and economic factors.
- Superior for operations with many controllable parameters that are Multivariable, strong coupling.
- Consider sensor failures, temporal delays, or inherent non-linearities when predicting complex dynamics.
- Allows for the restricting of both MV and CV's abilities to function under limitations [30].

3.2.2. Proposed Methodology

This section describes the working infrastructure of the conventional ANN and FLC methods along with the proposed MPC technique in the MPPT of the PV system. In this methodology, all three techniques (ANN, FLC, and MPC) are compared, and optimization is done for the best-performing technique as shown in Fig. 7.

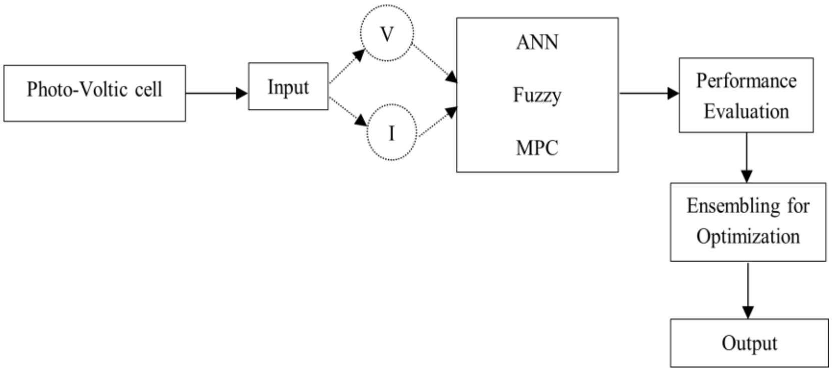

Fig. 7. Proposed Methodology

Step 1: Photo-Voltic cell gets the input as solar energy which converts it into electric energy in the form of current I and voltage V.

Step 2: Converted electric energy flows for the process of calculation and tracking of maximum power in suggested techniques i.e., ANN, Fuzzy Logic Controller, and MPC to track the maximize the power.

Step 3: Evaluation of the process is done based on the best performance of the selected techniques.

Step 4: After the evaluation process of optimization is done through the assembling method which combines several base techniques to produce one optimal predictive technique.

4. Simulation Model, Result Analysis and Comparative Study

4.1. Simulation Model

The Sim-Power-System toolbox for Matlab/Simulink is used to create a mathematical model of a 104 KW PV array. The PV module specifications are given in the Appendix. A series type of electrical configuration has been implemented as it enhances the voltage level. The I vs T, P vs T, and P vs T characteristic curves have been drawn, in which V, I, P and T represent the PV array's voltage, current, power and time respectively.

Fig. 8 depicts five PV modules linked in series to create a PV array capable of producing 104KW of electricity at nominal irradiation of 1000W/m^2 and a temperature of 25^o C.

In this PV array ANN, FLC and MPC techniques are used to track MPP.

Fig. 9 depicts a 104KW PV power generating system that was meticulously constructed using Matlab/Simulink software. The PV system is made up of five PV modules connected in series at a temperature of 25^{o}C. The partial shading patterns with a different insolation value, are as follows: 1000W/m^2, 800W/m^2, 600W/m^2, 400 W/m^2, and 200 W/m^2. The DC-DC boost converter connects the PV system to the inverter and three-phase grid. At nominal temperature and irradiance, the PV array produces 104KW. The MPPT procedures are used to adjust the boost converter's duty ratio.

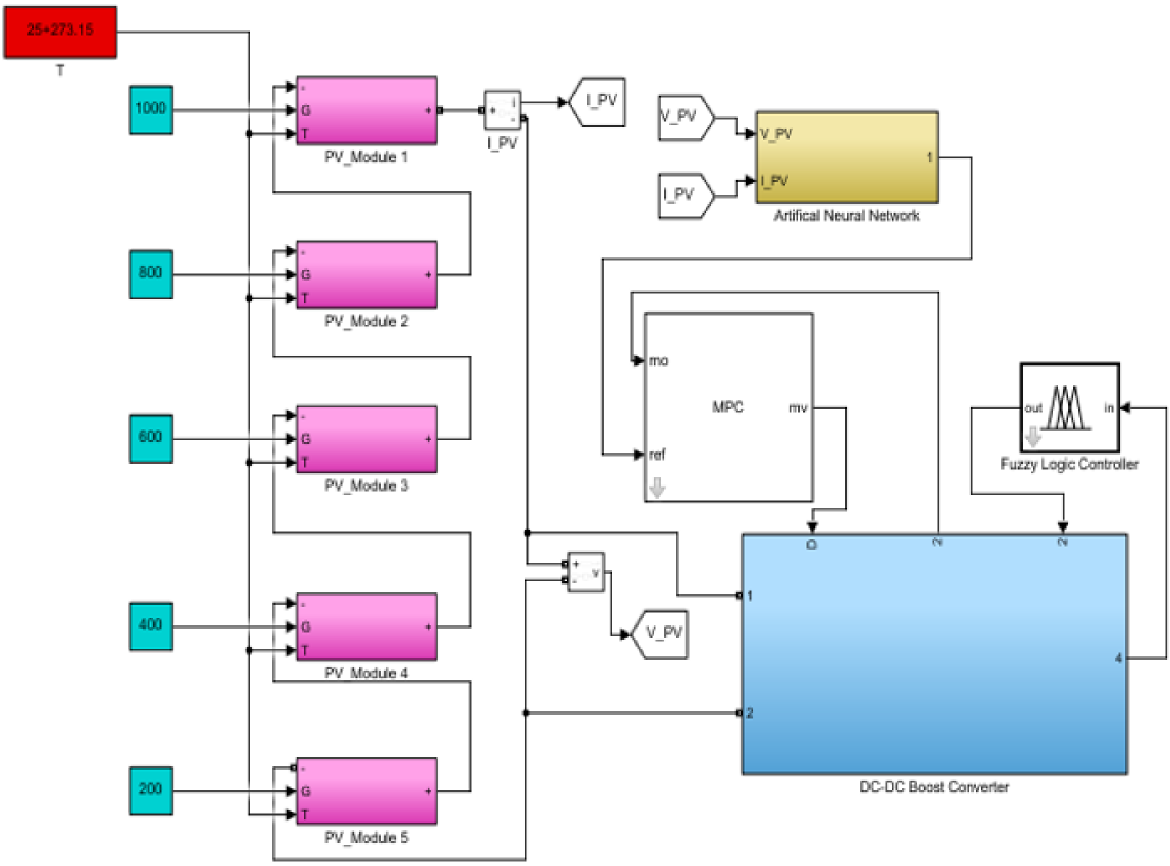

Fig. 8. 5 PV modules connected in series to form a PV array

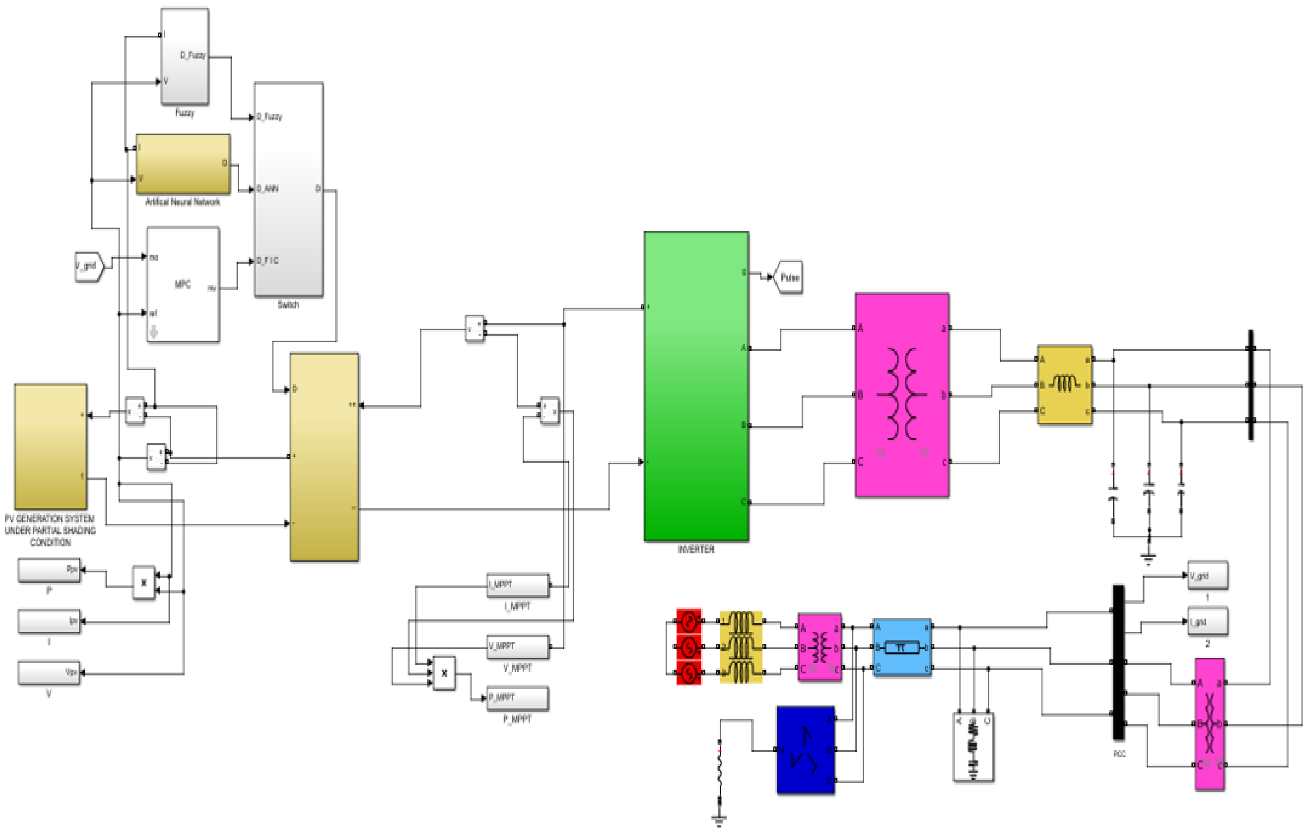

Fig. 9. MATLAB/Simulink model of on-grid PV system

4.2. Result Analysis

4.2.1. Fuzzy Logic Controller (FLC)

Fig. 10 depicts the current of the system under partial shading using FLC which can obtain the current around 6.5 amperes to 4.5 amperes in 0.4 sec to 0.6 sec, and without using FLC it can obtain a current around 7 amperes to 3 amperes in 0 to 0.2 sec.

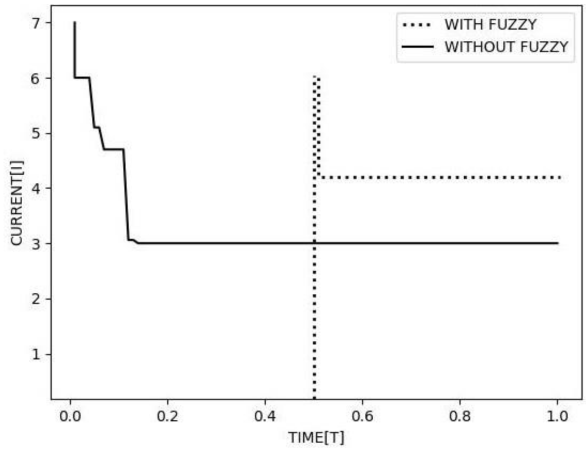

Fig. 10. Current with FLC under partial shading

Fig. 11 depicts the voltage of photovoltaic under partial shading using FLC which can obtain the voltage of around 65 volts in 0.4sec to 0.6sec, while without using FLC it can obtain a voltage of around 80 volts in 0 to 0.2 sec.

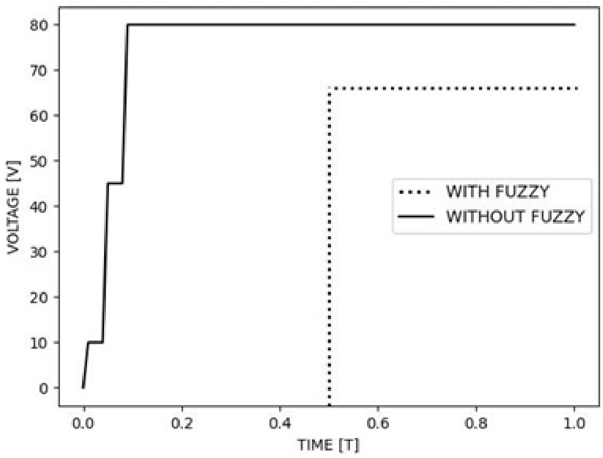

Fig. 11. Voltage with FLC under partial shading

Fig. 12 depicts the power of photovoltaic under partial shading using FLC which can obtain the power of around 300 Watt in 0.4sec to 0.6sec. Meanwhile, the power of photovoltaic under partial shading without using FLC can obtain the power of around 240 watts in 0 to 0.2 sec. Thus, it can be concluded that the FLC method can track maximum power.

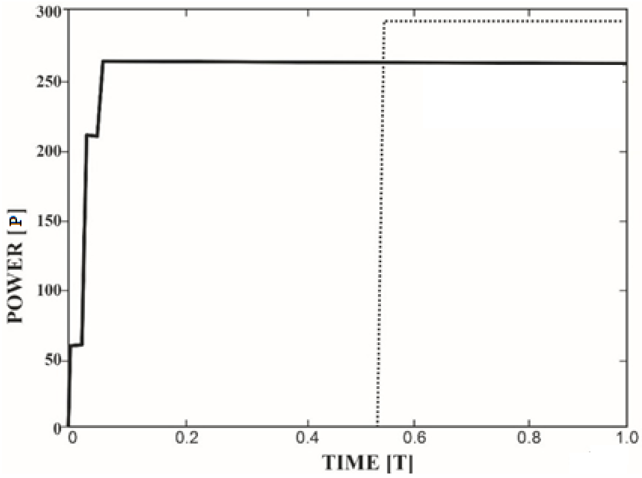

Fig. 12. Power with FLC under partial shading

4.2.2. Artificial Neural Network (ANN)

Fig. 13 displays the output current of the PV module using the ANN technique. The given results show that the maximum current achieved by the module is approximately 80 amperes.

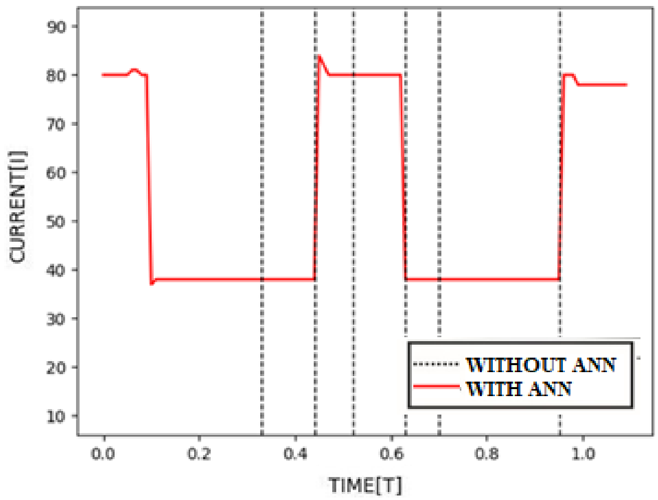

Fig. 13. Current with ANN under partial shading

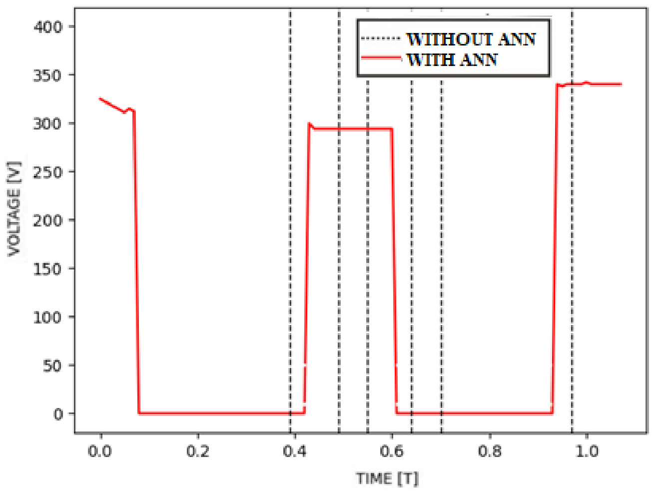

Fig. 14. Voltage with ANN under partial shading

Fig. 14 shows that the ANN technique, which is superior to the Fuzzy method, can monitor the MPPT voltage quickly and without steady-state errors where the irradiance fluctuates slowly or fast. The graph below shows clearly that the ANN approach performs better as compared to the FLC technique.

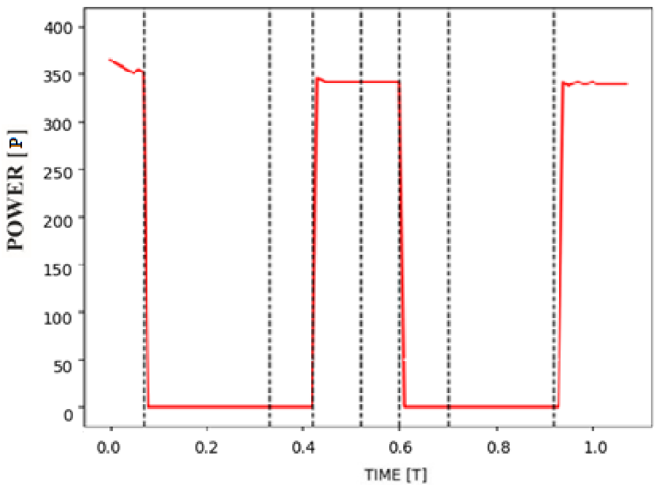

Fig. 15. Power with ANN under partial shading

Fig. 15 displays the modelling procedure, in which the ANN technique is superior to the Fuzzy method, which can monitor the MPPT power quickly and without steady-state errors where the irradiance fluctuates slowly or fast. The graph below shows clearly that the ANN approach performs better and the system achieves a maximum power of 365 watts in between 0 to 0.2 seconds.

4.2.3. Proposed Model Predictive Controller (MPC)

The current, voltage and power characteristics of the photovoltaic system for the proposed MPC technique are discussed below. According to the outcomes, the MPC enabled results to outperform the other techniques in terms of the better capability of tracking MPP and enhanced steady-state stability.

Fig. 16 displays the output current of the PV module using the MPC technique. The given results show that the maximum current achieved by the module is approximately 150 amperes.

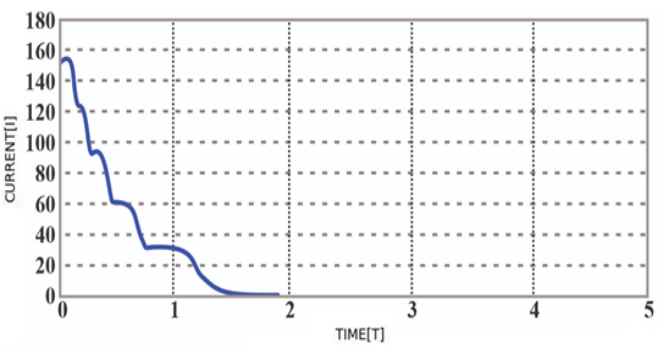

Fig. 16. Current with MPC under partial shading

Fig. 17 shows that the MPC technique can monitor the MPPT voltage quickly and without steady-state errors where the irradiance fluctuates slowly or fast. The graph below shows clearly that the MPC approach performs better than FLC and ANN methods with 950 volts.

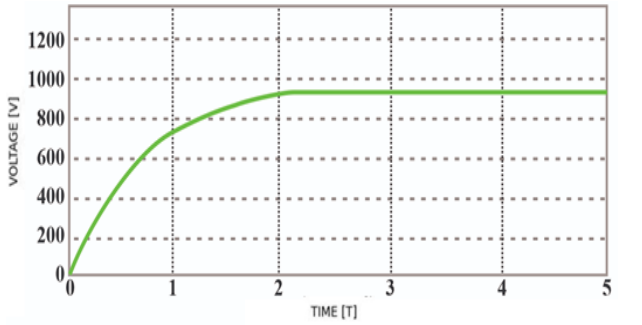

Fig. 17. Voltage with MPC under partial shading

Fig. 18 shows the power characteristics of the MPC method. The power obtained from MPC with ΔI=0.025 reaches the MPPT at the time of 2.55 sec. As seen, MPC with ΔI=0.1 shows a better response and a difference in the dynamic speed. The photovoltaic power increases with increases in PV voltage and attained a maximum PV power. It can be observed that the power tracking with the proposed MPC technique is 450Watts which is more than the traditional ANN and FLC method.

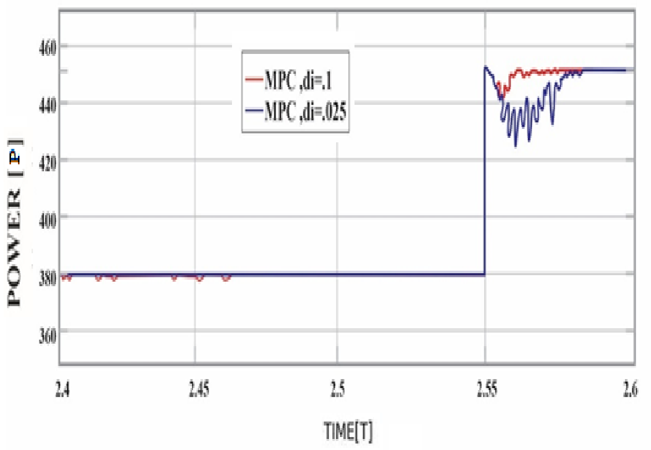

Fig. 18. Power with MPC under partial shading

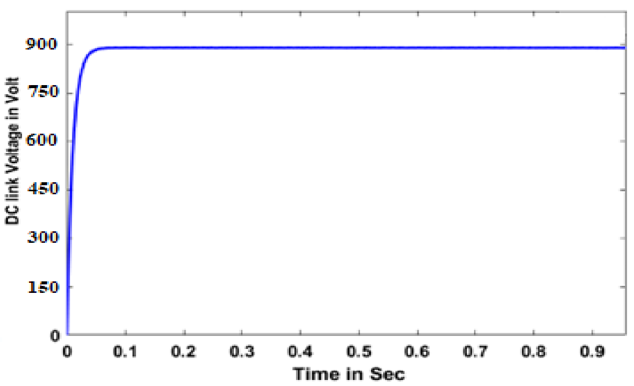

Fig. 19. DC-Link Voltage for MPC

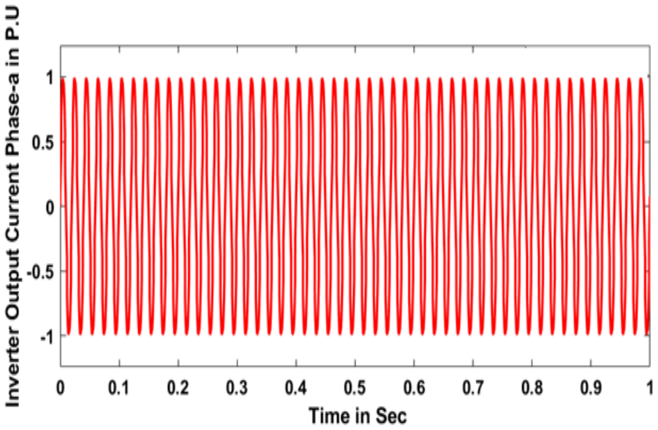

Fig. 20. Inverter Current for MPC

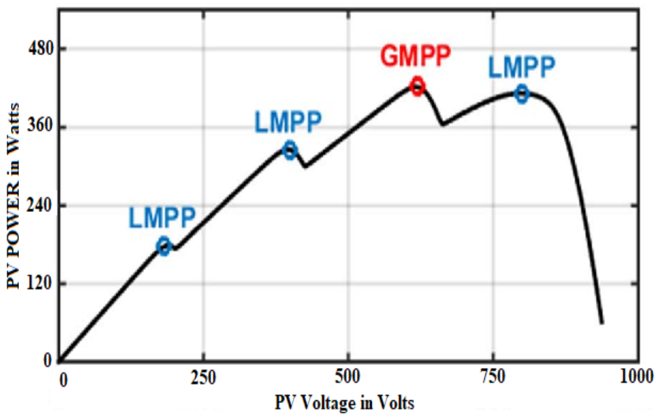

Fig. 21. Inverter Current for MPC

Fig. 19, Fig. 20 and Fig. 21 depict the DC link voltage, the inverter current and the PV curve of the PV system under partial shading conditions respectively for the proposed MPC controller. The results from Fig. 19 and Fig. 20 depict that the proposed technique is capable of maintaining the level of DC-link voltage almost constant and also can generate sinusoidal inverter current. Fig. 21 shows the PV curves for the given PV system under partial shading conditions and demonstrates the local and global maxima. Further Fig. 21 ensures that the proposed MPC force the PV system to operate at GMPP.

4.3. Comparison Analysis

Table 4 and Fig. 22 below show the comparison of the current, voltage and power between traditional FLC and ANN along with the proposed MPC.

Table 4. Comparison of V, I and P between ANN, FLC and MPC

Technique	FLC	ANN	MPC
Current	7 amp	80 amp	150 amp
Voltage	80 volts	325 volts	950 volts
Power	240 watts	365 watts	450 watts

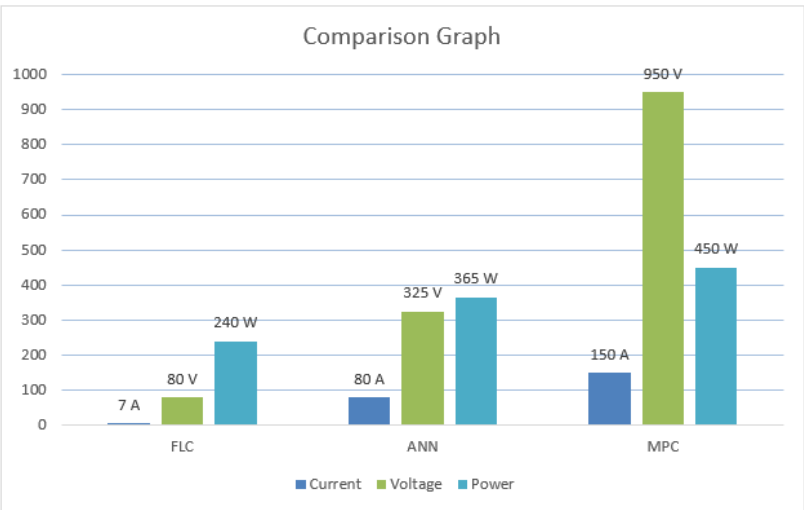

Fig. 22. Comparison Graph based on current, voltage and power for ANN, FLC and proposed MPC

5. Future Scope

- ➢ The application of the proposed technique could help in the design and development of hybrid algorithms for PV systems.
- ➢ Possible to design and implement in the hardware of a reprogrammable MPPT controller, with an open license, to test the proposed MPC algorithm.
- ➢ The feasibility of using small board computers (SBC) such as the Raspberry Pi to create an MPPT based on the MPC method.
- ➢ Energy storage devices can be integrated with the proposed MPC technique and PV system for backup purposes [31].

➢ The MPC method can be used along with Flexible AC Transmission Systems (FACTS) for better reactive power compensation and enhanced dynamic stability.

6. Conclusion

MPPT has evolved into a critical component of photovoltaic systems. This research article presents a detailed comprehensive study of popular MPPT methods discussed in the literature along with their merits and shortcomings. In this regard, this article proposes a Model Predictive Controller for effect tracking of MPP for a partially shaded grid-tied photovoltaic system. The system was modelled using Matlab/Simulink software and to prove the efficacy of the proposed approach the characteristics of the MPC controller were studied and compared with two traditional methods such as Artificial Neural Network (ANN) and Fuzzy Logic Controller (FLC). The results obtained justify that the power tracking capability of the proposed MPC technique is far better than the ANN and FLC methods. Further, the simulation results of the current, voltage and power are contrasted using a table that reveals that MPC has a superior dynamic and steady-state response to FLC and ANN as MPC obtains maximum power of 450 watts whereas FLC and ANN obtain 240 watts and 365 watts respectively. The simulation results obtained and the analysis done proves the efficiency of the suggested MPC method for real-time implementation. Additionally, the article also discusses the future prospects regarding the application of the proposed MPC controller.

Appendix

PV module specifications: Ns=54; Gn,ref= 1000W/m^2; Tn,ref=25^{0}C; Im=7.61; Vm=36.3 V; Pm=104KW; $V_{OC,ref}$= 32.9 V; $T_{SC,ref}$= 68.21A; Rsh=415**Ω**; Rs=0.22 **Ω**.

DC-DC Boost Converter: L_{PV}=290µH; Cin=250 µF; Cout=330µF.

Grid parameters: 4.4KV, 50Hz, X/R=7

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