COMPARATIVE ANALYSIS OF DIFFERENT COMPUTATIONAL INTELLIGENCE TECHNIQUES FOR MAXIMUM POWER POINT TRACKING OF PV SYSTEMS

MOYO R.T.*, TABAKOV P.Y.**, MOYO S.***

*Department of Mechanical Engineering, Durban University of Technology, South Africa;
**Department of Mechanical Engineering and Institute for Systems Science, Durban University of Technology, South Africa;
***Department of Research, Innovation and Engagement and Institute for Systems Science, Durban University of Technology; South Africa;
moyoranganai@gmail.com

Abstract - The performance of a photovoltaic (PV) module can be improved by employing maximum power point tracking (MPPT) controllers. MPPT controllers are algorithms that are included in PV battery charge controllers or inverters to extract the maximum available power from PV modules for any given temperature and irradiance. Several studies report that the use of PV modules without MPPT controllers results in power losses, which ultimately results in the need to install more solar panels for the same power requirement. Numerous techniques of varying complexities have been proposed in the literature to solve the MPPT objective function. This paper presents a comparative analysis of three computational intelligence (CI) based MPPT techniques namely, the fuzzy logic (FL) based controller, artificial neural networks (ANN) based controller, adaptive neuro-fuzzy inference system (ANFIS) based controller and one conventional technique, the perturbation and observation (P&O) controller. These MPPT controllers are designed, simulated and analysed in the MATLAB/Simulink environment. The performance of the studied MPPT techniques is evaluated under steady-state weather conditions, rapidly changing weather conditions and varying load conditions. CI-based MPPT controllers are found to be more efficient than the P&O controller. Moreover, the ANFIS-based MPPT controller shows an outstanding MPPT performance for all the scenarios studied.

Keywords: Maximum power point tracking, computational intelligence, photovoltaic, comparative analysis, adaptive neuro-fuzzy inference system

1. INTRODUCTION

Climate change and the escalating energy demand are the driving force behind sustainable energy research and developments that are impacting all countries and organizations [1]. To achieve the environmental goals for the future energy mix, many countries are strongly promoting renewable energy technologies and energy efficiency systems. Thus, the study of renewable energy technologies is now a critically active and growing research topic. Among the renewable energy sources, solar photovoltaic (SPV) is considered one of the fastest-growing renewable energy technologies as shown in **Fig. 1** [2].
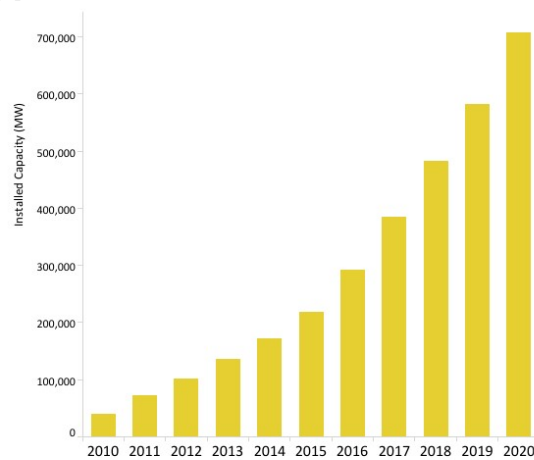

Fig. 1 - Installed capacity of SPV systems from 2010 to 2020 [3]

The interest in SPV is growing worldwide due to the continuous price drop of both the photovoltaic (PV) modules and solar batteries as well as the advances in power electronics [4]. However, SPV power generation is still comparatively costly as compared to traditional energy sources [5]. And considering their relatively high installation costs and their low energy conversion efficiency, SPV systems are not widely applied. Despite all these challenges, there are so many new innovative technologies such as machine learning, computational intelligence (CI) & the internet of things (IoT), that are being employed to advance SPV systems thereby improving the competitiveness of solar energy in the marketplace [6]. CI techniques such as particle swarm optimization (PSO), artificial neural networks (ANN), fuzzy logic (FL) and genetic algorithms (GA) are currently being utilized in several SPV technologies. These

techniques have the potential to reduce energy losses, lower energy costs, and facilitate & accelerate the use of clean energy sources worldwide [7]. Thus, CI techniques have become an imperative technology as the energy sector is relentlessly looking for ways to cater for the rapidly increasing demand for clean, cheap, and reliable energy. One of the SPV technologies where CI techniques are being applied is for tracking the maximum power point (MPP) of PV modules. The maximum power point tracking (MPPT) concept remains an important technology for improving the efficiency of PV modules. Several studies report that the use of PV modules without MPPT controllers results in power losses, which ultimately results in the need to install more solar panels for the same power requirement. Numerous techniques of varying complexities have been proposed in the literature to solve the MPPT objective function.

The perturbation and observation (P&O) [8], [9]; incremental conductance [10], [11] and open-circuit voltage [12], [13] are the examples of conventional techniques used for maximum point tracking. The P&O and incremental conductance are the widely used conventional MPPT controllers because of their simplicity in hardware implementation, fewer sensor requirement and low cost. However, several studies show that these conventional techniques have various challenges such as high fluctuations about the maximum power point (MPP), slow tracking speed and drift issues that arise when there is rapidly changing weather conditions [14], [15], [16]. In addition, conventional techniques are only efficient for uniform environmental conditions and they fail to track the global maximum power point (GMPP) under partially shaded weather conditions. With the rise of computational intelligence, soft computing methods emerged as an alternative to solve issues associated with conventional MPPT controllers [17]. These CI-based MPPT controllers proved to be more efficient because of their ability to solve complex and non-linear problems. The Refs. [18], [19], [20], [21] reported the superiority of the FL concept for MPPT. However, the efficiency of the FL-based MPPT controller depends on the proper design of fuzzy rules and membership functions. Thus, there must be a good understanding of PV systems for one to be able to design an efficient FL-based MPPT controller. The ANN-based MPPT controller is also considered as one of the powerful techniques as given in [22]. The main advantages of artificial neural networks are that they are capable of solving very complicated and non-linear problems. However, ANN-based MPPT controllers have some disadvantages such as the need for a large amount of training data and appropriate design of the ANN architecture [23]. As a result, the efficiency of the ANN-based MPPT depends on the availability of the training data and the training procedure. Recently, the ANFIS, which is a combination of FL and ANN have been suggested for MPPT. This hybrid system proved to be more efficient with small oscillations about the MPP as reported in Refs. [24], [25], [26], [27]. The main advantage of the ANFIS-based MPPT controller is that it combines the benefits of two machine learning techniques to overcome the drawbacks of the individual techniques. Other common CI techniques that have been reported in the literature for MPPT include particle swarm optimization (PSO) [28],

[29],[30]; cuckoo search [31], [32]; genetic algorithms [33], [34] and artificial bee optimization [35], [36]. This paper presents a comparative analysis of three CI-based MPPT techniques namely, the FL-based controller, ANN-based controller, ANFIS-based controller and one conventional technique, the P&O controller. It should be noted that the comparative studies of the above-stated MPPT techniques given in the literature are only limited to steady-state weather conditions and varying weather conditions as given in Refs. [37], [38], [39], [40]. This comparative study aims to simulate real-life conditions by taking a step further and evaluate the controllers under varying load conditions.

1.1. The Concept of Maximum Power Point Tracking

MPPT controllers achieve maximum power transfer from the source to the load through impedance matching between the solar modules and the load connected [41]. They force PV modules to always operate at their maximum power point (MPP) for any given environmental and loading conditions. The PV power output is non-linear due to the variation of solar irradiance and temperature. At any given instant, the PV module's operating point corresponds to some unique point on the power-voltage (P-V) curve. And for the PV module to generate the maximum power possible, the operating point must always correspond to the highest value on the P-V curve as given in **Fig. 2**. However, when a solar module is directly connected to the load, the operating point is dictated by the load connected, that is, it can be at any point on the P-V curve that may not be the MPP, depending on the impedance interaction between the solar modules and the load connected.
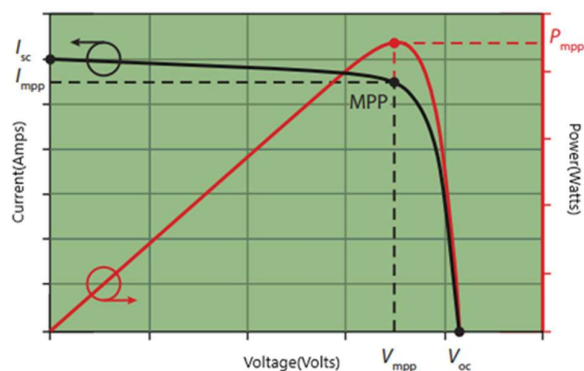

Fig. 2 - Power-Voltage and Current-Voltage curves of a PV module [42]

Therefore, MPPT controllers are connected between the solar cells and the load to continuously match the source and load impedances of the PV systems such that the PV modules always operate at MPP under varying solar irradiance, temperature and load.

2. SYSTEM COMPONENTS MODELLING

The studied solar system is made up of a PV module, a DC-DC boost converter, an MPPT controller and a 10Ω resistive load. The schematic diagram of the system components is shown in **Fig. 3**.
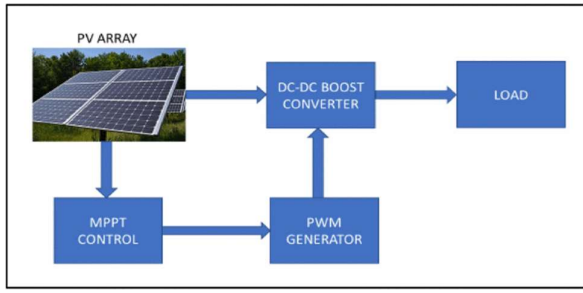
Fig. 3 - System components

2.1. PV modelling

Photovoltaic (PV) can be defined as a process whereby the solar irradiance is converted into electricity using semiconductors materials that exhibit a property called the photovoltaic effect [43]. The equivalent circuit of solar cells can be derived from the physical characteristics of a diode, normally called the single diode model. **Fig. 4** shows the equivalent circuit of a single diode model. From **Fig. 4,** the current source, I_L represents the flow of electrons when solar radiation hits the surface of a solar PV cell. And the diode represents the characteristic behaviour of the *PN* junction of the solar PV cell. The model has two resistances namely series resistance and parallel resistance.
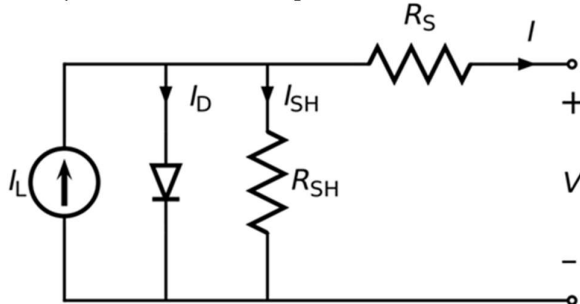
Fig. 4 - Equivalent circuit of a single diode model [44]

A PV module is formed by connecting several solar cells and the output current of the module is given by,

$$I = I_{ph} - I_o \left[e^{\frac{q(V+IR_s)}{nKN_sT}} - 1 \right] - I_{sh} \qquad (1)$$

where I_{ph} is the photo-current; I_o is the saturation current; q is the electron charge; V is the output voltage of the PV module; n is the ideality factor of the diode; K is the Boltzmann constant; N_s represents the number of solar cells connected in series; T is the solar cell temperature; I_{sh} is the current through the shunt resistor. The current produced from the incidence of radiation at a given temperature is then given as,

$$I_{ph} = \left[I_{sc} + k_i(T - 298) \frac{G}{1000} \right] \qquad (2)$$

where I_{sc} is the short circuit current; k_i is the temperature coefficient of the I_{sc} at Standard Test Conditions (STC); G is the solar irradiance. The reverse saturation current of the diode is given by,

$$I_{rs} = \frac{I_{sc}}{e^{\left(\frac{q V_{oc}}{n N_s K T} \right)} - 1} \qquad (3)$$

where V_{oc} is the open-circuit voltage. The module's saturation current at any given temperature is given by,

$$I_o = I_{rs} \left(\frac{T}{T_n} \right)^3 e^{\left[\frac{q E_{go} \left(\frac{1}{T_n} - \frac{1}{T} \right)}{n K} \right]} \qquad (4)$$

where, T_n = 298 K; E_{go} is the bandgap energy. The ART solar module - 360Wp, 39.0 V Si-monocrystalline type module was selected for this study. **Table 1** represents the parameters of the selected module at standard test conditions (STC). The parameters of the module at STC are given in **Table 1.**

Table 1 - Specifications of the ART-solar-360Wp

Quantity	Value
Maximum power, P_{MPP}	360Wp
The voltage at MPP, V_{MPP}	39.0V
The current at MPP, I_{MPP}	9.24A
V_{oc}	47.5V
I_{sc}	9.71A
Number of cells, N_s	72
Temperature coefficient of the I_{sc}, k_i	0.050 %/°C
Temperature coefficient of the P_{max}	-0.39 %/°C

By using the equations given above and parameters presented in **Table 1**, current-voltage (I-V) and power-voltage (P-V) characteristics curves can be plotted. **Fig. 5 & Fig. 6** shows the P-V and I-V curves of the PV module at 25 °C respectively.
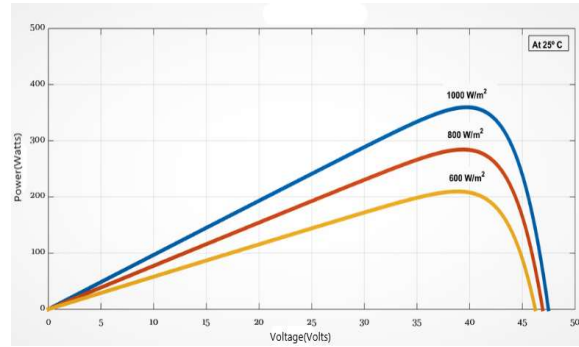
Fig. 5 - P-V curve of the PV module
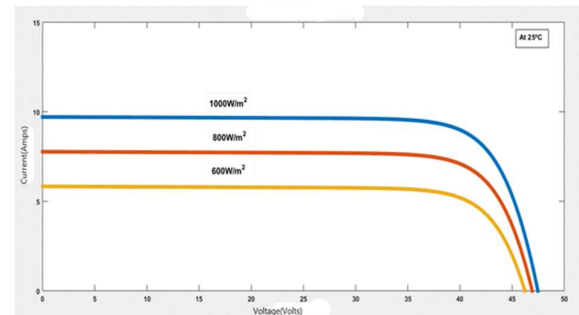
Fig. 6 - I-V curve of the PV module

2.2. DC-DC boost converter

MPPT controllers are implemented using DC-DC converters. In this study, a boost converter is utilized for transferring the maximum power from PV modules to the load. A boost converter is comprised of two semiconductor switches namely, the diode & Mosfet, an inductor and a capacitor. The boost converter is turned ON when the Mosfet switch is closed. During the ON-state, the inductor current increases and the energy is stored in an inductor in the form of a magnetic field. On the other hand, by opening the Mosfet switch, the boost converter gets into the OFF-state. In this state, the inductor discharges and the current flows through the diode, capacitor, and load. The input/output relationships of the voltages and currents of the boost converter are given by,

$$V_o = \frac{V_{in}}{1 - D} \quad (5)$$

$$I_o = (1 - D)I_{in} \quad (6)$$

where V_o is the output voltage of the converter, V_{in} is the input voltage to the converter, I_o is the output current of the converter, I_{in} is the input current to the converter. The detailed design of the boost converter is explained in Refs. [45], [46]. Therefore, the specifications of the DC-DC boost converter for this study are given in **Table 2**.

Table 2 - DC-DC boost converter specifications

Parameter	Symbol	Value
Input voltage	V_{in}	39 V
Input current	I_{in}	9.24 A
Duty ratio	D_{in}	0.35
Inductor	L	$3.7\ mH$
Load resistance	R	$10\ \Omega$
Output capacitor	C_o	$87.5\ \mu F$
Input capacitor	C_i	$4000 \mu F$
Switching frequency	f	$20\ kHz$

2.3. THE STUDY OF FOUR TECHNIQUES USED FOR MPPT

MPPT is generally a process of searching for the optimum operating point, where the maximum available power can be extracted from PV modules. In this study, four MPPT controllers are here presented,
- FL-based controller.
- ANN-based controller.
- ANFIS-based controller.
- P&O controller.

(a) FL-based MPPT controller
Fuzzy logic control was invented to address uncertainty and imprecision which widely exist in real-life engineering problems. FL controllers were adopted for MPPT to resolve the challenges in conventional controllers such as too many oscillations about the MPP and high settling time. The inputs for fuzzy logic based MPPT controllers are usually an error, E, and change in error, ΔE and the output can be the duty cycle itself, or the V_{mp} and I_{mp}. The FL algorithm uses the voltage or power values from the PV system to calculate the error value and change in error as

follows,

$$E_k = \frac{\Delta P}{\Delta V} = \frac{P_k - P_{(k-1)}}{V_k - V_{(k-1)}} \quad (7)$$

$$\Delta E_k = E_k - E_{(k-1)} \quad (8)$$

where P_k and V_k are the instantaneous power and voltage of the SPV system respectively. **Fig. 7** shows a schematic diagram of an FL-based MPPT controller.
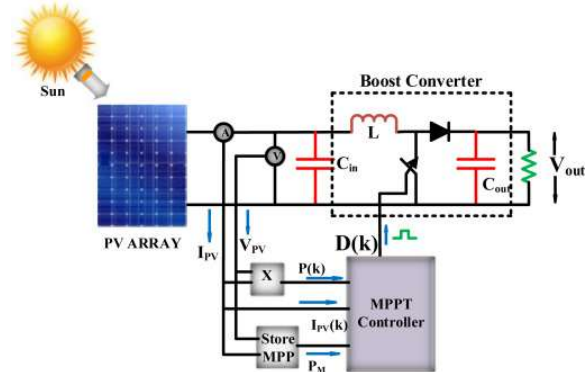

Fig. 7 - Schematic diagram of an FL-based MPPT controller

Table 3 - Merits and demerits of an FL-based MPPT controller

Advantages	Drawbacks
Very few fluctuations about the MPP	Unable to learn from the environment.
Very good dynamic response.	Very difficult to derive fuzzy rules and membership functions.
No need for the training data, the design is based on real-time variables.	The system performance is directly affected by the fuzzy rules

(b) ANN-based MPPT controller
An artificial neural network (ANN) is a mathematical method that tries to simulate how biological neural networks work. Artificial neurons learn from previous or given examples so that if they encounter such a situation again in the future, they will be able to give a solution. For MPPT, the ANN inputs are usually PV array parameters like V_{OC} and I_{SC}, environmental data like solar irradiance and solar cell temperature or any combination of these [22]. The output can be the voltage or current at the MPP or the duty cycle which will then drive the PV module to operate at the MPP. **Fig. 8** shows an ANN-based MPPT controller connected to the utility grid.

Table 4 - Merits and demerits of an ANN-based MPPT controller

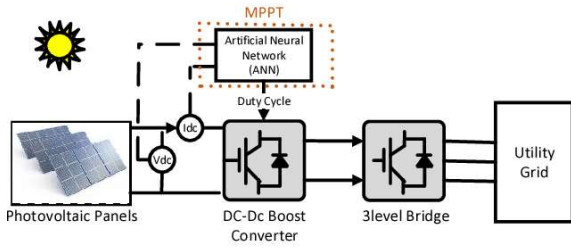| Advantages	Drawbacks
Very efficient with a few fluctuations about the MPP	A large amount of datasets is needed for training the system
Fast response and very accurate	A proper design of the ANN architecture is required
Limited dependence on the system parameter variations	Periodic tuning is needed because of the ageing of PV cells

Fig. 8 - A setup of an ANN-based MPPT controller

(c) ANFIS based MPPT controller

An adaptive neuro-fuzzy inference system is a data learning technique that integrates fuzzy logic with artificial neural networks. It uses fuzzy logic for transforming system inputs into the desired outputs by using highly interconnected artificial neural networks. ANFIS combines the benefits of two machine learning techniques to overcome the drawbacks of the individual techniques.
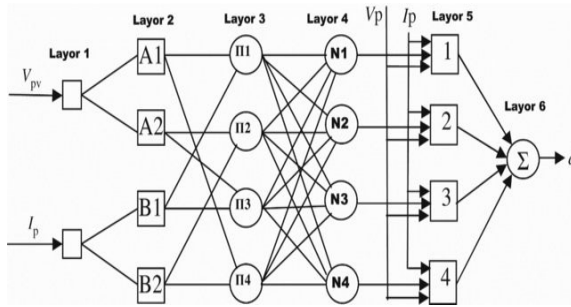

Fig. 9 - The ANFIS architecture

ANFIS based MPPT controller can have different input variables such as irradiance, temperature, V_{OC} and I_{SC}. The output to the ANFIS controller can be the current or voltage at the MPP or the duty cycle of the converter which then drives the PV module to operate at the MPP. **Fig. 9** shows the architecture of an adaptive neuro-fuzzy inference system.

Table 5 - Merits and demerits of an ANFIS based MPPT controller

Advantages	Drawbacks
Highly efficient for both steady and rapidly varying environmental conditions.	A large amount of datasets is needed to train the system
Fewer oscillations about the MPP	Relatively expensive to implement because more sensors are needed.
Low computational time	Periodic tuning is needed because of the ageing of PV cells

(d) P&O MPPT controller

This method is also well-known as hill climbing and is one of the oldest algorithms for MPPT. The Perturbation and Observation method is considered the cheapest MPPT technique due to its easy implementation and the requirement of fewer parameters [9]. **Fig. 10** illustrates the concept of the P&O technique. The first step in this method is to introduce a perturbation/disturbance in the PV module's operating voltage. The modification of the module's voltage is achieved by varying the duty cycle of

the DC-DC converter. After introducing a disturbance, the present value of the power output is calculated and compared to the previous value to give a difference in power, ΔP. If ΔP is greater than zero, the perturbation is kept in the same direction and when it becomes negative the perturbation is reversed. This process is repeated several times until the MPP is reached.
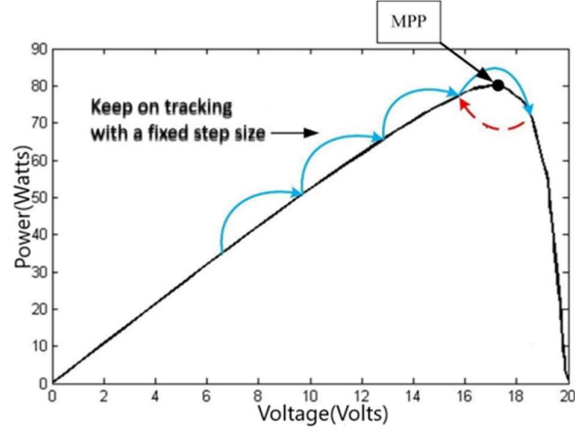

Fig. 10 - MPPT using the P&O techniques

Table 6 - Merits and Demits of a P&O MPPT technique

Advantages	Drawbacks
Relatively low-cost, easy and simple to implement.	Slow tracking speed and drift issues
Periodic tuning is not needed because this technique doesn't depend on the PV module's parameters	Poor performance for tracking the GMPP and under rapidly varying weather conditions.

3. RESULTS ANALYSIS AND DISCUSSION

Three computational intelligence-based MPPT techniques (FL based controller, ANN-based controller & ANFIS-based controller) and one conventional MPPT technique (P&O controller) are designed and implemented in this comparative study. They are designed, modelled and analysed in the MATLAB/Simulink environment. The MPPT controllers are simulated for steady-state weather conditions, rapidly varying weather conditions and varying load conditions to analyse their dynamic response.

Case 1: Simulating the controllers at Standard Test Conditions (STC).

All the MPPT controllers are simulated at STC (1000W/ m^2 & 25 °C), and then a comparative analysis is performed to study the behaviour of each controller. The ideal MPP of the PV module at STC is 360W. The comparison of the MPPT controllers is shown in **Fig. 11**.

The MPPT controllers are compared in terms of their tracking efficiency and speed. The tracking efficiency (T_{Eff}) is given by,

$$T_{Eff} = \frac{\int_0^t P_{MPP}\, dt}{\int_0^t P_{ideal\, MPP}\, dt} \times 100\% \qquad (9)$$

where P_{MPP} represents the maximum power point for each controller and $P_{ideal\ MPP}$ represents the desired/ideal maximum power point for given environmental conditions. The tracking speed is measured as the time the controllers take to settle down.

It is observed that the settling times for the ANFIS-based MPPT controller and ANN-based MPPT controller are very small whilst the FL-based MPPT controller and P&O controller take much time to track the MPP. The P&O controller fluctuates a lot as compared to the other three controllers as given in **Fig. 12**. It should also be noted that although the FL-based MPPT controller doesn't oscillate a lot about the MPP, it has a poor efficiency as compared to the other three controllers. The overall performance of all the controllers is satisfactory for steady-state weather conditions, however, the ANFIS-based MPPT controller demonstrates the best performance as compared to other controllers. **Table 7** gives the tracking efficiencies and speed of the studied MPPT controllers for steady-state weather conditions.

Table 7 - Tracking efficiencies of the controllers for steady-state weather conditions.

MPPT Technique	Tracking efficiency	Settling time
ANFIS	99.92%	0.02s
P&O	99.68%	0.1s
ANN	99.60%	0.02s
FL	96.68%	0.05s

Case 2: Simulating the controllers under rapidly varying solar irradiance and constant temperature.

At this point, the performance of the studied MPPT controllers is evaluated under rapidly varying solar irradiance levels ($1000W/m^2$, $850W/m^2$ $500W/m^2$, and $50W/m^2$). The power output comparison of the four controllers is given in **Fig. 13**.
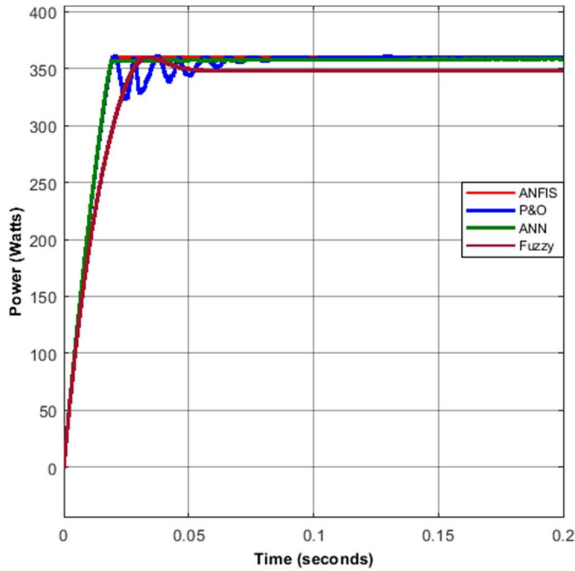

Fig. 13 - Simulations of the controllers under varying solar irradiance levels.
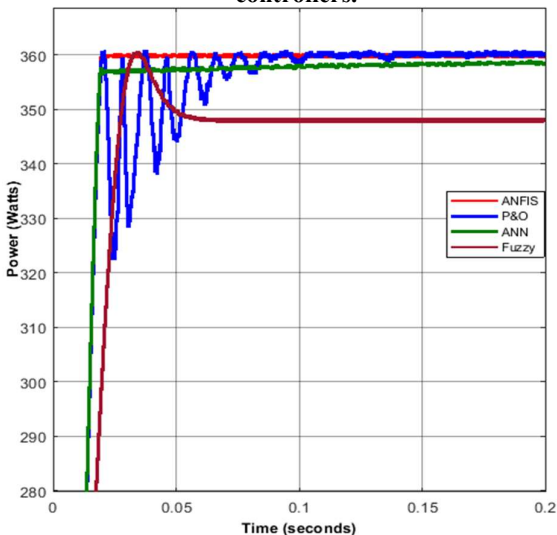

Fig. 11 - Steady-state comparison of the MPPT controllers.

Fig. 12 - Zoomed diagram of the dynamic response of the controllers.

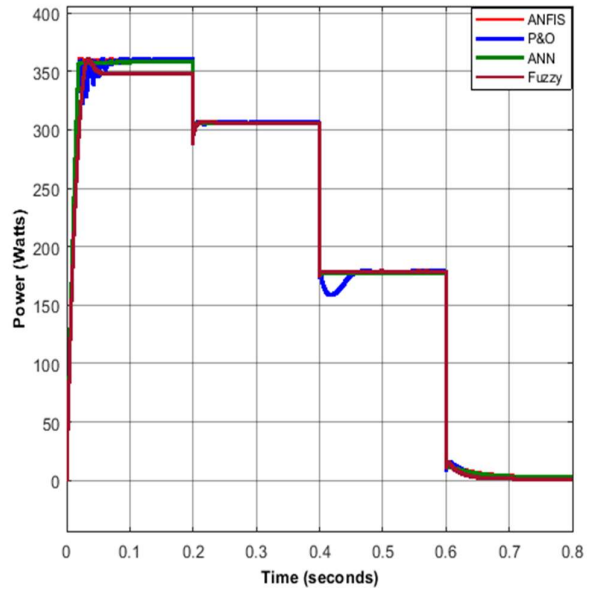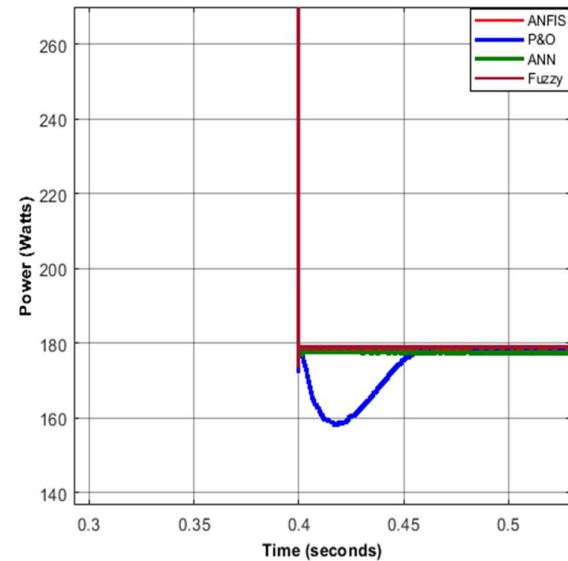**Fig. 14 - The drift phenomenon of the P&O controller.**

All controllers exhibit a satisfactory tracking performance but with different levels of accuracy. CI-based MPPT controllers show a better dynamic response as compared to the P&O controller. The P&O encounters a drift phenomenon, a condition where there is an incorrect decision for either decreasing or increasing the duty cycle for rapidly changing solar irradiance levels. The drift phenomenon of the P&O controller is illustrated in **Fig. 14** (between 0.4s to 0.5s).

Case 3: Simulating the controllers under varying solar irradiance and varying temperatures.
The MPPT controllers are simulated whilst varying both the solar irradiance and temperature. In this case, four real data sets of solar irradiance and temperature are used. The data sets are given in **Table 8**. **Fig. 15** shows the dynamic response of the controllers for rapidly varying solar irradiance and temperature. The ANFIS-based MPPT controller and ANN-based MPPT controller give the best performance for rapidly changing weather conditions. The tracking efficiency of the FL-based MPPT controller and P&O controller is very poor as shown in **Fig. 15**.
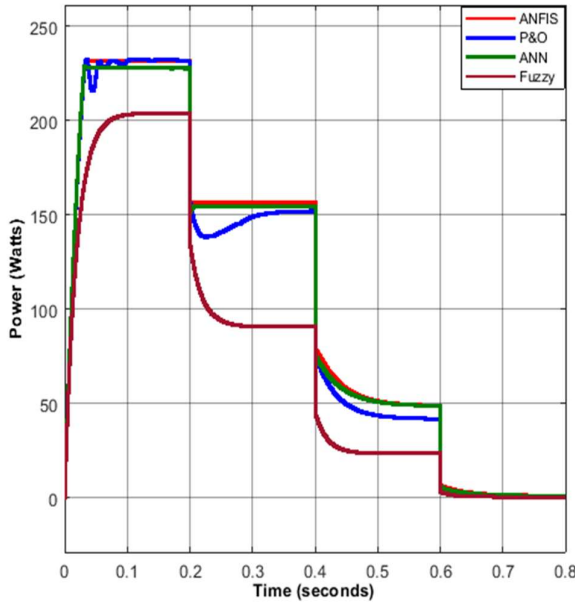

Fig. 15 - Simulations of the controllers under varying solar irradiance and temperature

Table 8 - Data sets of solar irradiance and temperature

Solar Irradiance	Temperature
633 W/m^2	30.6 ℃
440 W/m^2	25.2 ℃
222 W/m^2	20.1 ℃
30 W/m^2	15.2 ℃

Case 4: Simulating the controllers under varying load conditions.
At this point, the MPPT controllers are evaluated under varying load conditions to extra evaluate their robustness and effectiveness of these controllers. The load is changed as shown in **Fig. 16**. It should be noted that all CI-based MPPT controllers show an outstanding performance under varying load conditions. Moreover, the ANN-based MPPT

controller and ANFIS-based MPPT controller offer a better tracking efficiency as compared to the FL-based MPPT controller. The P&O MPPT controller suffers from high oscillations for higher load conditions (40Ω, 25Ω & 35Ω). It performs fairly under low load conditions (between 0.4s and 0.6s) as shown in **Fig. 17**.
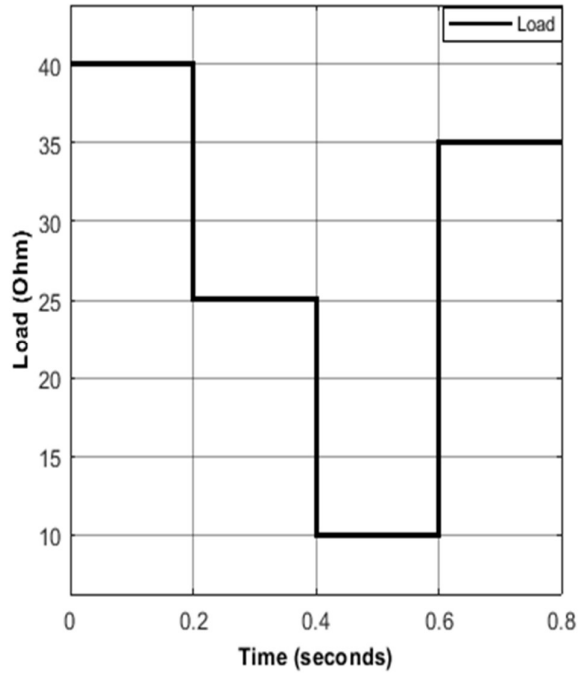

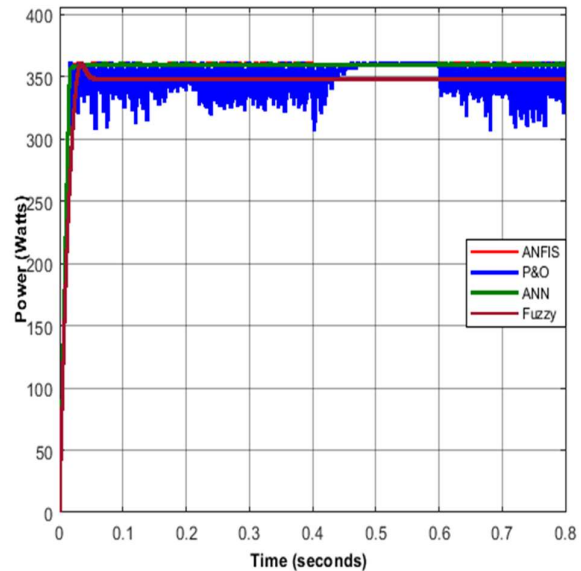**Figure 16 - Load variations for the MPPT controllers.**

Fig. 17: MPPT controllers under varying load conditions and constant weather conditions.

The poor performance of the P&O MPPT controller can be explained by the fact that this controller depends on fixed step sizes to either increase or decrease the duty cycle of the boost converter and it doesn't adapt to any changes to the variables in the system. **Fig. 18** shows a diagram of heavy oscillations of the P&O MPPT controller under varying load conditions.
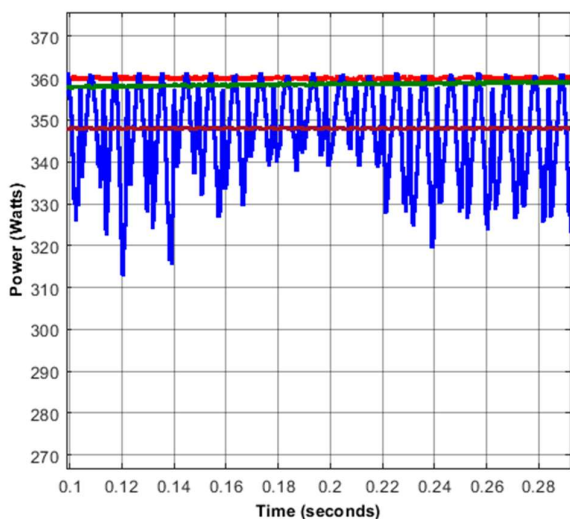
Fig. 18 - Zoomed view of the P&O MPPT controller oscillations.

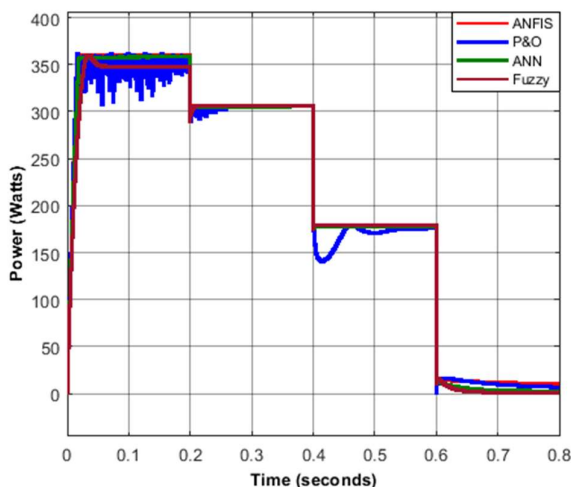**Case 5: Simulating the controllers under varying solar irradiance and load conditions.**

Fig. 19 - Simulations of the controllers for varying load conditions and varying weather conditions.

The controllers are also evaluated under varying weather conditions and varying load conditions to find out the best MPPT controller for the worse scenario. **Fig. 19** gives the power output curves for the controllers. CI-based MPPT controllers can effectively track the MPP of the solar modules while the P&O MPPT controller suffers from heavy oscillations about the MPP.

4. CONCLUSION

In this article, four MPPT controllers are described and compared for extracting the maximum available power from a PV module. The MPPT controllers are designed, simulated and analysed in the MATLAB/Simulink environment. For evaluation, the controllers are studied under steady-state weather conditions, rapidly changing weather conditions and varying load conditions. Simulation results show that all CI-based MPPT

controllers perform better than the P&O MPPT controller. Additionally, the ANFIS-based MPPT controller offers the best performance for every scenario studied, with the same level of consistency. The performance of the FL-based MPPT controller is poor for rapidly varying solar irradiance as compared to other MPPT controllers. For future work, the performance of the FL-based MPPT controller may be enhanced by optimizing the design of its membership functions using optimization techniques like genetic algorithms and particle swarm optimization. The P&O MPPT controller suffers from heavy oscillations for varying load conditions and the tracking speed is slow resulting in power wastages.

REFERENCES

[1] T. H. Oh, S. Y. Pang, and S. C. Chua, "Energy policy and alternative energy in Malaysia: Issues and challenges for sustainable growth," *Renewable and Sustainable Energy Reviews,* vol. 14, no. 4, pp. 1241-1252, 2010/05/01/ 2010, doi: https://doi.org/10.1016/j.rser.2009.12.003.
[2] S. Lawan and W. A. W. Z. Abidin, "A Review of Hybrid Renewable Energy Systems Based on Wind and Solar Energy: Modeling, Design and Optimization," 2020.
[3] IRENA. "Solar Energy." International renewable energy agency. https://www.irena.org/solar (accessed 2021).
[4] M. Malinowski, J. Leon, and H. Abu-Rub, "Solar Photovoltaic and Thermal Energy Systems: Current Technology and Future Trends," *Proceedings of the IEEE,* vol. PP, pp. 1-15, 04/28 2017, doi: 10.1109/JPROC.2017.2690343.
[5] J. Hossain and A. Mahmud, *Renewable energy integration: challenges and solutions*. Springer Science & Business Media, 2014, p. 1.
[6] R. Belu, "Artificial intelligence techniques for solar energy and photovoltaic applications," in *Robotics: Concepts, methodologies, tools, and applications*: IGI Global, 2014, pp. 1662-1720.
[7] B. Makala and T. Bakovic, "Artificial intelligence in the power sector," 2020.
[8] D. Sharma and G. Purohit, *Advanced perturbation and observation (P&O) based maximum power point tracking (MPPT) of a solar photo-voltaic system*. 2012.
[9] X. Liu and L. A. C. Lopes, "An improved perturbation and observation maximum power point tracking algorithm for PV arrays," in *2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551)*, 20-25 June 2004 2004, vol. 3, pp. 2005-2010 Vol.3, doi: 10.1109/PESC.2004.1355425.
[10] R. I. Putri, S. Wibowo, and M. Rifa'i, "Maximum Power Point Tracking for Photovoltaic Using Incremental Conductance Method," *Energy Procedia,* vol. 68, pp. 22-30, 2015/04/01/ 2015, doi: https://doi.org/10.1016/j.egypro.2015.03.228.
[11] A. Safari and S. Mekhilef, "Incremental conductance MPPT method for PV systems," in *2011 24th Canadian Conference on Electrical and Computer Engineering(CCECE)*, 8-11 May 2011 2011, pp. 000345-000347, doi: 10.1109/CCECE.2011.6030470.
[12] P. Das, "Maximum Power Tracking Based Open Circuit Voltage Method for PV System," *Energy Procedia,* vol. 90, pp. 2-13, 2016/12/01/ 2016, doi: https://doi.org/10.1016/j.egypro.2016.11.165.
[13] S. B. Ch, J. Kumari, and T. Kullayappa, "Design and Analysis of Open Circuit Voltage Based Maximum Power Point Tracking for Photovoltaic System," *International*

Journal of Advances in Science and Technology, vol. 2, pp. 51-60, 02/01 2011.

[14] N. S. D'Souza, L. A. Lopes, and X. Liu, "Comparative study of variable size perturbation and observation maximum power point trackers for PV systems," *Electric Power Systems Research,* vol. 80, no. 3, pp. 296-305, 2010.

[15] V. Kamala Devi, K. Premkumar, A. Bisharathu Beevi, and S. Ramaiyer, "A modified Perturb & Observe MPPT technique to tackle steady state and rapidly varying atmospheric conditions," *Solar Energy,* vol. 157, pp. 419-426, 2017/11/15/ 2017, doi: https://doi.org/10.1016/j.solener.2017.08.059.

[16] A. Kumar, P. Chaudhary, and M. Rizwan, "Development of Fuzzy Logic based MPPT controller for PV system at varying meteorological parameters," in *2015 Annual IEEE India Conference (INDICON)*, 17-20 Dec. 2015 2015, pp. 1-6, doi: 10.1109/INDICON.2015.7443203.

[17] R. T. Moyo, P. Y. Tabakov, and S. Moyo, "Design and Modelling of the ANFIS based MPPT controller for a Solar Photovoltaic (SPV) System," *Journal of Solar Energy Engineering,* pp. 1-9, 2020, doi: 10.1115/1.4048882.

[18] C. Ben Salah and M. Ouali, "Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems," *Electric Power Systems Research,* vol. 81, no. 1, pp. 43-50, 2011/01/01/ 2011, doi: https://doi.org/10.1016/j.epsr.2010.07.005.

[19] A. Gupta, P. Kumar, R. K. Pachauri, and Y. K. Chauhan, "Performance analysis of neural network and fuzzy logic based MPPT techniques for solar PV systems," in *2014 6th IEEE Power India International Conference (PIICON)*, 2014: IEEE, pp. 1-6.

[20] C. S. Chim, P. Neelakantan, H. P. Yoong, and K. T. K. Teo, "Fuzzy logic based MPPT for photovoltaic modules influenced by solar irradiation and cell temperature," in *2011 UkSim 13th International Conference on Computer Modelling and Simulation*, 2011: IEEE, pp. 376-381.

[21] D. Menniti, A. Pinnarelli, and G. Brusco, "Implementation of a novel fuzzy-logic based MPPT for grid-connected photovoltaic generation system," in *2011 IEEE Trondheim PowerTech*, 2011: IEEE, pp. 1-7.

[22] S. A. Rizzo and G. Scelba, "ANN based MPPT method for rapidly variable shading conditions," *Applied Energy,* vol. 145, pp. 124-132, 2015.

[23] L. L. Jiang, D. R. Nayanasiri, D. L. Maskell, and D. M. Vilathgamuwa, "A hybrid maximum power point tracking for partially shaded photovoltaic systems in the tropics," *Renewable Energy,* vol. 76, pp. 53-65, 2015/04/01/ 2015, doi: https://doi.org/10.1016/j.renene.2014.11.005.

[24] N. Khaehintung, P. Sirisuk, and W. Kurutach, "A novel ANFIS controller for maximum power point tracking in photovoltaic systems," in *The Fifth International Conference on Power Electronics and Drive Systems, 2003. PEDS 2003.*, 17-20 Nov. 2003 2003, vol. 2, pp. 833-836 Vol.2, doi: 10.1109/PEDS.2003.1283074.

[25] F. Khosrojerdi, S. Taheri, and A. Cretu, "An adaptive neuro-fuzzy inference system-based MPPT controller for photovoltaic arrays," in *2016 IEEE Electrical Power and Energy Conference (EPEC)*, 12-14 Oct. 2016 2016, pp. 1-6, doi: 10.1109/EPEC.2016.7771794.

[26] A. M. Noman, K. E. Addoweesh, and A. I. Alolah, "Simulation and Practical Implementation of ANFIS-Based MPPT Method for PV Applications Using Isolated Ćuk Converter," *International Journal of Photoenergy,* vol. 2017, p. 3106734, 2017/12/21 2017, doi: 10.1155/2017/3106734.

[27] M. A. Sarhan, M. Ding, X. Chen, and M. Wu, "Performance Study of Neural Network and ANFIS Based MPPT Methods For Grid Connected PV System," presented at the Proceedings of the 2017 VI International Conference on Network, Communication and Computing, Kunming,

China, 2017. [Online]. Available: https://doi.org/10.1145/3171592.3171623.

[28] K. Ishaque, Z. Salam, M. Amjad, and S. Mekhilef, "An improved particle swarm optimization (PSO)–based MPPT for PV with reduced steady-state oscillation," *IEEE transactions on Power Electronics,* vol. 27, no. 8, pp. 3627-3638, 2012.

[29] R. B. Koad, A. F. Zobaa, and A. El-Shahat, "A novel MPPT algorithm based on particle swarm optimization for photovoltaic systems," *IEEE Transactions on Sustainable Energy,* vol. 8, no. 2, pp. 468-476, 2016.

[30] K. Sundareswaran and S. Palani, "Application of a combined particle swarm optimization and perturb and observe method for MPPT in PV systems under partial shading conditions," *Renewable Energy,* vol. 75, pp. 308-317, 2015.

[31] J. Ahmed and Z. Salam, "A Maximum Power Point Tracking (MPPT) for PV system using Cuckoo Search with partial shading capability," *Applied Energy,* vol. 119, pp. 118-130, 2014.

[32] J. Ahmed and Z. Salam, "A soft computing MPPT for PV system based on Cuckoo Search algorithm," in *4th International Conference on Power Engineering, Energy and Electrical Drives*, 2013: IEEE, pp. 558-562.

[33] A. Harrag and S. Messalti, "Variable step size modified P&O MPPT algorithm using GA-based hybrid offline/online PID controller," *Renewable and Sustainable Energy Reviews,* vol. 49, pp. 1247-1260, 2015.

[34] A. A. Mohamed, A. Berzoy, and O. A. Mohammed, "Design and hardware implementation of FL-MPPT control of PV systems based on GA and small-signal analysis," *IEEE Transactions on Sustainable Energy,* vol. 8, no. 1, pp. 279-290, 2016.

[35] D. Kumar and K. Chatterjee, "Design and analysis of artificial bee-colony-based MPPT algorithm for DFIG-based wind energy conversion systems," *International Journal of Green Energy,* vol. 14, no. 4, pp. 416-429, 2017.

[36] A. soufyane Benyoucef, A. Chouder, K. Kara, and S. Silvestre, "Artificial bee colony based algorithm for maximum power point tracking (MPPT) for PV systems operating under partial shaded conditions," *Applied Soft Computing,* vol. 32, pp. 38-48, 2015.

[37] A. Arora and P. Gaur, "Comparison of ANN and ANFIS based MPPT Controller for grid connected PV systems," in *2015 Annual IEEE India Conference (INDICON)*, 2015: IEEE, pp. 1-6.

[38] L. Farah, A. Haddouche, and A. Haddouche, "Comparison between proposed fuzzy logic and ANFIS for MPPT control for photovoltaic system," *International Journal of Power Electronics and Drive Systems,* vol. 11, no. 2, p. 1065, 2020.

[39] M. R. Javed, A. Waleed, U. S. Virk, and S. Z. ul Hassan, "Comparison of the adaptive neural-fuzzy interface system (ANFIS) based solar maximum power point tracking (MPPT) with other solar MPPT methods," in *2020 IEEE 23rd international multitopic conference (INMIC)*, 2020: IEEE, pp. 1-5.

[40] M. Muthuramalingam and P. S. Manoharan, "Comparative analysis of distributed MPPT controllers for partially shaded stand alone photovoltaic systems," *Energy Conversion and Management,* vol. 86, pp. 286-299, 2014/10/01/ 2014, doi: https://doi.org/10.1016/j.enconman.2014.05.044.

[41] R. T. Moyo, "Artificial intelligence based solar/diesel hybrid water pumping system," 2021.

[42] K.-D. Jäger, O. Isabella, A. H. Smets, R. A. van Swaaij, and M. Zeman, *Solar energy: fundamentals, technology and systems*. UIT Cambridge, 2016.

[43] S. Bhatia, *Advanced renewable energy systems,(Part 1 and 2)*. CRC Press, 2014.

[44] M. T. Boyd, S. A. Klein, D. T. Reindl, and B. P. Dougherty, "Evaluation and validation of equivalent circuit photovoltaic solar cell performance models," *Journal of solar energy engineering,* vol. 133, no. 2, 2011.

[45] S. K. Kollimalla and M. K. Mishra, "A Novel Adaptive P&O MPPT Algorithm Considering Sudden Changes in the Irradiance," *IEEE Transactions on Energy Conversion,* vol. 29, no. 3, pp. 602-610, 2014, doi: 10.1109/TEC.2014.2320930.

[46] R. T. Moyo, P. Y. Tabakov, and S. Moyo, "Design and Modeling of the ANFIS-Based MPPT Controller for a Solar Photovoltaic System," *Journal of Solar Energy Engineering,* vol. 143, no. 4, p. 041002, 2021.