# Comparative Efficiency Assessment of MPPT Algorithms in Photovoltaic Systems

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**Abstract-** Algorithms of maximum power point tracking are widely used in most of photovoltaic systems to optimize the output power which depends on ambient conditions such as solar irradiance and PV arrays' temperature. In general, these techniques can be classified into two categories: conventional algorithms such as Perturb and Observe (P&O) and Incremental Conductance (INC), and artificial intelligence algorithms such as Artificial Neural Network (ANN). In this investigation, a comparison of these algorithms is conducted to analyse, compare, and assess their performances when they are integrated in a PV power system under dynamic changed conditions. The simulation results obtained from MATLAB/Simulink environment show that the dynamic performances of intelligent MPPT controller are much better than those of traditional algorithms such as P&O and INC. Under any circumstances that solar radiance varies rapidly or slowly, ANN MPPT algorithms always track MPP point correctly within the varying duration to provide maximum output power. On the contrary, P&O and INC techniques only show effectiveness under the case of slowly changing irradiance.

**Keywords** Photovoltaic, MPPT, P&O, INC, Artificial Neural Network.

## 1. Introduction

Photovoltaic (PV) panels change sunlight irradiance to electric power. The amount of generated DC power depends on the luminosity of the sun and the ambient temperature. It also varies corresponding to the increasing number of loads [1-2]. Under consistent radiation and temperature, a PV panel exhibits characteristic voltages and currents at a single point, called the peak power point, where the PV panel delivers its highest power. To provide the maximum output, a technique to track the maximum power point (MPP) is essential for these panels. The MPPT algorithm regulates the power converter to capture the instant peak power of the PV system continuously. Over the years, multiple MPPT techniques have been introduced and implemented such as Perturb and Observe (P&O) [3-5], incremental inductance (INC) [6-8], Fuzzy logic [9-11], or neural networks [12-13]. In [14], the advantages and drawbacks of conventional and intelligent algorithms were also discussed in detail. However, these studies have-not exposed the comparisons of these algorithms' efficiency in the same condition of changed irradiation.

In this paper, a comparative investigation of efficiency assessment of popular MPPT techniques is presented. The investigation was simulated under different scenarios of solar radiance to find out the advantages and drawbacks of each algorithm applying to a sample PV system. The simulated models were performed in Matlab/Simulink environment to describe behaviours of models in details.

## 2. Fundamentals of PV Array

### *2.1. PV Characteristics*

PV cells all share a common characteristic that the voltage, current, and output power are quite small, so they cannot be used as a single unit in practical applications. Manufacturers often combine $N_S$ PV cells in series into a series, and the parallel combination of $N_P$ series in each product is commercialized to create a battery source with a larger capacity [15-16]. Equation (1) describes mathematically for the coupled structure of a PV panel which is similar to that of a PV cell:

$$I_{PV} = I_{ph} - I_0 \left[ exp\left( \frac{V_{PV} + I_{PV} R_s}{n V_{th}} \right) - 1 \right] - \frac{V_{PV} + I_{PV} R_s}{R_p} \quad (1)$$

where: $I_{PV}$ and $V_{PV}$ are output current and voltage, respectively, of PV panels; $I_0$ is the reverse saturated current of the diode in the equivalent circuit model; $R_P$ and $R_S$ are equivalent parallel and series resistance, accordingly, in the equivalent model of PV panels; $V_{th}$ is the equivalent thermal voltage.

The instantaneous power emitted from PV panels is determined by the formula:

$$P = I \times V \quad (2)$$

With the relationship of current *(I)* and voltage *(V)* in equation (1), the *I - V* and *P - V* characteristics of PV panels are determined as shown in Fig. 1. It can be seen that the characteristic curve defines three special points namely short circuit, open circuit and maximum power points (MPP). These special spots will be characterized by the short circuit current value of each panel ($I_{SC}$), the parameter at MPP of each panel ($V_{MPP}$ voltage, $I_{MPP}$ current and $P_{MPP}$ capacity) and open circuit voltage of each panel ($V_{OC}$).

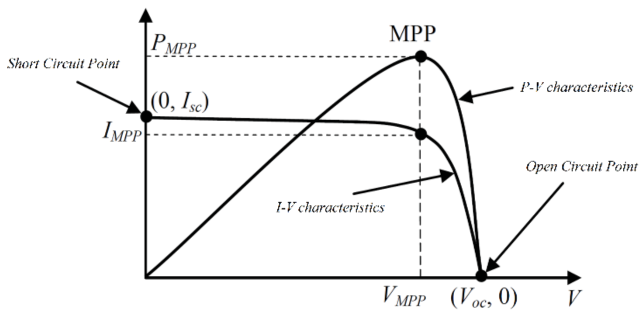


**Fig. 1.** I-V and P-V characteristics of a PV panel.

### *2.2. MPPT Devices*

The MPP point determined on the $I_{PV}$ - $V_{PV}$ and $P_{PV}$ - $V_{PV}$ characteristic curves always changes under changing radiation and temperature conditions. From there, we see a shift of the MPP point once the solar irradiance or the working temperature of the panel changes [15, 17]. In addition, when the PV array is connected directly to the load (also known as a direct coupled system), the operating point of the system will be the intersection of the PV cell array curve and the load curve. Thus, in a direct coupled system, the PV array must be large enough to ensure that the required power can be supplied to the load. This may come to a more costly built PV system.

To surpass this issue, a power electronic converter, named the Maximum Power Point (MPP) Tracker is required to keep the operating point of the PV battery array at the MPP point [16]. The MPPT unit does this by controlling the voltage or current of the PV cell membrane. If a proper MPPT technique is applied, the MPPT unit is able to identify and trace the MPP point of PV cells.

Depending on practical applications, two types of DC/DC [18-20] power conversion circuits commonly are used to make MPPTs: boost converters and buck converters. It showed that the usage of Arduino in DC/DC converters for MPPT conventional and intelligent algorithms provide low effective cost [21]. In this study, the Boost converter was chosen for investigation.

## 3. Maximum Power Point Tracking Method

### *3.1. Perturb and Observe (P&O) Technique*

P&O is a relatively simple and most widely used method. This technique considers the voltage variation according to the cycle to find the working point with the largest capacity. The flowchart and characteristics of this algorithm are illustrated in Fig. 2 and Fig. 3, respectively [3]. If a change in voltage triggers power to increase, then the following variation will stay in the same direction of increase or decrease. On the other hand, if the variation triggers the power to decrease, the subsequent deviation will opt to change in the opposite direction. When the operating MPP point is identified on the *P-V* characteristic curve, the voltage deviation will happen around that maximum power operating point (MPP point) [3].

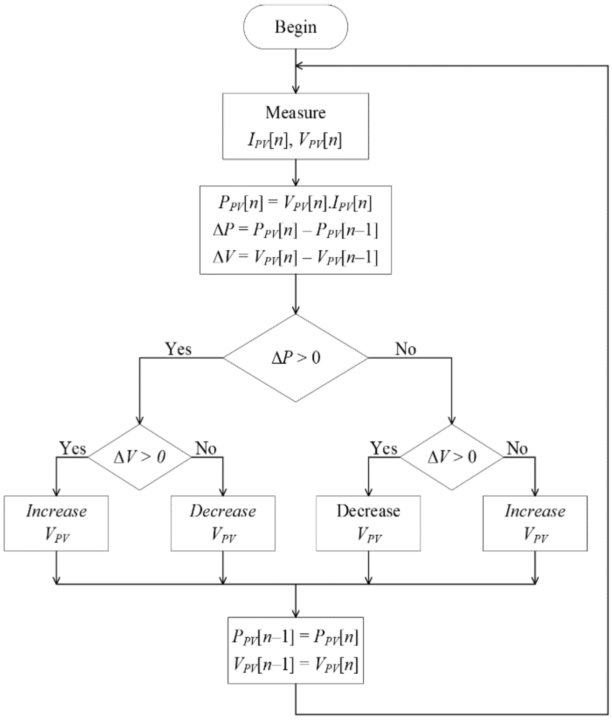


**Fig. 2**. P&O flow chart.

### *3.2. INC Technique*

The INC technique uses the incremental total inductance of the solar cell to identify the optimal power point is shown in Fig. 4 and Fig. 5. This method is relied on the following characteristic: the slope of the curve pin is zero at the MPPT point, this value is positive when locating to the left of the MPP point, negative when positioning to the right of the MPP point [6-7]. This technique evaluates the instant inductance value *(I/V)* with the increment inductance *(ΔI/ΔV)* to determine the working point with the maximum capacity.

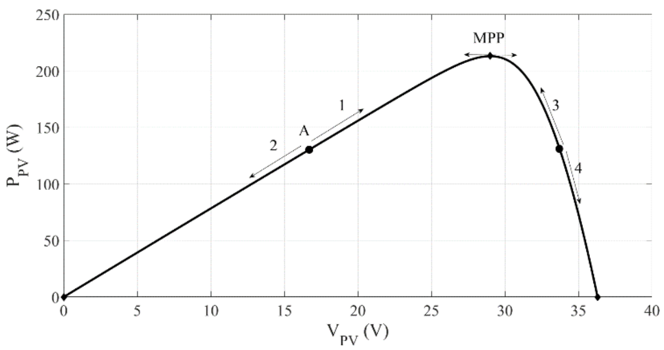


**Fig. 3.** P-V characteristics of P&O algorithm.

At the MPP point, the reference voltage $V_{ref} = V_{MPP}$. This INC algorithm has the advantage of giving good results in the case of a correspondingly large increase in inductance value in sudden weather conditions.

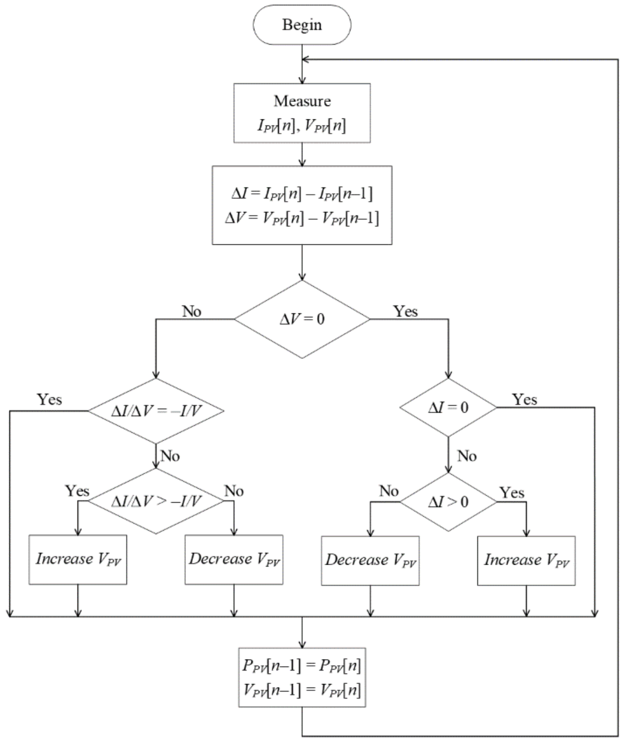


**Fig.4.** INC flowchart.

### *3.3. Artificial Neural Network (ANN) Algorithm*

ANN was born from the idea of simulating the human brain [22-25]. Like humans, ANNs are learned by experience, saving those experiences and using them in the right situations.

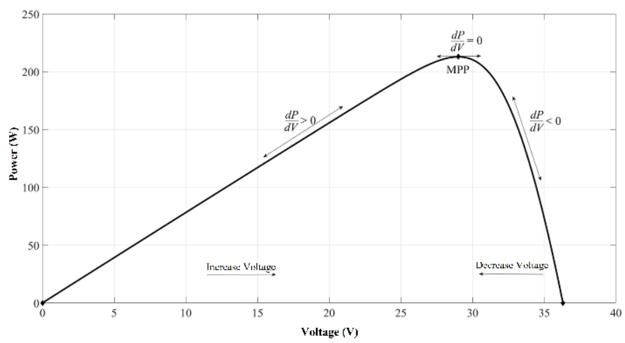


**Fig. 5.** P-V characteristics of INC algorithm.

Supervised learning is a group of algorithms that predict the output of new input based on a number of known pairs of data. These data pairs are called as data-label. It is the common group of machine learning techniques.

Mathematically, supervised learning includes an input set of "n" variables of $X = \{x_1, x_2, \dots ,x_n\}$ together with a comparable set of "n" labels of $Y = \{y_1, y_2, \dots , y_n\}$. Pairs of known data $(x_i, y_i)$ are called training values. Based on these quantities, it is necessary to generate a function mapping a single element of input variables to a approximately matching element in set Y as follows:

$$\hat{y} = \int (x_i) \tag{3}$$

The purpose of this mapping is to estimate the function *f* properly under any circumstance when a new data x is available, the corresponding label y can be deduced from the function.

This research study introduces and uses a regular neural network for implementation because of its simple and accessible calculation method.

An ANN usually organizes neurons into layers, and each layer is responsible for a specific task. ANN usually has 3 layers: input, hidden and output layers [22]. The first layer gives the network with the necessary data. The number of neurons in this layer depends on input parameters provided to the network, and these input parameters are assumed to be in vector form. The hidden layer contains hidden neurons that help connect input values to output values. A neural network may have one or multiple hidden layers that are primarily responsible for processing the neurons of the input layer and delivering the information to the neurons of the output layer. These neurons are suitable for classifying and identifying the relationship between input parameters and output parameters. The output layer contains output neurons to transfer the output information of computations from the ANN to the user. An ANN can be built to have multiple output parameters.

The amount of neurons of the input and output layers is decided by the problem whereas the parameters of hidden layers are decided by the user [12-13]. However, choosing the type and quantity of input parameters has a great influence on the quality of the network. In such a model, a neuron point is a handling node that first linearly balances inputs, then builds the summation using the nonlinear activation function (AF) and finally, sends the outcomes to subsequent neurons. The model of an ordinary neuron is given by equation (4) as follows:

$$z = \sum_{n=1}^{n} w_n x_n + \alpha \tag{4}$$

where z is the AF argument and $x_1, x_2, x_3, \ldots, x_n$ are N input signals, and $w_1, w_2, \ldots, w_n$ are the weights of the synapses involved.

Various activation functions are introduced such as tanh, liner and sigmoid functions; in this study using the sigmoid function [26] as follows:

$$y = \frac{1}{1 + e^{-z}} \tag{5}$$

The structure of a multilayer straight-propagation ANN counted in the investigation is depicted in Fig. 6, where the input layers' neurons act as buffers to deliver input signals ($V_{PV}$, $I_{PV}$) or environmental conditions such as radiation and temperature or a combination of the above [7]. There is a neuron in the output layer that provides the $V_{MPP}$ value according to the MPP or the duty cycle manipulated to control the power converter to work closely to the MPP point. In the proposed ANN method, the group uses the input pair ($V_{PV}$, $I_{PV}$) and the output is a duty cycle. The training data was obtained using Matlab/Simulink to simulate the PV panel parameters provided by the manufacturer.

Back propagation (BP) algorithm is used to train the ANN with Bayesian Regularization optimization method. The supervised learning aims to provide it with some combination of desired suggestions and associated values of the inputs. Firstly, the weights are usually assigned with random values. Supervised learning is then operated to properly tune the weights for reducing the difference between each requested output and the result from the ANN for each relevant input.

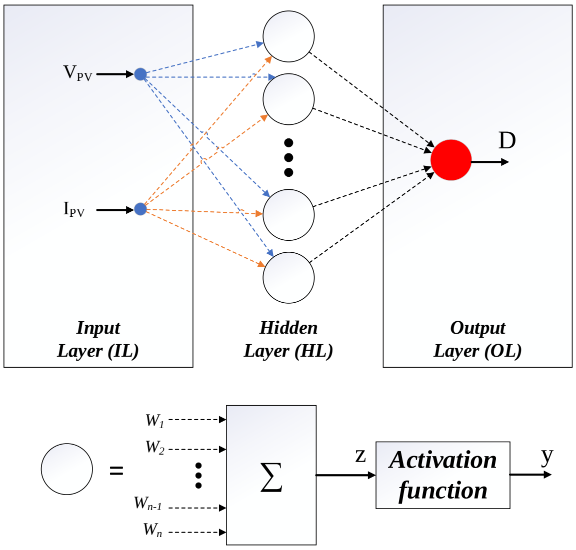


**Fig. 6.** Multilayer straight-propagation ANN structure.

## 4. Simulation Results and Discussions

The ANN algorithm is implemented using the "nnstart" tool in Matlab/Simulink with training data taken from the parameters of the solar panels. The PV system used in the simulation here is the Average Model of 100 kW PV Array in MATLAB/Simulink which is set up with an output power of 100.7kW, an open-circuit voltage of 64.2 *V* and consists of 66 parallel series, each consisting of 5 PV panels in series. The ANN training results are shown in Fig. 7. The details of simulation parameters are tabulated in Table 1.

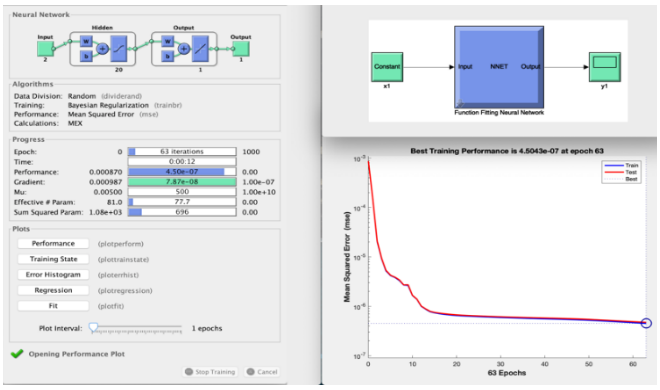

**Fig. 7.** ANN training results.

The solar radiation in the simulation scenario is programmed to change rapidly as shown in Fig. 8. The rapid change in radiation can be caused by transient shading effects due to clouds and trees. Thereby showing the response of ANN algorithms to environmental conditions. Simulation with variable radiation assumptions as shown in Fig. 8 with constant temperature of 25°C. In this radiation assumption is divided into the following scenarios:

- Scenario 1: radiation increases rapidly with small change (200W/m$^2$ within 0.5s).

- Scenario 2: radiation increases rapidly with a large change (from 200W/m$^2$ to 1000W/m$^2$ within 1s).

- Scenario 3: radiation increases slowly with a large change (from 200W/m$^2$ to 1000W/m$^2$ within 10s).

**Table 1.** Simulation parameters

| PV cell characteristics | |
|---|---|
| $V_{oc}$ (V) | 64.2 |
| $I_{SC}$ (A) | 5.96 |
| $V_{MPP}$ (V) | 54.7 |
| $I_{MPP}$ (A) | 8.58 |
| Details PV array | - 66 series connected in parallel<br>- 5 cell connected in series in each |
| Maximum output power $P_{MPP}$ (kW) | 100.7 |
| **Configuration of MPPT Boost Circuit** | |
| Switching frequency $f_{sw}$ | 20 kHz |
| Sample frequency $f_s$ | 10 kHz |
| Inductane value | 5 mH |
| Output Capacitance | 12 mF |
| Initial pulse width value | 0.5 |
| Step of pulse width variation $D_{step}$ | $3\times10^{-4}$ |

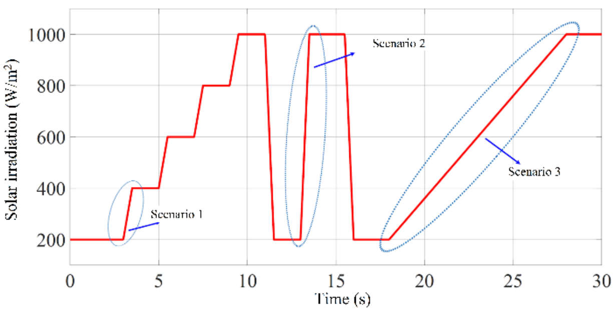


**Fig. 8.** Solar irradiation in each scenario.

Based on the ability to trace the MPP point of the ANN, P&O and INC algorithms in the respective scenarios, thereby giving the MPP tracking performance. The obtained simulation results are shown in Fig. 9.

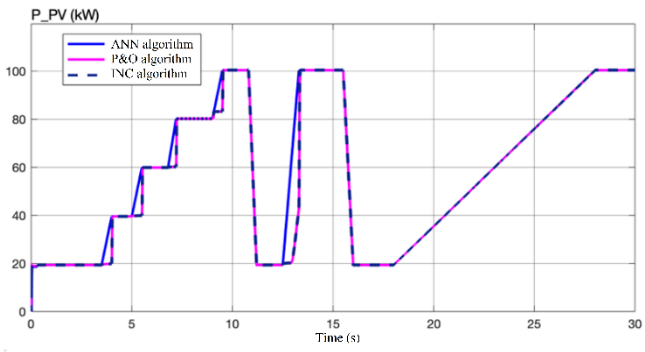


**Fig. 9.** PV output power according to MPPT algorithms.

In this paper, the signal tracking along the peak power line $\eta_{MPPT}$ is used to evaluate the efficiency of various MPPT techniques. The tracking factor is defined as follows:

$$\eta_{MPPT} = \frac{\int_{t1}^{t2} P dt}{\int_{t1}^{t2} P_{max} dt} \tag{6}$$

In which $t_1$, $t_2$ are the starting and ending points of the survey process. $P$ is the values obtained through MPPT algorithms, $P_{max}$ is the maximum output power that can be achieved by the PV system. We can calculate the $P_{max}$ value corresponding to each specific radiation, thereby constructing the $P_{max}$ characteristic curve according to the survey scenario.

### *4.1. Scenario 1: Simulation When Radiation Increases Rapidly with Minor Changes*

The irradiance changes slightly from 200 W/m$^2$ to 400 W/m$^2$ in 0.5s with the consistent ambient temperature of 25°C. The output power of the received algorithms is as shown in Fig. 10. As can be seen in Fig. 10, the conventional P&O and INC algorithms cannot track the MPP point correctly when the irradiance changes rapidly with small amount from 5s to 5.5s. Therefore, the output power of PV system suddently increase at 5.5s when the radiance stops fluctuating. On the other hand, the ANN algorithm always follow the MPP point in duration from 5s to 5.5s. It is obvious that the ANN MPPT algorithm trace the maximum power line better than classical algorithms such as INC and P&O.

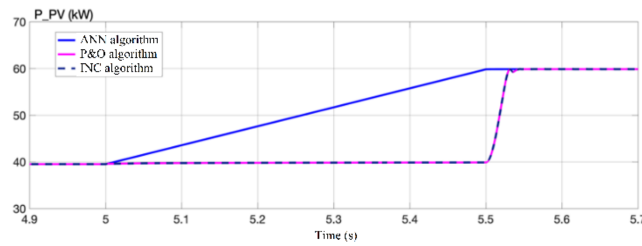


**Fig. 10.** PV output power in according to scenario 1.

### *4.2. Scenario 2: Simulation When Irradiance Changes Rapidly with Substantial Changes*

The irradiance changes slightly from 200 W/m$^2$ to 1000 W/m$^2$ in 1s while the ambient temperature is constant at 25°C. The received output power of three algorithms is as shown in

Fig. 11. The obtained results show that the ANN algorithm has a much faster response. Similarly in scenario 1, conventional MPPT algorithms, i.e. P&O and INC, cannot track the MPP point accordinly when the irradiance changes suddenly with large amount from 12.4s to 13.4s. On the contrary, the ANN always follow the MPP point in this duration.

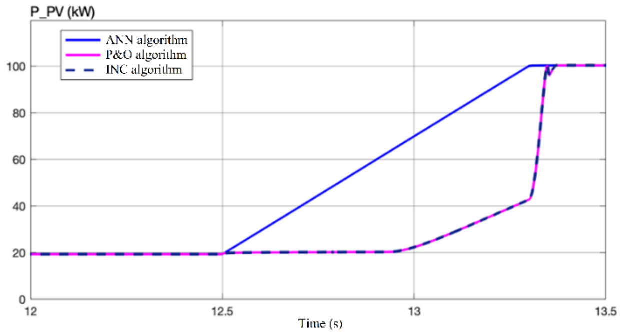


**Fig. 11.** PV output power in according to scenario 2.

*4.3. Scenario 3: Simulation When Radiation Changes Slowly with Substantial Changes*

The irradiance changes slightly from 200 W/m$^2$ to 1000 W/m$^2$ in 10s at 25°C during the simulation. The output power of all algorithms is obtained as shown in Fig. 12. The results show that for a sufficiently slow change time, the tracking performance of the algorithms is almost similar. All three algorthims can track MPP point in the duration of slowly changed irradiance condition.

The efficiency of maximum power point tracking algorithms is shown in the simulation results of Figs. 10, 11 and 12, corresponding to 3 scenarios of radiation changes. The simulated outcomes show that maximum power output line tracing efficiency of the ANN algorithm is always above 99%. Meanwhile, the P&O and INC techniques respond well only to the case of slow-changing radiation. With the rapidly-changing radiation case, the above algorithms do not respond in time and the power loss increases greatly as summarised in Table 2.

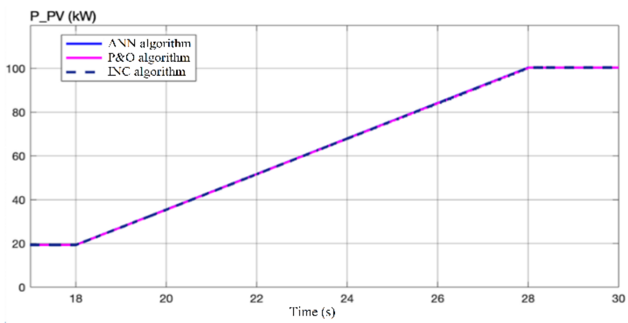


**Fig. 12.** PV output power in according to scenario 3.

**Table 2.** Efficiency of MPPT algorithms

| **Algorithm** | **MPP tracking efficiency** $\eta_{MPPT}$ (%) | |
|---|---|---|
| | **Slowly changed irradiation** | **Rapidly changed irradiation** |
| ANN | 99.60 | 99.10 |
| P&O | 99.52 | 34.42 |
| INC | 99.55 | 34.46 |

In addition, a rapid change in radiation will result in a value of the ratio of the oscillating power to the time of that power oscillation ($\Delta P/\Delta t$) with larger P&O and INC algorithms. a lot in ANN-based control algorithms. Therefore, the ANN control algorithm, if applied, will reduce the influence on the grid frequency and increase the penetration of solar energy into the microgrid system [27].

## 5. Conclusion

Integrating MPPT peak power scoring algorithms into DC - DC power converters will make it possible to get more energy from the same amount of solar radiation. The simulation results using MATLAB/Simulink simulation software in this paper prove that the P&O, INC and ANN algorithms are all capable of detecting the maximum power point. The obtained results also show that in each different weather condition, the algorithms will have different response times and performance.

The obtained research results confirm that the most effective algorithm is the proposed ANN control algorithm with the efficiency $\eta_{MPPT}$ always reaching over 99% under various changing radiation conditions. The current commonly used algorithms, i.e. P&O and INC, can only respond effectively to the case when the radiation change is slow.

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