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Comparative Analysis of Different Maximum Power Point Tracking Algorithms for Photovoltaic System

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***Abstract*—This paper presents a comprehensive comparative analysis of Golden Section Search (GSS), Artificial Neural Network (ANN), and Adaptive Neuro Fuzzy Inference System (ANFIS), alongside well-known Perturb & Observe (P&O) and Incremental Conductance (INC) Maximum Power Point Tracking (MPPT) algorithms for Photovoltaic (PV) system. The methodology involves theoretical development, simulation, and real-time experimentation using Matlab/Simulink and the Humusoft MF 634 data-acquisition card. Real-time experiments validate algorithm effectiveness under real-world conditions, facilitated by precise control mechanisms using Taraz's power electronics converter modules. The results contribute to ongoing efforts in optimizing MPPT technology and advancing the efficiency of PV systems for renewable energy generation.**

Keywords*— maximum power point tracking (MPPT), photovoltaic (PV) system, golden section search (GSS), artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS)

I. Introduction

Photovoltaic (PV) systems are gaining significant traction as sustainable and renewable energy sources worldwide. However, maximizing the energy output from PV systems remains a critical challenge due to the inherent non-linear characteristics of PV modules. Algorithms for Maximum Power Point Tracking (MPPT) are crucial for increasing PV systems' efficiency, as they continuously adjust the operating point to maximize power extraction. To ensure effective MPPT, a power electronics converter is positioned between the PV module and the load, adjusting its signals to optimize voltage and current levels based on the PV module's maximum power point (MPP), thereby maximizing power extraction [1]. Conventional MPPT techniques like Perturb & Observe (P&O) and Incremental Conductance (INC), are extensively utilized for their simplicity and efficiency in MPP tracking [2]. In [3], an adaptive INC algorithm of MPPT technique is introduced, which monitors peak power by analysing the slopes of the I-V and P-V characteristics of solar PV under varying irradiation conditions. Authors in [4] introduced a modified Perturb & Observe (PO) MPPT algorithm with the goal of minimizing steady-state oscillations. Simulation results confirm that the proposed algorithm achieved convergence speed with a time of 15 milliseconds. In response to the limitations of traditional algorithms, researchers have proposed and developed advanced MPPT techniques based on various principles. One such approach involves heuristic search methods, such as the Golden Section Search (GSS), which iteratively refines the search space to converge on the MPP [5]. Reference [6] proposed a solution for optimizing grid-connected PV systems, combining different methods like GSS, P&O, and INC for quicker convergence and less oscillation, with simulation and experimental results showing a high MPPT efficiency of 98.99%. Additionally, machine learning methods such as Artificial Neural Networks (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) have garnered interest for their capacity to dynamically learn and enhance MPPT strategies using historical data [7].

Numerous MPPT methods have been proposed and implemented, highlighting the significant importance of optimizing power tracking in PV systems [5-15]. These methods vary in complexity, sensor requirements, convergence speed, cost, efficiency, hardware compatibility, and popularity. With a multitude of algorithms available, it can be challenging to discern essential distinctions and identify the most suitable one for a particular PV system. In PV applications, various approaches exist to address partial shading conditions alongside employing the MPPT controller to extract the global MPP [5]. Conventional MPPT methods demonstrate faster performance when contrasted with metaheuristic algorithms such as genetic algorithms, grey wolf optimization, cuckoo search, and artificial bee colony. Conversely, metaheuristic approaches, including random searching, are commonly utilized to identify the global MPP [6]. Reference [7] provides a thorough review of cutting-edge MPPT methods for PV systems under partial shading, highlighting their significance in ensuring reliable power extraction. It categorizes and analyses 62 MPPT algorithms, including 25 meta-heuristic algorithms. Authors in [8] presented a hybrid controller for PV MPPT system based on ANN using Matlab/Simulink. In comparison to both P&O and INC techniques, an MPPT controller based on ANN proposed reduced steady-state error and quicker adaptation to abrupt changes in solar irradiance and temperature [9]. In [10], a comparison of three algorithms is presented for PV system. The study evaluates the performance of handling the trained dataset and provides a clear and detailed description of the algorithms. A three-layer neural network with three inputs was devised to identify the global MPP under partial shading, implemented on a Field-Programmable Gate Array (FPGA) [11]. Another investigation employed an ANN structure within the Simulink environment, using temperature and radiation data as inputs, demonstrating that the experimental outcomes closely matched simulation results [12]. The study [13] assessed the ANN-based methos in maximizing efficiency while minimizing power ripple. The comparison shows that the new method is better than traditional ones at efficiently tracking maximum power points in various conditions and keeping power fluctuations low. In [14], thirty-three papers were presented, encompassing ANN algorithms as well as their integration with other methodologies like Fuzzy Logic (FL) and metaheuristic algorithms. Reference [15] introduced a method involving a comparative examination of the following ANN methods: Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG) and Bayesian Regularization (BR) specifically tailored for PV systems. The approach utilized a two-layer feedforward neural network trained with real-time input datasets comprising solar irradiance, panel temperature, and generated voltage output, particularly utilizing the Levenberg-Marquardt algorithm, exhibits superior performance with near-zero errors and high validation efficiency.

This paper introduced experimentally developed GSS, ANN and ANFIS algorithms, which are compared with the established P&O and INC methods. The sections are organized as follows: Section I provides an introduction with a literature review, followed by the methodology in Section II. Section III presents the theoretical description of the MPPT algorithms. Simulation results are detailed in Section IV, while experimental results are outlined in Section V. Finally, conclusions and future work are presented in Section VI.

II. METHODOLOGY

The proposed methodology includes the theoretical development and simulation of three MPPT algorithms: GSS, ANN and ANFIS compared to the traditional P&O and INC, implemented in MATLAB/Simulink environment. For simulation purposes, a model of a PV module [16] was employed, which adheres to the specifications provided by the PV module manufacturer. The input parameters for this model include the intensity of solar irradiation (G) and the ambient temperature (T). Simulations play a crucial role in anticipating the behaviour of MPPT algorithms before transitioning to practical experiments. This phase provides a platform for fine-tuning algorithm parameters to enhance performance. The experimental setup is conducted under real-time conditions used in [16] consisting of Humusoft MF 634 multifunction I/O card and DC/DC buck converter. The Humusoft MF634 data-acquisition card serves as a vital link between the PV modules and the Matlab/Simulink environment, enabling seamless communication and control during experiments. DC/DC buck converter is employed between the PV modules and the load, with the duty cycle serving as a crucial parameter for the MPPT process, controlled by a pulse width modulator (PWM). The converter adjusts the operating line slope, thereby facilitating MPPT. Taraz's power electronics converter modules and gate driver modules are employed for this purpose, ensuring precise control and efficiency. An essential aspect of methodology involves the utilization of training databases for advanced MPPT algorithms such as ANN and ANFIS. These databases enable the algorithms to learn and adapt based on historical data, ultimately optimizing their performance to deliver the best power outputs in real-time applications.

III. MPPT ALGORITHMS

A. GSS Algorithms

Due to the unimodal characteristic of the PV module's power curve, which is dependent on the PV voltage, the GSS algorithm is an effective approach for identifying the maximum power point of a PV module. This curve effectively represents a single peak for given operating conditions. In the context of the GSS algorithm's procedure as outlined in [6], the operation of the GSS algorithm for finding the maximum of unimodal function *f(x)* can be explained as presented in Figure 1. Initially, a single point representing the maximum value of the function *f(x)* within the interval [x_1, x_3] is established. Subsequently, x_2 and x_4 are positioned within this interval according to the principles of the GSS algorithm. The starting points are x_1, x_2, and x_3. The values of *f(x)* at x_2 and x_4 are evaluated, and their values are compared. If $f(x_2) < f(x_4)$, it is inferred that the maximum lies within the interval [x_2, x_3], and the points are updated to x_2, x_4, and x_3. Conversely, if $f(x_2) > f(x_4)$, it is deduced that the maximum is within [x_1, x_4], and the points are updated to x_1, x_2, and x_4. This iterative process continues, progressively narrowing the interval until it becomes smaller than a specified threshold.

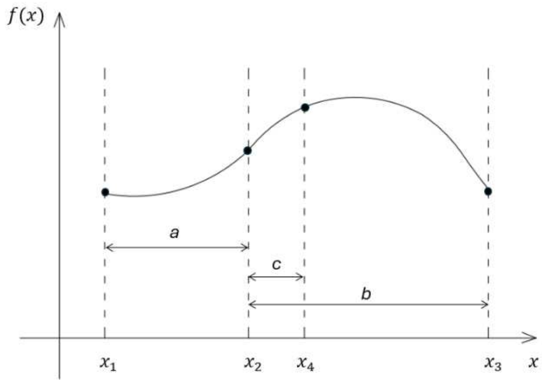


Figure 1. GSS scheme for locating MPP of unimodal function *f(x)*

The interval widths between points x_1 and x_4 is noted as $a + c$, while the interval between points x_3 and x_3 is denoted as b. As per the GSS algorithm, both intervals must possess equal widths. Hence, b is equated to $a + c$. To maintain this balance, the equation for x4 is derived as follows:

$$x_4 = x_1 + x_3 - x_2$$

The GSS algorithm dictates that the distance ratio between points x_1, x_2, and x_3 be consistent with that between subsequent points x_2, x_4, and x_3, or x_1, x_2, and x_4. By ensuring this ratio remains constant, it is required to prevent x_2 from being excessively close to x_1 and x_3, thus ensuring an equal decrease in the width of the new interval in each iteration. This mathematical expression can be simplified to:

if $f(x_4) > f(x_2)$, then

$$\frac{b-c}{c} = \frac{b}{a}$$

and if $f(x_4) < f(x_2)$, then

$$\frac{a}{c} = \frac{b}{a}$$

Removing c, the following equation is as follows:

$$(\frac{b}{a})^2 - \left(\frac{b}{a}\right) - 1 = 0$$

Replacing $\frac{b}{a} = \varphi$, φ, which represents the golden ratio, is calculated as follows:

$$\varphi = \frac{1+\sqrt{5}}{2} \approx 1.61$$

Environmental conditions, the GSS algorithm described is well-matched for identifying the MPP of the PV module, which is a function of the PV voltage, exhibits a unimodal behaviour.

In relation to Figure 1. and the GSS algorithm procedure, the function $f(x)$ denotes the PV module's power, with x representing the duty cycle D. As the operating point relies on the duty cycle D, the argument of the PV power is D. The initial values of points x_1, x_2, x_3 and x_4 are 0, 0.382, 1, and 0.618 respectively. The minimum width of the interval $[x_1, x_3]$ is represented by δ (where δ<<1), ensuring termination of the algorithm when $|x_1 - x_3| < \delta$. The PV module's power values at $D=x_2$ and $D=x_4$ are denoted by $f(x_2)$ and $f(x_4)$, respectively. Simulink model of the GSS-based MPPT algorithm is illustrated in Figure 2.

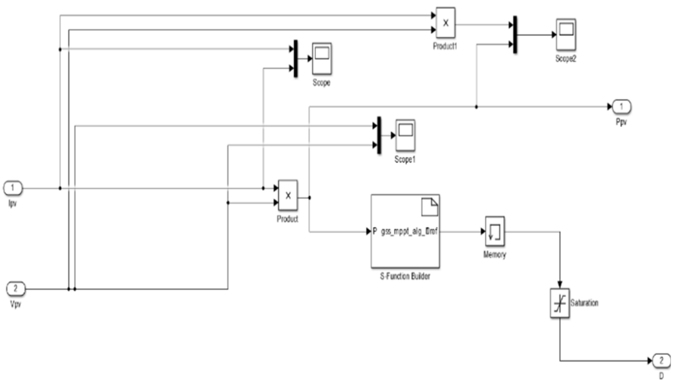


Figure 2. Simulink model of the GSS MPPT algorithm

B. ANN Algorithm

ANNs are computational models inspired by the neural networks found in biological organisms, particularly animal brains. In ANNs, artificial neurons, like those found in the brain, are interconnected units or nodes. These neurons communicate by transmitting signals through connections, which resemble synapses in the human brain. Each artificial neuron receives input signals, processes them, and transmits signals to connected neurons. The output of each neuron is influenced by a non-linear function applied to the sum of its inputs, with the signal strength at each connection being dictated by both the neuron's weight and the connection. Typically, ANNs comprise layers of neurons, with input signals undergoing transformations as they pass through these layers. The signals propagate from the input layer to the output layer, undergoing various transformations along the way. During the learning process, the weights of neurons and connections are adjusted iteratively [17].

In this paper, an ANN is developed using Matlab, utilizing a database with 22,239 inputs. 70% of the database is allocated for training the network, while the remaining 30% is used for validation and testing. The ANN is structured as a feed-forward network with two layers, incorporating hidden sigmoid and output linear neurons. The Levenberg-Marquardt backpropagation algorithm is employed for training, with 21 hidden layers utilized. After 141 epochs of training, the network achieves a mean squared error of 0.00034031 and a test regression value of 0.99997.

The network had two inputs and one output. The inputs were the current and voltage of the PV module, while the output was the reference voltage utilized as input to the voltage controller, responsible for generating the duty cycle for the transistor in the buck converter. Inputs were generated for temperatures ranging from -5°C to 35°C, with a 2°C increment, while for each temperature, the curve was derived for insolation ranging from 50 W/m^2 to 1200 W/m^2, with a step of 50 W/m^2.

C. ANFIS Algorithm

ANFIS for MPPT leverages both ANNs and FL to dynamically modify the parameters of the fuzzy inference system in response to input data. In this approach, the Sugeno fuzzy inference system is employed, where the fuzzy controller is trained using ANN techniques. By integrating both neural networks and FL within a single framework, ANFIS leverages the strengths of both approaches. Its inference system encompasses a series of fuzzy IF-THEN rules adept at approximating nonlinear functions through learning, rendering it a versatile universal estimator. This facilitates meticulous adjustment of membership functions and rule sets, culminating in effective and precise tracking of the maximum power point amidst changing environmental conditions. ANFIS MPPT possesses a notable advantage in its capacity to effectively manage the nonlinear and dynamic attributes of PV systems. By utilizing the learning capabilities of ANNs, the system can adapt to changes in solar irradiance, temperature, and other environmental factors in real-time, ensuring optimal performance even in fluctuating conditions. [18].

In this paper, ANFIS is developed using Matlab, utilizing the same database employed for the creation of the ANN algorithm. The ANFIS system consists of 36 rules, with 6 membership functions allocated for each input and 36 output membership functions. The input membership functions are Gaussian functions, while the output membership function is linear. ANFIS employs the current and voltage readings of the PV module as inputs and produces the reference voltage as its output. This reference voltage is crucial for the voltage regulator, which calculates the duty cycle for the transistor in the buck converter.

IV. Simulation Results

Simulink models provide a platform for analysing and evaluating the performance of each MPPT algorithm under various operating conditions. The database necessary for training the ANN and ANFIS algorithms were extracted from the PV module's model. These algorithms were constructed using the Matlab/Simulink Neural Net Fitting tool, facilitating the development, and training of the neural network to accurately predict the maximum power point of the PV module based on input parameters. The comparisons of duty cycles, voltages, and powers of PV module for different MPPT algorithms are illustrated in Figures 3, 4 and 5.

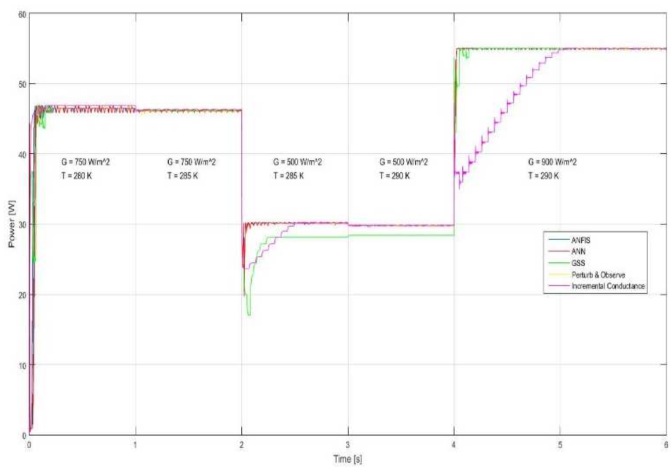


Figure 3. Comparison of powers of PV module for different MPPT algorithms

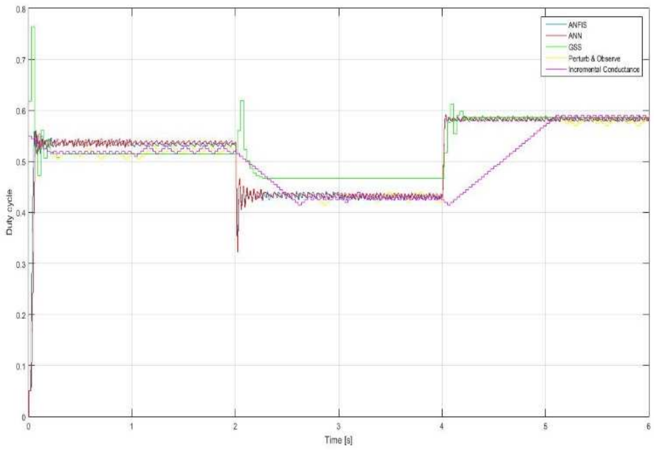


Figure 4. Comparison of duty cycles for different MPPT algorithms

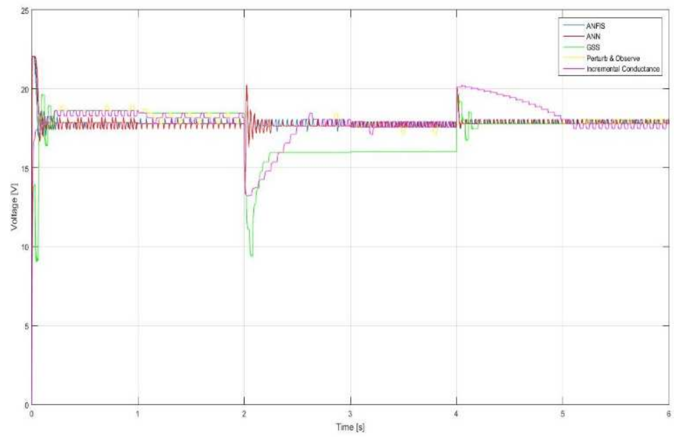
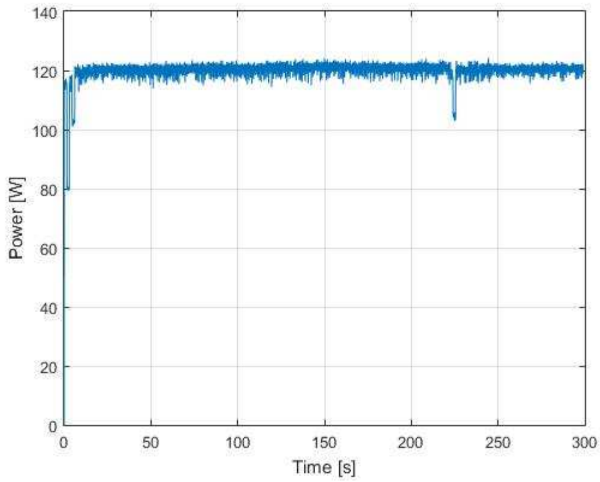


Figure 5. Comparison of voltages of PV module for different MPPT algorithms

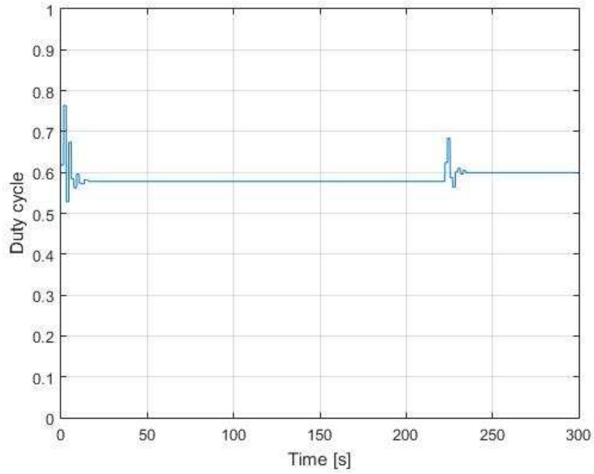
From the simulation results, it is evident that all MPPT algorithms perform well in maximizing power output. Nonetheless, each algorithm possesses its own set of advantages and disadvantages. The ANN and ANFIS algorithms stand out as the fastest and most suitable for quick environmental changes. By adjusting the voltage controller parameters, minimizing overshoots, and achieving steady state faster is possible. The GSS algorithm is faster than P&O and INC algorithms but slower than ANN and ANFIS algorithms. However, it tends to have overshoots during rapid environmental changes, although it exhibits minimal oscillations once steady state is reached. In contrast, the ANN and ANFIS algorithms show fewer oscillations compared to P&O and INC algorithms, with the oscillations primarily attributed to the voltage controller rather than the algorithm itself. Optimizing the voltage controller further can reduce oscillations in steady state.

V. Experimental Results

The following figures provide insights into the power and duty cycle variations across the GSS, ANN, and ANFIS algorithms. Specifically, the measured power of the PV module was obtained using Analog Input blocks, while the generation of the PWM signal for the buck converter's transistor was facilitated by the Frequency Output block, specified in Simulink scheme for real-time implementation.

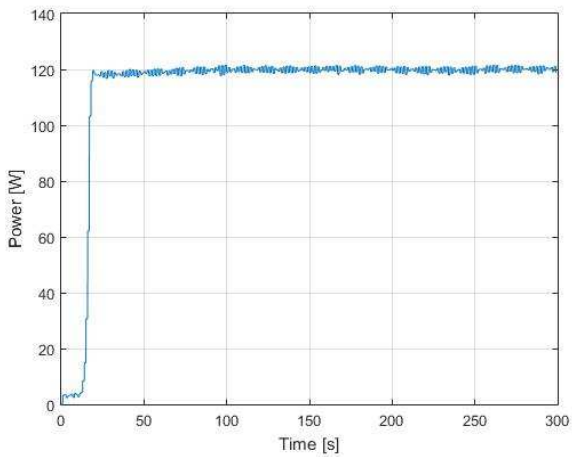


(a)

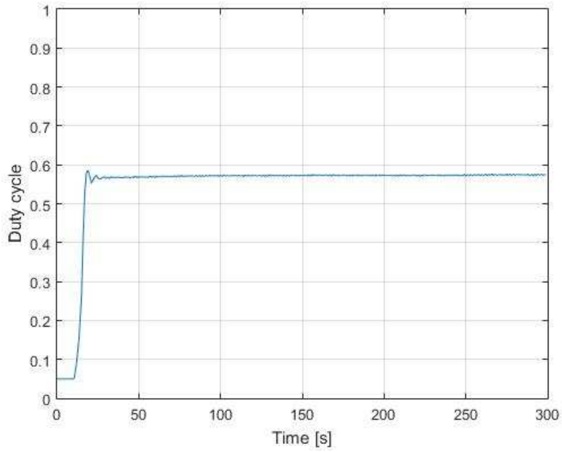


(b)

Figure 6. PV module’s power (a) and duty cycle (b) of GSS algorithm

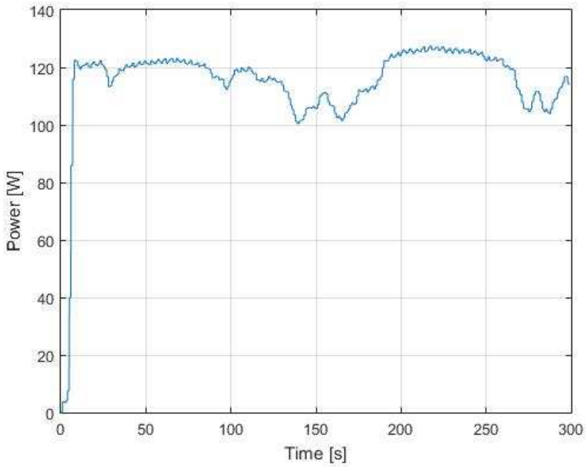


(a)

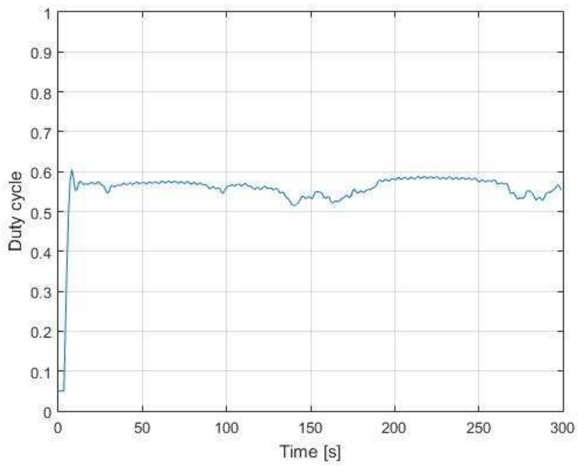


(b)

Figure 7. PV module's power (a) and duty cycle (b) of ANN algorithm



(a)



(b)

Figure 8. PV module's power (a) and duty cycle (b) of ANFIS algorithm

From the graphs, the GSS MPPT algorithm effectively identifies and sustains the MPP throughout the experiment. Notably, there are no oscillations once the algorithm reaches a stable state. In comparison to the P&O and INC algorithms, the GSS algorithm demonstrates the MPP faster. The ANN results indicate a fast response, with minimal to no oscillations in steady state. The ANFIS algorithm effectively identifies and sustains the MPP, exhibiting a rapid response and minimal oscillations in steady state. Despite variations in solar radiation intensity during the experiment, the algorithm adeptly adjusts to maintain optimal power output. However, the necessity for scaling indicates potential areas for enhancement in these algorithms.

VI. Conclusion and Future Work

The GSS algorithm, while faster than P&O and INC algorithms, is still slower than ANN and ANFIS algorithms. It maintains a steady state without oscillations but may struggle to detect small environmental changes, leading to power loss during rapid changes. Both ANN and ANFIS MPPT algorithms demonstrate the fastest response times and minimal oscillations during steady state. However, relying on a mathematical model of the PV module poses challenges as real-world parameters evolve over time, requiring constant adjustment of the database. Future work could focus on addressing this issue for ANN and ANFIS algorithms. One approach could involve obtaining database updates directly from real PV modules in controlled environments, but periodic updates may prove inefficient. Alternatively, developing an algorithm capable of online adaptation and training without disconnecting PV modules from the grid could be explored.

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