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Department of Electrical-Electronic Engineering

ENHANCEMENT PERFORMANCE AND EFFICIENCY OF PHOTOVOLTAIC SYSTEM BASED ON HYBRID MAXIMUM POWER POINT TRACKING

Master Thesis

Mina Tuqa Mahdi AL-MAYYAHI

Supervisor
Asst. Prof. Dr. Yusuf Gürcan ŞAHIN

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

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The thesis study of Mina Tuqa Mahdi AL-MAYYAHI titled as Enhancement Performance and Efficiency of Photovoltaic System Based on Hybrid Maximum Power Point Tracking has been accepted as MASTER in the department of Electrical-Electronic Engineering by out jury.

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(Supervisor)

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SUMMARY

In recent years, renewable energy sources have been used in the fight against climate change, and reducing carbon dioxide emissions (CO2) is extremely promising. Solar photovoltaic (PV) generation systems are highly dependent on the operating conditions in which they are deployed to be technologically and economically viable. The instability of the weather is the main obstacle for this source. Therefore, stabilizing the PV system's output with maximum harvesting energy requires a strong control strategy. Partial shading (PS) results in substantial power losses and significantly complicates the nonlinear control task.

Many metaheuristic algorithm-based Maximum Power Point Tracking (MPPT) control systems described in the literature have flaws, such as slow tracking, long settling times, and oscillations at the global point under PS conditions. This research aims to determine the most reliable MPPT approaches for PV systems and proposes two modified hybrid metaheuristic methods. These methods are the hybrid Arithmetic Optimization Algorithm (AOA) based on incremental conductance algorithm and fractional PI controller, AOA based, and AOA based artificial neural network (ANN). The first MPPT enhances the PV systems' performance by maximizing the amount of power extracted from solar panels, enabling faster and more precise tracking and reducing oscillations to a deficient level.

In the second MPPT strategy, the hybrid AOA and ANN MPPT Controller is used to improve the performance of tracking the maximum power point in photovoltaic systems that are partially shaded. The hybrid AOA-ANN technique is used to study and compare the recently developed MPPT strategies of Perturb and Observe (P&O), incremental conductance (IC), Grey Wolf Optimization (GWO), MPPT-based PID controller, and MPPT-based fractional PID controller. The proposed MPPT strategies are run through a computer program called Matlab. Simulation verification has shown that the AOA-ANN-based MPPT controller is a good idea.

The EN50530 standard test shows that the AOA-based fractional PI controller has an average tracking efficiency of about 99.3%. At the same time, the hybrid AOA-ANN control technique stands out for how easy it is to use, how strong it is, and how it can track steady-state power with an efficiency of up to 99.55%.

Key Words: Maximum Power Point Tracking (MPPT), Artificial Neural Network (ANN), Arithmetic Optimization Algorithm (AOA), Photovoltaic (PV), Hybrid optimization MPPT.

ÖZET

Son yıllarda iklim değişikliği ile mücadelede yenilenebilir enerji kaynakları kullanılmaya başlandı ve karbondioksit emisyonlarının (CO_2) azaltılması son derece ümit verici. Güneş fotovoltaik (PV) üretim sistemleri, teknolojik ve ekonomik olarak uygulanabilir olmaları için yerleştirildikleri çalışma koşullarına büyük ölçüde bağımlıdır. Havanın istikrarsızlığı bu kaynağın önündeki en büyük engeldir. Bu nedenle, PV sisteminin çıktısını maksimum hasat enerjisiyle dengelemek, güçlü bir kontrol stratejisi gerektirir. Kısmi gölgeleme (PS), önemli güç kayıplarına neden olur ve doğrusal olmayan kontrol görevini önemli ölçüde karmaşıklaştırır. Literatürde açıklanan birçok metasezgisel algoritma tabanlı Maksimum Güç Noktası İzleme (MPPT) kontrol sistemi, PS koşulları altında küresel noktada yavaş izleme, uzun yerleşme süreleri ve salınımlar gibi kusurlara sahiptir.

Bu araştırma, PV sistemleri için en güvenilir MPPT yaklaşımlarını belirlemeyi amaçlamaktadır ve iki modifiye hibrit metasezgisel yöntem önermektedir. Bu yöntemler, artımlı iletkenlik algoritmasına ve kesirli PI denetleyiciye dayalı hibrit Aritmetik Optimizasyon Algoritması (AOA), AOA tabanlı ve AOA tabanlı yapay sinir ağıdır (YSA). İlk MPPT, güneş panellerinden çekilen güç miktarını en üst düzeye çıkararak, daha hızlı ve daha hassas izleme sağlayarak ve salınımları yetersiz bir düzeye indirerek PV sistemlerinin performansını artırır.

İkinci MPPT stratejisinde, kısmen gölgeli fotovoltaik sistemlerde maksimum güç noktasını izleme performansını artırmak için hibrit AOA ve YSA MPPT Denetleyicisi kullanılır. Hibrit AOA-ANN tekniği, son zamanlarda geliştirilen Perturb and Observe (P&O), artımlı iletkenlik (IC), Gri Kurt Optimizasyonu (GWO), MPPT tabanlı PID kontrolörü ve MPPT tabanlı fraksiyonel PID MPPT stratejilerini incelemek ve karşılaştırmak için kullanılır. denetleyici. Önerilen MPPT stratejileri, Matlab adlı bir bilgisayar programı aracılığıyla yürütülür. Simülasyon doğrulaması, AOA-ANN tabanlı MPPT denetleyicisinin iyi bir fikir olduğunu göstermiştir. EN50530 standart testi, AOA tabanlı kesirli PI denetleyicinin ortalama %99,3'lük bir izleme verimliliğine sahip olduğunu göstermektedir. Aynı zamanda hibrit AOA-ANN kontrol tekniği, kullanımının ne kadar kolay olduğu, ne kadar güçlü olduğu ve %99,55'e varan bir verimlilikle kararlı durum gücünü nasıl takip edebildiği ile öne çıkıyor.

Anahtar Kelimeler: Maksimum Güç Noktası Takibi (MPPT), Yapay Sinir Ağı (ANN), Aritmetik Optimizasyon Algoritması (AOA), Fotovoltaik (PV), Hibrit optimizasyon MPPT.

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ABBREDIVATIONS

AOA	:	Arithmetic Optimization Algorithm
ABC	:	Artificial Bee Colony
ANN	:	Artificial Neural Network
ACO	:	Ant colony Optimization
AI	:	Artificial Intelligence
AC	:	Alternative Current
BSC	:	Back Stepping Controller
RCC	:	Ripple Correlation Control
IC	:	Incremental Conductance
P&O	:	Perturb and Observe
GWO	:	Grey Wolf Optimizer
PID	:	Proportional Integral Derivative
PSO	:	Particle Swarm Optimization
FOPID	:	fractional Order PID
FLC	:	Fuzzy Logic Controller
FWA	:	Fireworks Algorithm
HPF	:	High-Pass Filter
GA	:	Genetic Algorithm
GMPP	:	Global Maximum Power Point
SSA	:	Slap Swarm Algorithm
SMC	:	Sliding Mode Control
SA	:	Simulated Annealing
STC	:	Standard Test Condition

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CHAPTER ONE

INTRODUCTION AND LITERATURE REVIEW

1.1. Introduction

The increasing population growth has led to increased demand for electrical energy and the expected depletion of traditional energy sources in the future, such as gas, coal, and fossil fuels. These environmental effects increase the need for renewable energy sources (RES) such as solar, wind, and geothermal. The most promising sources among these RES are solar photovoltaic (PV) because they have no emissions, need less maintenance, and are abundant in natural *M. H. Zafar (2021).* Despite the benefits mentioned above, the solar PV system has nonlinear performance, which affects the system directly with the change in radiation and temperature. This indicates the relation between radiation and current ($G \propto I$). The effect of irradiation is empathetic because of the direct proportion between irradiation and current, While the connection between temperature and voltage ($T \propto \frac{1}{V}$) slightly appeared because of the Inverse proportion between temperature and voltage *R. Shah(2015).*

In recent years the solar PV system has become a hot topic for researchers because of the demand for the PV system. Consequently, the European Union has set a renewable energy generation target, contributing to about 32% of total production by 2030 and achieving 100% by 2050 M. H. Zafar *(2021), R. Shah (2015).*

PV systems can be divided into grid-connected and stand-alone *M. H. Zafar (2021)*.

To extract the maximum power point (MPP) with the rapid change in weather and environmental conditions, we need to connect a maximum power point tracking (MPPT) controller to help the PV system reach the global peak (GP) with an accurate and fast response. Without the MPPT controller system is unable to distinguish between local maximum point (LMP) and global maximum power point (GMPP) under the rapid change in climatic conditions S. Ravyts.(2020)

To operate the PV system with high efficiency, accuracy, fast response, stability, and reliability proposed, many strategies consist of different specifications that make selecting which technique is better for them complicated *M. Sarvi. (2021)* Researchers classify the MPPT techniques as shown below *M. Sarvi (2021)*:

- MPPT methods based on measurement: This type's process depends on the input parameters radiation and temperature, i.e. (current and voltage). The operation of this type is done by calculating the input parameters and comparing the results with the previous calculation. The strategies based on these methods are the open-circuit voltage (OCV) strategy *T. Anuradha (2017)*, short-circuit current (SCC) technique *S. Zouirech (2019)*, Pilot cell algorithm, Temperature algorithm, Lookup table, Load current or load voltage maximization, The only current of PV, PV output senseless (POS) control, and Perturbation and observation (P&O) method *M. Sarvi (2021)*.
- MPPT methods based on calculation: The MPP can be calculated using the equation calculations of each algorithm in this category. The strategies based on these methods are the state-space based MPPT method, dP/dV or dP/dI feedback control, linear reoriented coordinates method (LRCM) *M. Sarvi (2021)*, Sliding mode control method *M. R. Mostafa (2020)*, ripple correlation control *A. Trivedi (2016)*, Parasitic capacitance method *M. Sarvi. (2021)*, and incremental conductance (IC) method *A. Trivedi (2016)*.
- MPPT methods based on intelligent schemes: MPP can also be found using new optimization strategies based on intelligent methods. The approach based on these methods are fuzzy logic control (FLC) *U. Yilmaz (2018)*, artificial neural network (ANN) *C. G. Villegas-Mier (2021)*, particle swarm optimization (PSO) *R. B. Koad, A. F. Zobaa (2016)*, ant colony optimization (ACO), artificial bee colony optimization (ABC) *F. Belhachat (2018)*, cuckoo search algorithm (CS) *F. K. Abo-Elyousr (2020)*, chaotic search algorithm, and other metaheuristic algorithms.
- MPPT methods based on hybrid systems: These methods employ a hybrid of traditional and intelligent techniques. The strategies based on these methods are the hybrid grey wolf optimizer sine cosine algorithm *(HGWOSCA M. H. Zafar (2021)* , hybrid GWO and FLC algorithm *A. M. Eltamaly (2019)* ABC-P&O algorithm *C. Restrepo (2021)*, ACO-P&O algorithm *K. Sundareswaran (2015)*, and another hybrid MPPT methods.

1.2. Literature Review

The main goal is to use the MPPT controller to reach a global peak of the P-V curve to propose a suitable duty cycle for the DC-DC converter in the PV system with less ripple, zero oscillation, and faster response.

(Satyajit Mohanty, et al.,2016) This paper's main idea is to propose a new hybrid MPPT algorithm called GWO-PO for the PV system subjected to rapid change in the radiation and partial shading conditions to limit the search space, increase efficiency, and make the system a fast response. However, this work does not address the issues such as high ripple, high oscillation, system complexity, and high overshoot and does not test the system under the European standard test EN50530.

(Loubna Bouselham, et al.,2017) This work proposed a novel strategy to capture the PV system's global peak under partially shaded conditions. The approach combines an artificial neural network controller with a scanning algorithm. This technique proves effective in reaching the global peak faster. However, this work does not address the issues in terms of high ripple, high oscillation, high overshoot, high cost, and system complexity, as well as does not test the system under the European standard test EN50530.

(Chao Huang et al.,2017) The article proposes a novel global maximum power point tracking method for PV systems using the Jaya algorithm under variable partial shading conditions. This work shows less convergence time because it uses less iteration and high dynamical tracking efficiency. This article does not address the problems of high ripple, high oscillation, high overshoot, high cost, and system complexity. It does not test the system under the European standard test EN50530.

(Sadeq D. Al-Majidi, et al.,2018) The article focuses on increasing the PV system's output power and connection to the grid. The technique used is a novel MPPT strategy based on FL control and the P&O algorithm. The system was subjected to the European standard test EN50530 and showed accurate tracking, lower oscillation, reduced processing time, less complexity, and efficiency of about 99.6%. However, this work does not address the high ripple and high overshoot.

(Haithem Chaieb and Anis Sakly, 2018) This paper presents a new MPPT algorithm called simplified accelerated particle swarm optimization (SAPSO), tested under the partial shading condition to extract global peaks from the PV system. This work's characteristic is simple to implement, fast response, and high efficiency. This work does not address the following issues: high ripple, high oscillation, high overshoot, and does not test the system under the European standard EN50530.

(F. Valenciaga, and F.A. Inthamoussou, 2018) This study provides a new MPPT algorithm based on the combination of a second order sliding mode observer (SOSMO) and a traditional PI controller to extract MPP from the PV system, the characteristic of this work is fast-tracking at the rapid change in environmental conditions, good accuracy, and moderate computational burden. However, this study does not address the following issues high ripple, high oscillation, and high overshoot, and does not test the system under the European standard test EN50530.

(Ali M. Eltamaly, and Hassan M.H. Farh, 2019) The MPPT controller is connected to catch the global maximum power point from the PV system. Traditional strategies reach a Maximum point in uniform climatic conditions, but these conventional methods cannot capture MP in rapid change conditions. The Soft computing strategies can capture MP under immediate change conditions but still have oscillation issues. This work proposes a hybrid GWO-FLC to overcome the existing methods. The characteristics of this hybrid can catch MP under rapid change conditions, almost zero oscillation, and high efficiency. However, this work does not address these issues high ripple, high overshoot, high system complexity, and high cost. In addition, the system does not test its performance under the European standard test EN50530.

(Sanjeevikumar Padmanaban et al., 2019) This paper presents a solar PV system connected to the grid to catch MPP. This research proposed a novel modified sine-cosine optimized (MSCO) to reach GP, characterized by a fast convergence rate, accurate tracking, easy implementation, and less computational onus. However, this research does not address several issues regarding high ripple, high oscillation, high overshoot, high system complexity, and high cost. In addition, the system does not test its performance under the European standard test EN50530.

(Yihao Wan et al., 2019) The article proposes a novel MPPT algorithm to track GP for the PV system. The algorithm was created by combining the salp swarm algorithm (SSA) with a grey wolf optimizer (GWO) called SSA-GWO. The advantage of the SSA-GWO method is accurate tracking and fast convergence. This study does not address high ripple, high oscillation, high overshoot, high cost, and increased system complexity. In addition, the system does not test its performance under the European standard test EN50530.

(Deepthi Pilakkat, and S. Kanthalakshmi, 2020) The solar PV system is connected with the grid in two-stage to reduce the size and volume and enhance the system's working efficacy. This work utilizes Artificial Bee Colony integrated Perturb & Observe (ABC-PO) MPPT method to track GP under stander test conditions, partially shaded conditions, and variable load. The merits of this method are high convergence and high efficiency. However, this article does not address several issues regarding high oscillation, high ripple, high overshoot, high cost, and increased system complexity. The system does not test its performance under the European standard test EN50530.

(CH Hussaian Basha, et al., 2020) The main idea is to use a solar PV system to meet the increasing demand for electrical energy in rural zones. The PV system with a highly efficient MPPT controller is connected to a SEPIC converter. This work proposed developing the cuckoo search MPPT method for tracking MP. The advantage of this method is low cost, accurate tracking, and less oscillation. However, this article does not address the issues of high ripple, high overshoot, and increased system complexity. The system does not test its performance under the European standard test EN50530.

(Ai-Qing Tian et al., 2020) The article proposes an MPPT controller to catch the global maximum power point tracking method from the PV systems using a new pigeon population method named parallel and compact pigeon-inspired optimization (PCPIO) under complex environmental conditions. The merits of this work are fast-tracking, high accuracy, high efficiency, and lower oscillation. This work does not address the issues of high ripple, high overshoot, high cost, and increased system complexity, and the PV system is not subject to the European standard test EN50530 to validate its performance.

(Ali M. Eltamaly, 2021) In the solar PV system, connected MPPT controller to tracking MPP. To work the system with high efficiency and accuracy using a novel optimization algorithm called the musical chairs algorithm (MCA) based MPPT controller, its main idea is to enhance exploration and reduce the convergence failure used a large number of search agents at the initial optimization steps as well as to strengthen exploitation the number of search agents reduces gradually until reach final step of optimization operation. The characteristic of the MCA method validates its superiority in terms of high efficiency, less convergence time, less oscillation, and increased stability in various climatic change conditions. However, this article does not address high ripple, high overshoot, high system complexity, and high cost. In addition, the system does not test its performance under the European standard test EN50530.

(Dalila Fares et al., 2021) This work presents a novel MPPT technique based on the improved squirrel search algorithm (ISSA) to capture GMMP under partial shading conditions from the PV system. The merits of this method are high efficiency, less convergence time, and less oscillation. While this paper does not address many issues like high ripple, high overshoot, high cost, and increased system complexity, the PV system does not subject to the European standard tests EN50530 to validate its performance.

(Rambabu Motamarri, et al., 2021) This work presents a modified grey wolf optimization (MGWO) based MPPT algorithm to extract GP for the solar PV system under partial shading conditions. This work's benefits are overcoming the issues of traditional techniques, such as successfully tracking GP under partial shading conditions and high convergence speed and re-initialization of parameters under dynamic conditions. However, this work does not address high ripple, high oscillation, high overshoot, high cost, and increased system complexity. The system does not test its performance under the European standard test EN50530.

(Sajid Sarwar et al., 2022) To operate PV system with high efficiency and fast response as well as to overcome the issues of conventional techniques which failed to track MPP under various climatic conditions. In this paper, a combination of traditional incremental conductance with variable step size and the dragonfly optimization (DFO) algorithms makes a hybrid INC-DFO; the merits of this work are high efficiency, simple structure, fast-tracking response, and less oscillation. This work's disadvantage does not address the following issues: high ripple, high overshoot, high cost, and increased system complexity. In addition, the system does not test its performance under the European standard test EN50530.

(Muhammad Mateen Afzal Awan et al., 2022) The article proposes a novel method to capture MPP for PV systems. This strategy is called an optimized ten-check algorithm (OTCA). The advantages of this method are high efficiency, fast response under various climatic conditions, less oscillation, simple structure, simple computational operations, and less memory required. However, the drawbacks of this method do not address these issues of high ripple, high overshoot, and high cost, and the system does not subject to the European standard test EN50530 to validate its performance.

(Chittaranjan Pradhan, et al., 2022) This work presents an MPPT controller to extract MPP for the PV system under various environmental conditions. This method is called a roach infestation optimization (RIO) algorithm, characterized by high efficiency, fast-tracking, high convergence, and high accuracy. This work's demerits do not address high ripple, high oscillation, high overshoot, and increased system complexity. The system is not subject to the European standard test EN50530 to validate its performance.

The above literature can be summarized in the table below for more details and specific issues.

Table 1. Summary of the previous work.

Reference	**Method**	**Issues Solved**	**Drawback**
(Satyajit Mohanty, et al.,2016)	GWO-PO	limit the search space, increase efficiency, and make the system fast response.	High ripple, high oscillation, system complexity, high overshoot, and not using standard test EN50530.

(Loubna Bouselham, et al.,2017)	combines an artificial neural network controller with a scanning algorithm	High efficiency and fast-tracking GP.	High ripple, high oscillation, high overshoot, high cost, and system complexity, and do not use standard test EN50530.
(Chao Huang et al.,2017)	Jaya algorithm	High efficiency, high convergence.	High ripple, high oscillation, high overshoot, high cost, and the system is highly complex and do not use standard test EN50530.
(Sadeq D. Al-Majidi, et al.,2018)	FL control and the P&O algorithm	The system was subjected to the European standard test EN50530 and showed accurate tracking, lower oscillation, reduced processing time, less complexity, and high efficiency.	High ripple and high overshoot.
(Haithem Chaieb and Anis Sakly, 2018)	Simplified Accelerated Particle Swarm Optimisation (SAPSO)	simple to implement, fast response, and high efficiency.	High ripple, high oscillation, high overshoot, and does not test the system under the European standard test EN50530.

(F. Valenciaga, and F.A. Inthamoussou, 2018)	combination of a Second Order Sliding Mode Observer (SOSMO) and a traditional PI controller	fast-tracking, good accuracy, and moderate computational burden.	High ripple, high oscillation, and high overshoot, and do not use standard test EN50530.
(Ali M. Eltamaly, and Hassan M.H. Farh, 2019)	hybrid GWO-FLC	High efficiency, high tracking speed, zero oscillation, and high efficiency.	High ripple, high overshoot, high system complexity, and high cost. Do not use standard test EN50530.
(Sanjeevikumar Padmanaban et al., 2019)	Modified Sine-Cosine Optimized (MSCO)	fast convergence rate, accurate tracking, easy implementation, and less computational onus.	High ripple, high oscillation, high overshoot, high system complexity, and high cost. Do not use standard test EN50530.
(Yihao Wan et al., 2019)	SSA-GWO	accurate tracking and fast convergence.	High ripple, high oscillation, high overshoot, high cost, and increased system complexity. Furthermore, do not use the standard test EN50530.
(Deepthi Pilakkat, and S. Kanthalakshmi, 2020)	ABC-PO	high convergence and high efficiency.	High oscillation, ripple, overshoot, cost, and increased system complexity do not use standard test EN50530.

(CH Hussaian Basha, et al., 2020)	the Development of the Cuckoo Search algorithm	low cost, accurate tracking, and less oscillation.	High ripple, high overshoot, and increased system complexity; do not use standard test EN50530.
(Ai-Qing Tian et al., 2020)	PCPIO	fast-tracking, high accuracy, high efficiency, and lower oscillation.	High ripple, high overshoot, high cost, and increased system complexity, and do not use standard test EN50530.
(Ali M. Eltamaly, 2021)	musical chairs algorithm (MCA)	high efficiency, less convergence time, less oscillation, and high stability.	High ripple, high overshoot, high system complexity, and high cost, and do not use standard test EN50530.
(Dalila Fares et al., 2021)	improved squirrel search algorithm (ISSA)	high efficiency, less convergence time, and less oscillation.	High ripple, high overshoot, high cost, and increased system complexity, and do not use standard test EN50530.
(Rambabu Motamarri, et al., 2021)	modified grey wolf optimization (MGWO)	fast-tracking GP, high convergence speed, and re-initialization of parameters under dynamic conditions.	High ripple, high oscillation, high overshoot, high cost, and increased system complexity do not use standard test EN50530.

(Sajid Sarwar et al., 2022)	Hybrid INC-DFO	high efficiency, simple structure, fast-tracking response, and less oscillation.	High ripple, high overshoot, high cost, and increased system complexity, and do not use standard test EN50530.
(Muhammad Mateen Afzal Awan et al., 2022)	Optimized ten check algorithm (OTCA)	high efficiency, fast response under various climatic conditions, less oscillation, simple structure, simple computational operations, and less memory required.	High ripple, high overshoot, and high cost; do not use standard test EN50530.
(Chittaranjan Pradhan, et al., 2022)	Roach infestation optimization (RIO) algorithm	high efficiency, fast-tracking, high convergence, and high accuracy.	High ripple, high oscillation, high overshoot, high system complexity, and do not use standard test EN50530.

1.3 Problem Statement

The increasing population growth daily causes an increase in the demand for electric energy. Traditional energy sources such as gas, coal, and fossil fuels cannot meet this increased demand. Conventional energy sources need expensive equipment and want maintenance annually, besides their negative effect on the environment. Renewable energy sources are utilized to address the above issues. The most promising type of sustainable energy source is the solar PV system. To operate a PV system with high efficiency, connect an MPPT controller to catch GP.

Researchers proposed various MPPT techniques, which have different specifications that classify into three types of traditional MPPT strategies as perturb and observe (P&O), incremental conductance (INC), Open-circuit voltage (OCV) strategy, Short-circuit current (SCC) technique, and hill-climbing (HC) *T. Anuradha (2017).*

The most common merits between them are simple, easy to implement, and able to reach GP under uniform climatic conditions, but the demerit under the rapid change conventional techniques unable to recognize MMP, so researchers proposed intelligent strategies are the second type of MPPT methods, such as Fuzzy logic control (FLC), Artificial neural network (ANN), Particle swarm optimization (PSO), ant colony optimization (ACO), Artificial bee colony optimization (ABC), Cuckoo search algorithm (CS), Grey Wolf Optimization (GWO), and Firefly algorithm (FFA). The most common merits between them are fast response, reliability, accuracy, and catching GP under rapid climatic change, but the demerit some strategies have a high cost and are complex to implement. Hence, researchers proposed hybrid methods are the third type of MPPT methods, such as the Hybrid grey wolf optimizer sine cosine algorithm (HGWOSCA), hybrid GWO and FLC algorithm, ABC-P&O algorithm, and ACO-P&O algorithm and another hybrid MPPT methods which are characterized to overcome the demerits of existing methods.

According to the mentioned above in this section, the main problem statement can be summarized as follows:

1. The main issues of traditional MPPTs like P&O and IC have higher ripple depending on fixed step size and initial duty cycle. For this reason, these algorithms cause higher oscillation under the rapid change in weather conditions.
2. Slow tracking under critical weather conditions (due to their process in the suggested fixed step size of the duty cycle to send it to the DC/DC converter, in the case of significant and rapid changes in radiation, try to accumulate the fixed step with the new step, so it takes a long time.
3. Hybrid intelligence MPPT has complexity and a higher time burden during the process and is very difficult to implement in real-time for industrial applications.

This thesis proposes a new hybrid of arithmetic optimization algorithm (AOA) and ANN strategy to solve the above issues. The whole design and simulation of this hybrid are presented in chapter three.

1.4. Thesis Objectives

The main goal of this thesis is to suggest an efficient maximum power point tracking based new metaheuristics optimization algorithm for extracting full power from PV systems and overcoming several issues of traditional MPPT like P&O, IC, OCV, and HC. To investigate this goal, the following points are the objective of this thesis:

1. Design and simulate the PV system based on traditional MPPT algorithms: perturb, observe, and incremental conductance IC algorithm.
2. To overcome the issues of P&O and IC algorithms, the AOA-based MPPT methods are designed and simulated in this thesis.
3. Develop the AOA MPPT based on the ANN algorithm to produce a new hybrid called (AOAANN) for more enhancement and reliable stability of the PV system under rapidly partial conditions.
4. To assess the performance of the proposed MPPT controllers based on hybrid optimizers, MATLAB SIMULINK was used to construct the PV system modeling and control.

1.5. Thesis contributions

In this work, a new hybrid MPPT algorithm-based artificial neural network (ANN) and arithmetic optimization algorithm(AOA) optimizer is proposed to overcome the issues of the traditional algorithm in terms of (oscillation, ripple, reliability, accuracy, and tracking speed under rapidly circumstances conditions).

1.6. Thesis Organization

This thesis is divided into five chapters, the first of which is the introduction. The following chapters include the following details:

Chapter 2: This chapter first presents the theoretical background of the PV system and the control MPPT strategies. The second described the DC-DC converter used with

MPPT to achieve MPP is explained and discussed in this chapter. Finally, intelligent optimizers that are used to enhance the traditional MPPT are presented in this chapter.

Chapter 3: The first section explains the proposed configuration with the demand load calculation to design the PV system sizing. The second section describes the design of the proposed number one with all details. The third section introduces the design of the proposed number two. The final part offers the hardware design with explains the details of each element used in this work.

Chapter 4: In this chapter, the first section presents the simulation requirements. The second section describes the cases of study for the two proposed. The third section introduces the design of the proposed number two. In addition, the following section offers a comparison among proposed MPPT methods. The final part provides a comparison with other related work.

Chapter 5: The final chapter in which the conclusions and future works recommendation to continue this work is proposed.

CHAPTER TWO

THEORETICAL BACKGROUND OF PV SYSTEM AND MPPT STRATEGIES

2.1. Introduction

This chapter presents the background PV system, the mathematical model of the PV cell, and MPPT control strategies. In addition, the DC/DC converter is used with the MPPT technique to investigate the maximum power point. The intelligent optimizers that are used to enhance the traditional MPPT techniques are presented in this chapter. Finally, it provides the most common MPPT techniques and compares them based on their standard features.

2.2. Work of PV Cell

PV cells are constructed from p-type and n-type silicon components. Whereas p-type materials are created by adding elements such as gallium or boron into silicon, boron and gallium have a single electron in their outer energy level. This electron will move to the silicon and create an electron vacancy or "holes." Besides, the n-type silicon material is produced by adding more than four electrons in its outer level, such as phosphorus which has five electrons *R. R. Hernandez (2014).* Therefore, this process will generate a free electron and then produce the PV cell's electrical current, as seen in Fig.2.1 *J. Jewell (2014).*

The PV cell is small, producing a low voltage of about 0.7V per cell. As a result, several cells are connected in series to raise the system's overall voltage and form the PV module. Also, these modules will connect parallel to produce more current and provide the required power to the load, called "arrays." The structure form of the cell, module, and the array is shown in Fig.2.2.

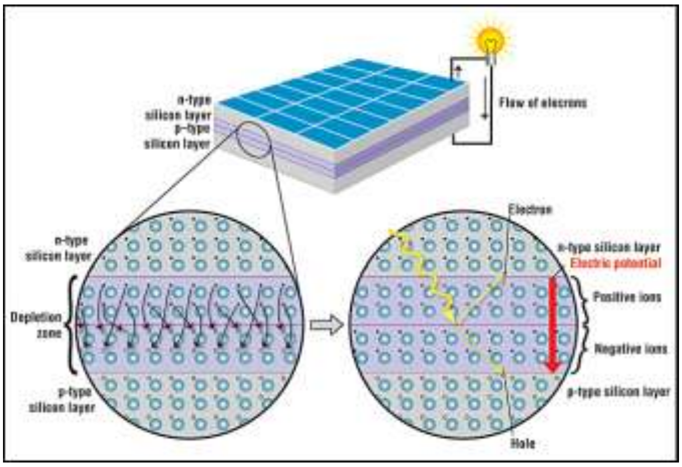


Figure 1. PV cell silicon layers.

Figure 2. PV cell, module, and array structure.

2.3. Mathematical Model of PV Cell

A standard PV module comprises several solar cells coupled in a parallel-series configuration to provide the desired rated voltage and current. The current-voltage characteristic mathematical model is an implicit nonlinear relationship whose complexity is exacerbated by additional parameters in solar cell models that change when environmental conditions change. In this investigation, a single diode-based model of each solar cell was chosen as the best compromise between analytical complexity and predicted accuracy among the many PV system analytical models presented in Figure 2.3 *M. Höök(2013)*. The model is illustrated by the relationships 2.1 to 2.3, which show how the PV array is influenced by solar irradiation and temperature.

$$I = I_{Ph} - I_d \left[\exp\left(\frac{qV}{K_v AT}\right) - 1\right] \tag{2.1}$$

$$I_{ph} = I_r[I_{sc} + K_i(T - T_r)] \tag{2.2}$$

$$I_d = I_o \left[\frac{T}{T_r}\right] \exp\left(\frac{E_g q}{KAQ}\left[\frac{1}{T_r} - \frac{1}{T}\right]\right) \tag{2.3}$$

I = total current (A),

T = solar cell temperature,

q = electron charge,

I_r = solar cell irradiance,

K_v= temperature coefficient of open circuit voltage,

k = Boltzmann's constant,

A = ideality factor,

Io = saturation current at T_r ,

T_r = temperature at reference,

Eg = band gap of the semiconductor material

I_{ph} = current of PV solar cell,

I_{sc} = short-circuit current at reference condition.

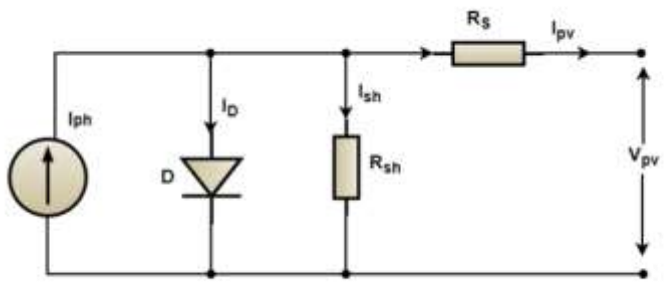


Figure 3. Equivalent circuit of PV cell *M. Höök(2013).*

2.4. Challenges of Photovoltaic Technology

2.4.1. Efficiency of the PV Cell

The output power of a PV cell varies depending on the surrounding weather conditions. When the irradiance increases, the producing power of the PV array increases due to the increasing quantity of photons hitting the electron hole of the cell, resulting in a greater PV output current. In contrast, at a high operating temperature, this decreases because the open-circuit voltage of PV cells reduces as temperature increases. When input irradiation is received during this period, the movement of PV electrons becomes less valence, resulting in a decreased energy loss *I. Yahyaoui(2018).*

2.4.2. Stability of PV System

The stability and reliability of PV power generation can be severely affected when atmospheric conditions are highly variable, especially regarding large-scale PV generation. The fluctuation of PV output power due to passing clouds is considered a major issue for grid-connected PV systems. Control of the flow of energy throughout a hybrid power system to adjust the PV generation for the grid system is essential *R. K. Pachauri (2014).*

2.4.3. Effect of Shading

A PV array has a single maximum power point (MPP) concerning the input solar irradiance and temperature operation under normal circumstances. The array will generate several MPPs when there is shading, which transmission lines may cause, buildings, moving clouds, trees, or dust. Because each PV module generates its MPP, many PV power peaks will be generated simultaneously *M. Pacesila(2016).*

2.4.4. Partial Shading Condition (PSC)

There is one operation point in the characteristic curves in which the maximum power is generated, known as the MPP. The most challenging aspect of managing the MPP is dealing with environmental changes. (PSC) is a phenomenon when the PV cells are partially shaded for various causes, including transmission lines, buildings, moving clouds, and trees. The cell with the lower irradiance value will function as a load and dissipate some power, causing the cell temperature to increase (known as a hotspot). As a result, the cell will be harmed. Furthermore, there is a substantial drop in power production under PSC compared to the uniform irradiance condition. In addition, Any MPPT method will fail to capture MPP points under partial shading conditions. A substantial power loss might occur if the algorithm fails to detect the PSC or discriminates between the local and global peaks *M. Pacesila(2016), F. Manzano-Agugliaro (2014)* .In this thesis, the capacity of the panel is 185w was selected. Figure 2.4 and Figure 2.5 shows the significant power losses caused under PSC.

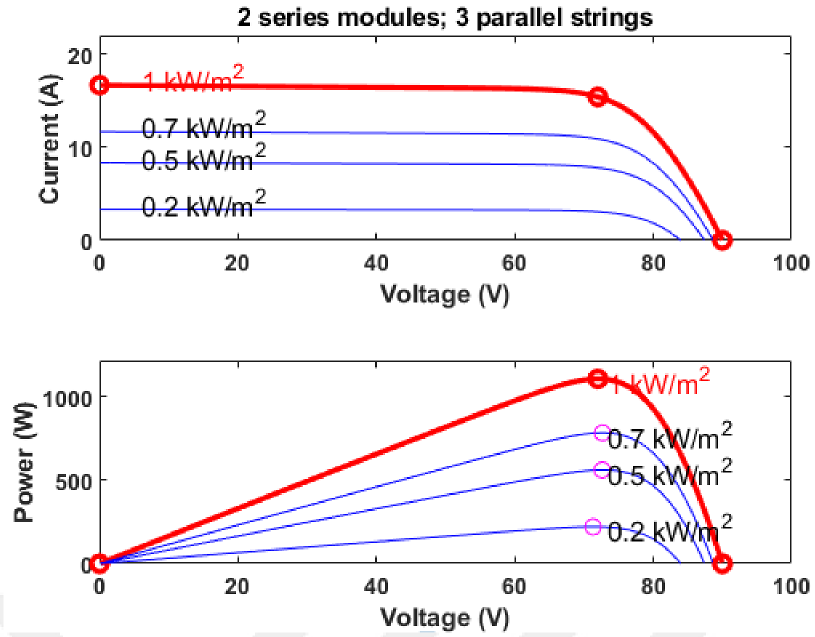


Figure 4. P-V & I-V characteristic curve under variation irradiation &constant temperature

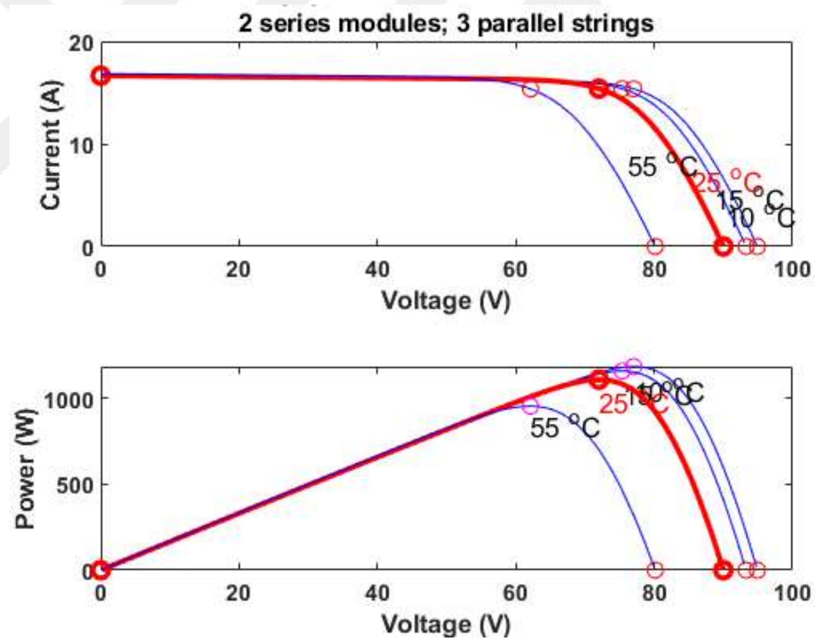


Figure 5. P-V &I-V characteristic curve variation temperature &constant irradiation.

2.5. Bypass Diode and Blocking Diode

Each cell is connected with a bypass diode to prevent current from passing through the shaded cell (an alternative path for current to pass through it). When one cell is shaded, its bypass diode behaves and allows current to flow through it from the rest of the cells, maximizing the system's performance. The bypass diode cannot protect the modules from damage in thin-film CIGS. A bypass switch (MOSFET) is also used to mitigate hot-spotting damage in the PV strings. When the shaded portion of a module exceeds 20%, the power loss is alleviated due to a huge current flowing through the bypass diode. While the blocking diode is connected in series with each string which enables current to flow from a solar panel to the battery but prevents or blocks current from flowing from the battery to the solar panel(It prevents reverse current from returning from another source) *M. Engelken(2016)*. Figure 2.6 shows how to protect cells from hit spots by connected bypass diode &blocking diode.

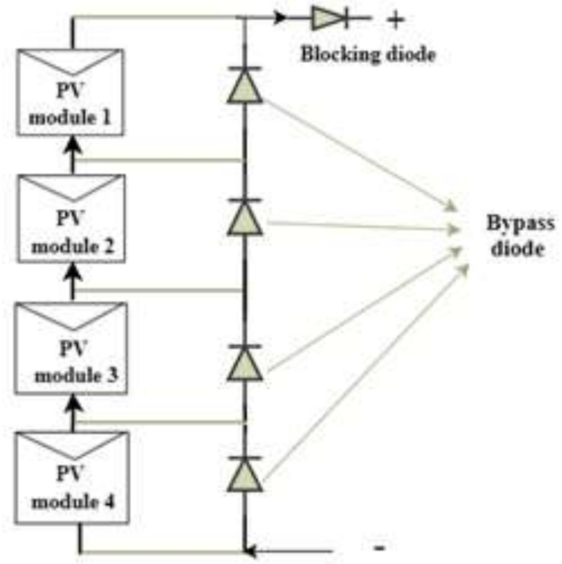


Figure 6. PV array with Bypass diode & blocking diode *M. Engelken(2016).*

2.6. DC/DC Converter

While several DC-DC converters, including boost, buck, and boost-buck converters, have been designed. The boost converter is commonly employed in PV systems due to boosts and regulates the output voltage than the input voltage, thus improving efficiency; in this thesis, the design of the step-up DC/DC converter is presented in chapter three. In the below section, the DC-DC converters are presented.

2.6.1. DC/DC Boost Converter

The boost converter can operate in either continuous conduction mode (CCM) or discontinuous conduction mode (DCM). Depending on the values of the components, the predicted current and voltage flowing through it. Because the duty ratio and other parameters in CCM have a linear connection, it is advantageous to design the boost converter to operate predominantly in this mode *B. Boukezata (2016)*.

The relationship between the PV array's terminal voltage and the duty ratio of the boost converter in CCM is shown in Eq. 2.4:

$$G = \frac{V_{out}}{V_{in}} = \frac{1}{1-D} \tag{2.4}$$

Fig 2.7 illustrates the boost converter, consisting of a single inductor, capacitor, and semiconductor components such as MOSFETs and diodes, PWM signals control the on/off state of switches. The duty cycle D is the ratio of the on-time ton over the switching period t_{sw}And the switching frequency is defined as f_s. According to the equation, a larger output voltage could be obtained by increasing the duty cycle D of the active switch. The diode Reverses bias when switch Q is on, and the inductor L charges the input source. When the switch is turned off, power from the input source and the inductor is transferred to the output load. Due to the immediate voltage, the inductor is represented as an equivalent voltage source, which boosts the output voltage *B. Boukezata (2016).*

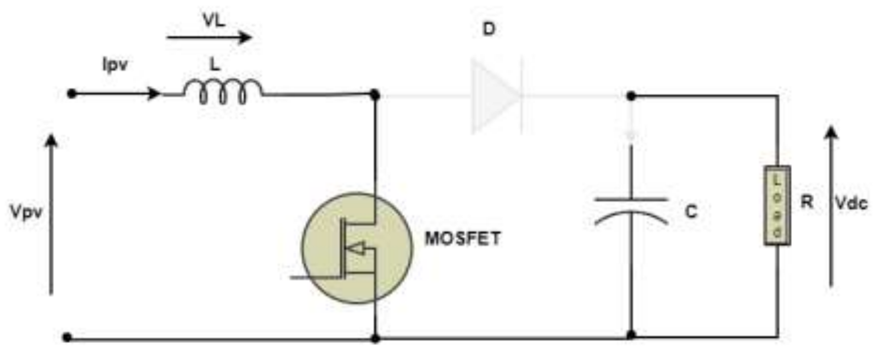


Figure 7. ON-state boost converter.

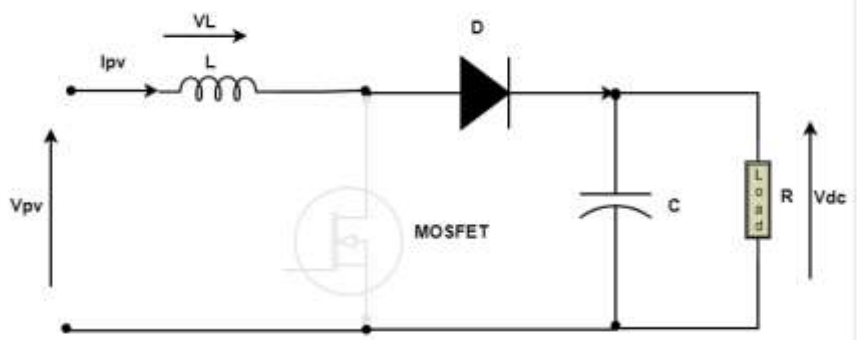


Figure 8. OFF-State Boost DC/DC Converter *B. Boukezata (2016).*

2.6.2. Buck DC/DC Converter

This converter is stepped down, meaning the output voltage is less than the input voltage *Y. Soufi (2017)*. The duty ratio of the buck converter is shown in Eq. 2.5. Figures 2.9 and 2.10 present the ON-State and OFF-state of the buck converter.

$$G = \frac{V_{out}}{V_{in}} = D \tag{2.5}$$

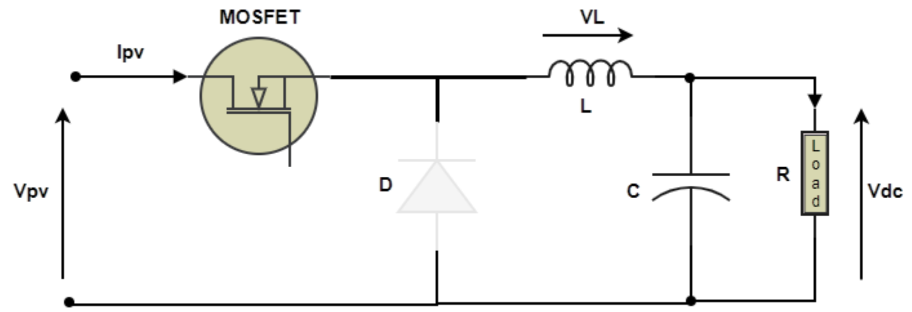


Figure 9. ON-State of the Buck DC/DC Converter.

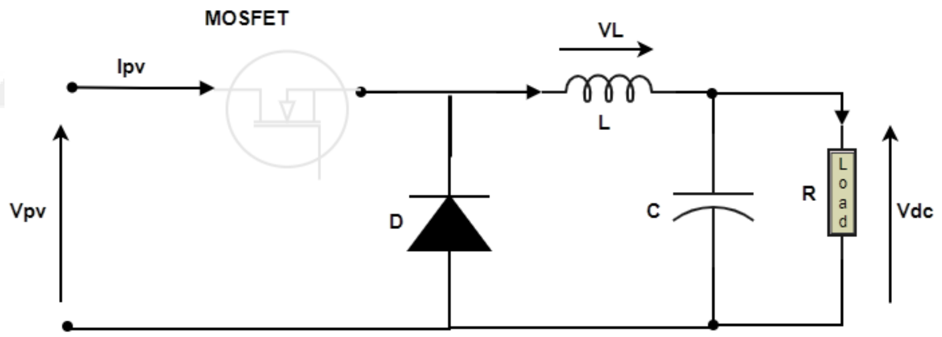


Figure 10. OFF-State of the Buck DC/DC Converter *Y. Soufi (2017).*

2.6.3. Buck-Boost DC/DC Converter

This converter is stepped up and down according to the duty cycle value. The duty ratio of the buck-boost converter is shown in Eq. 2.6. Figures 2.11 and 2.12 present the ON-State and OFF-state of the buck-boost converter *H. Rezk (2017).*

$$G = \frac{V_{out}}{V_{in}} = -\frac{1}{1-D} \tag{2. 6}$$

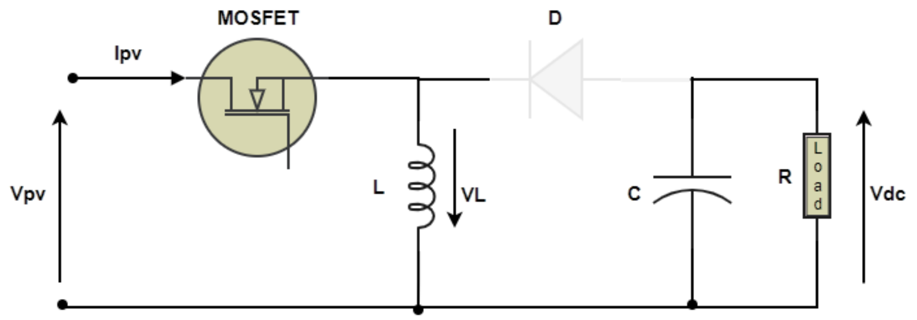


Figure 11. ON-State of the buck-boost DC/DC Converter.

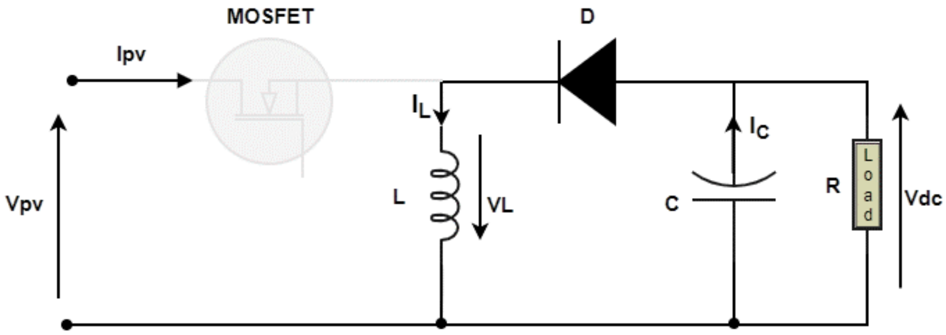


Figure 12. OFF-State of the buck-boost DC/DC Converter *H. Rezk (2017)*.

2.7. Maximum PowerPoint Tracking (MPPT) Strategies

There is one operation point in the characteristic curve in which the max power is generated, known as the MPP. Due to the nonlinear behavior of power generation of PV systems. It is affected by changing climatic conditions and at each change in weather gets power, which should be captured. Therefore, applying the maximum power point tracking methods is necessary to guarantee that the operating point is constantly on or near the maximum power point. The control signal is also applied via the DC-DC, which raises the output to the required level. The maximum power point tracking algorithms compute the ideal duty cycle (D) and deliver it to the converter to increase the power by measuring different parameters (voltage, current, or temperature) *M. Amer (2017), V. Tyagi (2013).*

2.7.1. Traditional MPPT Technique

There are several traditional MPPT methods such as Pilot cell algorithm *I. Yahyaoui (2018)*, Temperature algorithm *A. Gupta (2020)*, Lookup table *S. K.*

Kollimalla(2014), Maximizing loading current or loading voltage *K. A. Aganah(2011),* Perturb & observe(P&O) *F. Liu, S. Duan (2008),*State-Space *F. Liu, Y. Kang (2008)*,but the most public used techniques are:

2.7.1.1. Open Circuit Voltage (OCV) Technique

Depending on solar cell physics and information collected from its datasheet, there is a linear relationship between the $\mathrm{V_{OC}}$ and the max voltage that could be generated from it $\mathrm{V_{MPP}}$ *M. Sarvi (2021).*

$$\mathrm{V_{MPP}} = \mathrm{K_{OC}}\,\mathrm{V_{OC}}\ (\mathrm{K_{OC}} < 1) \tag{2.7}$$

These two voltages' converter parameter is proportionality constant (K_{OC}) This coefficient is empirically determined by continuously calculating voltages under various conditions, and the voltage is chosen as the best voltage at that point. The proportional constant chosen in that weather state is then confirmed by comparing the open-circuit voltage. Nevertheless, the algorithm's simplicity will not be without drawbacks; to measure the voltages in each period and weather condition, there is an interruption in the algorithm's process, which results in energy loss and, depending on the description, it is not very accurate in partial shading *M. Sarvi (2021).*

2.7.1.2. Short Circuit Current (SCC) Technique

Depending on the properties of the solar cell, there is a linear relationship between the short circuit current $\mathrm{I_{sc}}$ Furthermore, the max current that may be derived from it.

$$\mathrm{I_{MPP}} = \mathrm{K_{SC}}\,\mathrm{I_{SC}}\,, \qquad (\mathrm{K_{SC}} < 1) \tag{2.8}$$

K_{SC} is the constant of proportionality, as mentioned in the OCV technique, depending on the kind and design of the PV cell. This strategy is characterized by ease and simplicity of work, but it does not mean it is without defects. The drawback of this algorithm is that when measuring the current in each period and weather condition, there is an interruption in the algorithm's process, which results in energy loss, so it is not very accurate in partial shading *H. A. Sher (2015).*

2.7.1.3. Perturb & Observe(P&O) Technique

This algorithm is the most commonly utilized for tracking the maximum PowerPoint due to its simplicity, ease of Implementation, and investigation of the MPP point under regular operation tests (NOT) and uniform conditions. Still, it fails to track under rapidly changing needs and shows higher ripple, higher oscillation, and slow tracking due to its suggested a fixed step size of duty cycle not being compatible with the rapid changes in the weather conditions. The (P&O) method is an iterative strategy in which the solar PV operating point oscillates about the maximum PowerPoint. Figure 2.13 illustrates that it reaches the MPP when the change in power concerning voltage (dP/dV) is equal to zero and for the region before maximum power point, after maximum power point is positive, negative, respectively. Among the significant issues with P &O is that the exacting time it takes to reach the MPP could not be known, and its fluctuations were constantly around the max point [56]. It is dependent on the variant of power as follows in Eq. 2.9.

$$\left.\begin{array}{l} d_{new} = d_{old} + \emptyset \quad (\text{If P} > P_{old}) \\ d_{new} = d_{old} - \emptyset \quad (\text{If P} < P_{old}) \end{array}\right\} \tag{2.9}$$

$\emptyset$ is a perturbed duty cycle

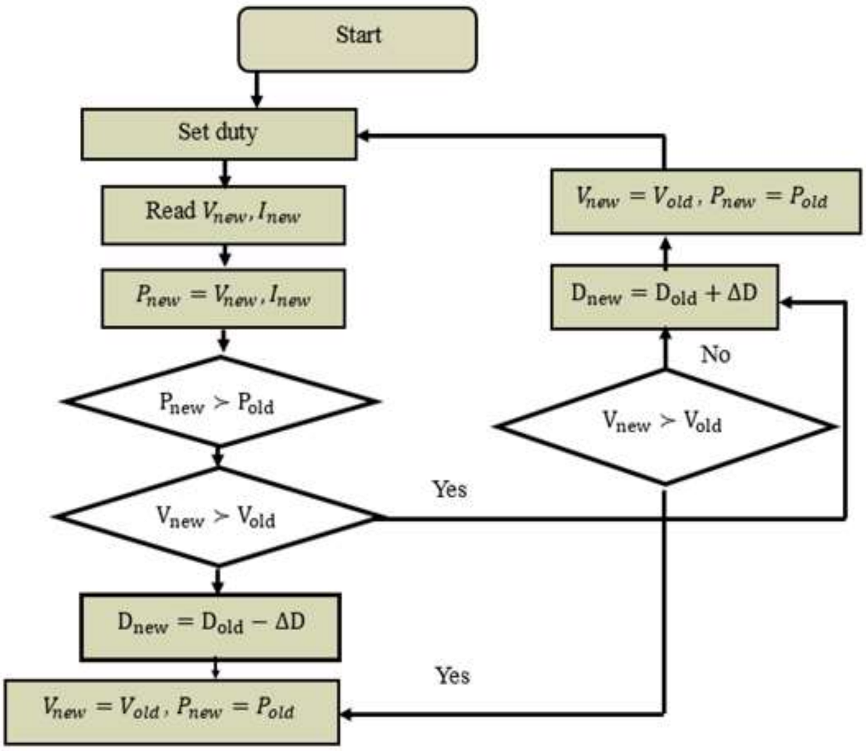


Figure 13. The flowchart of the P&O technique *L. P. Jyothy(2018).*

2.7.1.4. Incremental Conductance (IC) Technique

This technique utilizes the same path as P&O to get to MPP. Still, it uses the (current-voltage curve) relationship, calculates PV cell current and voltage, and measures the change PV current (dI) concerning the change PV voltage (dV). The IC method is based on how the product of the output power, the panel voltage V is equal to zero at the MPP. If the slope of the P-V curve or the derivative of the PV array power (dP=dV) is zero, then the tracking procedure is completed *X. Li, H. Wen (2019)*. MPP tracking will be more difficult under rapidly changing conditions. In certain situations, maintaining the operational point is difficult. Many adaptive step-size approaches are being developed to extract MPP without oscillations.

The mathematical formula for calculating MPP's position on the P-V curve is as follows

$$\left.\begin{aligned} \frac{V_{PV}}{I_{PV}} &= -\frac{\Delta V_{PV}}{\Delta I_{PV}} \text{ at MPP} \\ \frac{V_{PV}}{I_{PV}} &< -\frac{\Delta V_{PV}}{\Delta I_{PV}} \text{ left to MPP} \\ \frac{V_{PV}}{I_{PV}} &> -\frac{\Delta V_{PV}}{\Delta I_{PV}} \text{ right to MPP} \end{aligned}\right\} \qquad (2.10)$$

The essential benefit of the IC approach is its capacity to adapt under varying atmospheric conditions quickly. Moreover, compared to the P&O method, the oscillation around the MPP is far reduced with this methodology, with lower ripple and more complex. Still, when the P&O is adjusted, the effectiveness of these two methods will be similar *X. Li, H. Wen (2019)*. This approach, however, necessitates a complex control circuit. Figure 2.14 shows the flowchart of this technique.

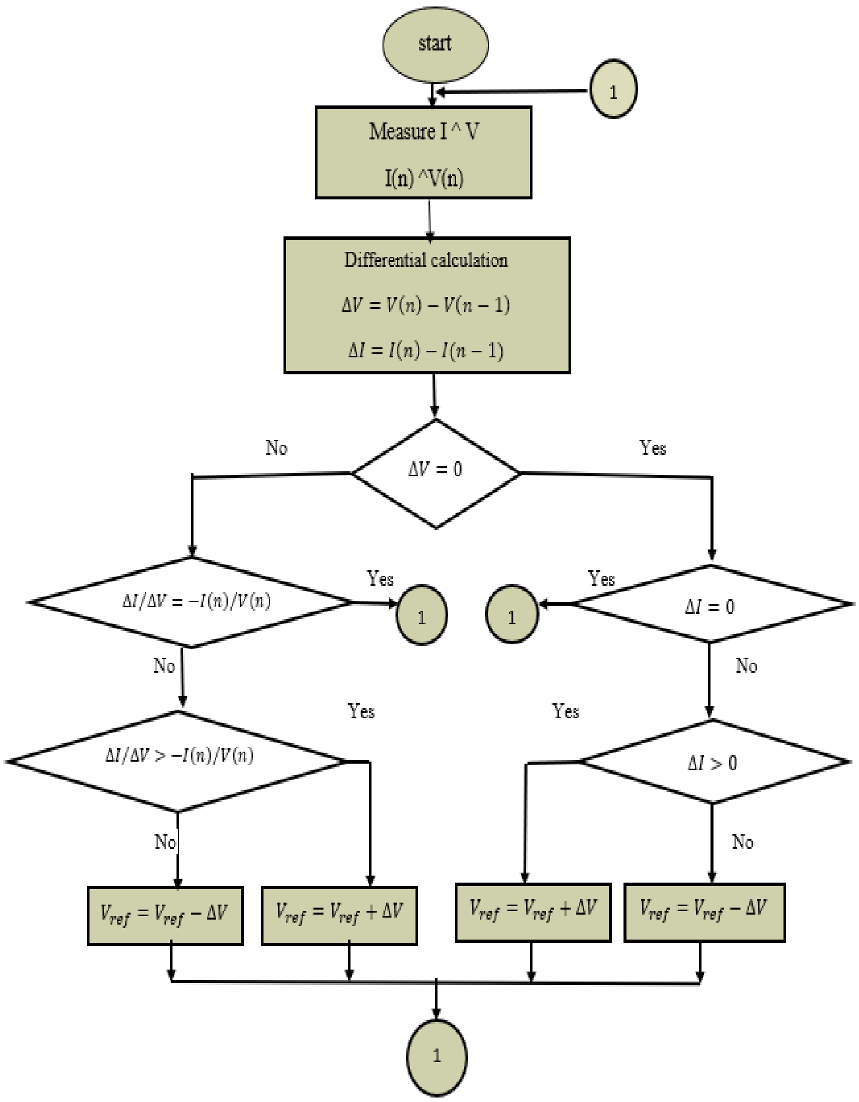


Figure 14. The flowchart of the IC technique *X. Li, H. Wen (2019)*.

2.7.2. Intelligent MPPT Techniques

Because of the dynamic behavior of PV systems and influenced by varying environmental circumstances, which is necessary to employ an adaptable controller that can adapt to change conditions quickly; in this section, artificial intelligence (AI) is presented to solve the issues mentioned above; however, compared to traditional procedures, the disadvantages of these techniques based on computational complexity limit their practical use, for example, ANN-based MPPT approaches require a considerable quantity of data for proper training (various irradiations, temperatures, and partial shade circumstances), making them viable only for large PV panels. In addition, Fuzzy Logic Control (FLC) provides medium computational complexity and is highly efficient compared to ANN. The FLC design necessitates a thorough understanding of PV functioning, and the FLC rule table, if not optimized effectively, can result in extra computations.

These techniques include:

2.7.2.1. Fuzzy logical controlling (FLC) Technique

The FLC-MPPT is one of the most efficient controllers in the photovoltaic system in terms of higher tracking, fast response, convergence time, and lower oscillation around the MPP point as compared with the traditional MPPT method, and it does not require extensive data for training unlike (ANN). ANFIS approaches Because it deals with inaccurate data input. Still, it is suffering fluctuations caused by irradiation and operational temperature variations. As a result, it is more challenging to implement than traditional MPPT techniques. Many proposals have been presented for an adaptive and optimized defined membership function, such as genetic algorithm (GA) and particle swarm optimization (PSO), that avoids the drift problem during changing irradiance. Still, their hardware becomes more complex in Implementation *A. A. Kulaksız and R. Akkaya (2012)*.

The fuzzy logic inference system is illustrated in the diagram below in Figure 2.15.

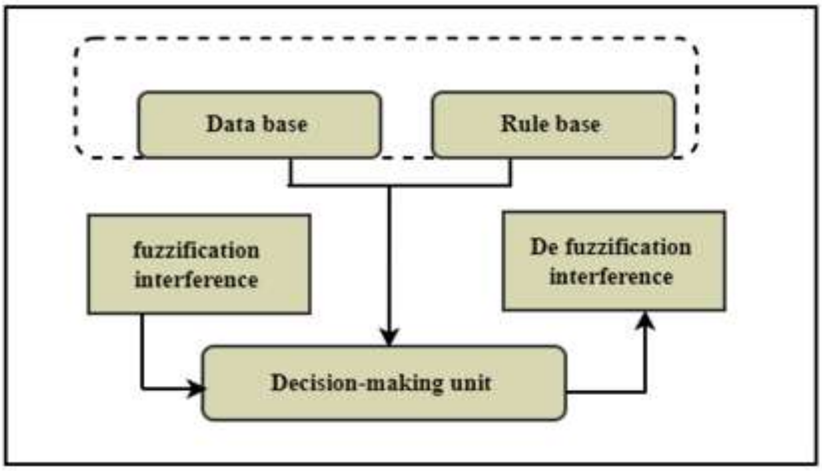


Figure 15. FL inference system circulation chart.

2.7.2.2. Artificial Neural Network (ANN)

ANN is a technique inspired by the brain of humans to solve the issues of large and complex systems, and the structure is made up of three parts; dendrites, cell body, and axon. One of this algorithm's benefits is its capacity to process a large amount of data. Many neurons receive inputs, which are processed depending on the training (weighting) processes, and produce outputs. The ANN approach was utilized to handle the issue of traditional FLC MPPT. It is more accurate for addressing the MPP in quickly changing conditions. However, slow training, complex calculations, storing large amounts of data, and the ANN model's training process are significant system shortcomings *B. Bendib, H. Belmili (2015)*. Figure 2.16 shows ANN MPPT for predicting the PV current based on three inputs.

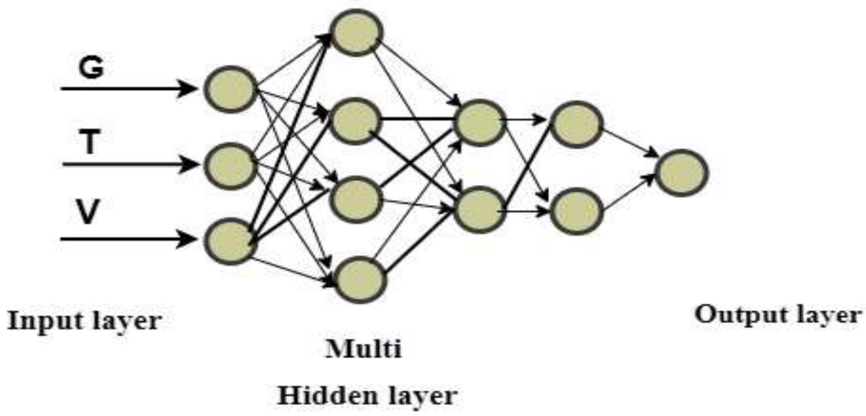


Figure 16. Example of neural network.

To solve these issues, many adjustments have been proposed to enhance the ANN model's performance using many optimization approaches, such as in *S. Yuvarajan (2003), N. Priyadarshi (2019)*. These techniques' methods may be separated into three categories: choosing sufficient training data, determining the optimum structure of an ANN model, and computing the ANN algorithm's parameters. However, this approach has an extensive training error.

2.7.2.3. Particle Swarm Optimization (PSO)

PSO is one of the most used random search techniques. Each particle moves randomly in velocity V at each iteration *C. Hemalatha (2016)*. After computing the number of iterations, all particles travel towards the main object. The working particles exchange information during their search to find the ideal duty cycle (D).

The position (X) and velocity are calculated from the following equations *C. Hemalatha (2016)*:

$$V^{a+1} = wV_i^a + C_1 r_1 (P_{best-i} - X_i^a) + C_2 r_2 (G_{best-i} - X_i^a) \quad (2.11)$$

$$X^{a+1} = X_i^a + V_i^{a+1} \quad (2.12)$$

Where X is a particle position; a is the number of iterations; W is the inertial weight which is updated according to the number of iterations; r_1, r_2 it is random variables; C_1, C_2indicates for acceleration parameters; In the first iteration, P_{best-i} is utilized to save the optimal particle location; Among all the particles, G_{best-i} Represents the best particle location.

2.7.2.4. Neuro-fuzzy models (ANFIS)

The ANFIS method is the most efficient intelligent strategy because it combines fuzzy logic and an artificial neural network. The difficulty of employing a fuzzy inference system is establishing "if-then" rules and optimizing model parameters. As a result, it is used ANFIS to solve the problem of determining undefined inference system parameters. The ANFIS based on the MPPT technique has less oscillation, zero ripples, higher tracking, and more robustness under critical weather conditions. Still, extensive data is required for training and optimizing the tuning of the ANFIS model to achieve higher accuracy compared with the other intelligent strategies. Many articles have been proposed to maximize the rules of the ANFIS model, such as *A. soufyane Benyoucef (2015), R. B. Koad (2016).*

Table 2: Comparisons among the most popular MPPT method strategies

MPPT technique	Implementation	Cost	Tracking speed	Oscillation	Calculating MPP	Efficiency
OCV method	Simple	Less expensive	Fast	Few	Approximate	Low
SCC method	Simple	Less expensive	fast	Few	Approximate	Low
P&O method	Simple	Less expensive	slow	High	Accurate	Low
IC method	Complex	Less expensive	Slow	Medium	Accurate	Low
FLC method	Complex	Expensive	fast	Medium	Accurate	Medium
ANN method	Complex	Expensive	fast	Few	Accurate	High
PSO method	Complex	Expensive	fast	Few	Accurate	High
ANFIS method	Complex	Expensive	Slow	Medium	Accurate	High

There are a lot of intelligent strategies presented in the field of Maximum power point tracking, such as sliding mode controller *J. Ahmed (2014)*, grew wolf optimization (GWO) *S. Mohanty (2015)*, Cuckoo search (CS) *M. N. Ali (2018)*, Ant colony Optimizing (ACO) *A. A. Aldair (2018),* Artificial bee colony (ABC) *C. G. Villegas-Mier (2021)*.

2.8. Summary

This chapter first presents the History of Photovoltaic energy followed by a mathematical model of PV cells using the single-diode model. the main issues facing the PV system and its solution methods have been presented. A brief of most types of DC/DC converters utilized in PV systems has been presented. A general overview of the most famous traditional MPPT strategies is explained and discussed, followed by an overview of the intelligent optimizers used to enhance the traditional MPPT techniques presented in this chapter. Finally, the comparison among them in terms of (tracking speed. Implementation, cost, efficiency, oscillation, and calculating MPP) has been covered. Essentially, MPPT-based AI approaches are more sophisticated, more cost required, and more challenging to implement. Still, they have higher tracking accuracy, higher tracking speed, and less oscillation than traditional MPPT methods.

CHAPTER THREE

DESIGN OF PROPOSED MAXIMUM POWER POINT TRACKING FOR PV SYSTEM

3.1. Introduction

The design of the PV system and DC-DC converter based on demand load calculation is explained in this chapter. The required number of panels that cover the demand load is calculated based on the Aavid solar ASMS-185M panel. In addition, the soft computing MPPT using the arithmetic optimization algorithm (AOA) and artificial neural network (ANN) is presented in this chapter. Finally, to reach fast tracking to the maximum power under shading conditions, the new hybrid based on AOA and ANN is proposed in this chapter which is the contribution of this thesis.

3.2. Demand Load Calculation

A small solar-powered house's electrical load calculation has been completed in this section. To size the various PV power plant components, it is first necessary to determine the daily load demand of the small building that the PV power system will power. Table 3.1 contains the results of the calculation for the demand load. The power capacity is calculated to be 2960 watts.

Table 3. daily consumption of appliances

Appliances	NO. Appliances	Power (W)	Hours (h)	Energy (Wh/day)
Refrigerator/Freezer	1	260	2	520
Desktop Computer	2	200	3	1200
Ceiling Fan	3	70	6	1260
Printer	1	40	1	40
Clothes Washing Machine	1	550	3	1650

Fluorescent Tube	4	40	5	800
Light bulb	4	12	5	240
TV	2	70	3	420
Air Conditioner	2	1100	4	8800
Total per day				14930

In order to cover the demand load and to make a safe design with taking into consideration the losses, the total energy multiplied by 1.25, we get:

$$\text{The total energy (Wh)} = 14930 \times 1.25 = 18662.5wh \tag{3.1}$$

3.3. PV Sizing

The final step consisted of calculating the overall amount of energy that must be consumed each day. This section determines the PV size by considering the sun arc rate and the module's power output choice. The mathematical computations are based on the entire amount of theoretically available daily energy *Mohammed, Rasha A. (2021)*:

$$\text{Total Power} = \frac{\text{Total Load}}{Sun\ Arc\ Rate} = \frac{18662.5\text{Wh}}{6.5\ h} = 2871.154W. \tag{3.2}$$

Power of PV module $= 185W$.

Therefore, the number of PV panels can be calculated as follows:

$$\text{No. of PV modules} = \frac{\text{Total Power}}{\text{Power of PV module}} = \frac{2871.154W}{185W} = 15.52 \approx 16\ pcs \tag{3.3}$$

3.4. Proposed Standalone System Configuration

The proposed configuration comprises four units: PV array, DC/DC boost converters, load, and one of the two proposed MPPT strategies, as depicted in figure 3.1. The PV system consists of 4x4 panels. The total PV panels are equal to 16 Panels according to the demand load calculation. The total output power of the PV system is (2960W) produced from $P = 16 \times 185 = 2960w$, and each PV module has 185W, which includes 72 cells. The specification parameters of the PV module are listed in Table 3.2. The design, mathematical model, and analysis of each unit of the proposed configuration are explained in the sub-section, which are included an introduction to the soft computing techniques called AOA and artificial neural network (ANN), which are used in this study to deal with a wide range of non-uniform conditions. Finally, the complete design of the DC/DC converter is explained.

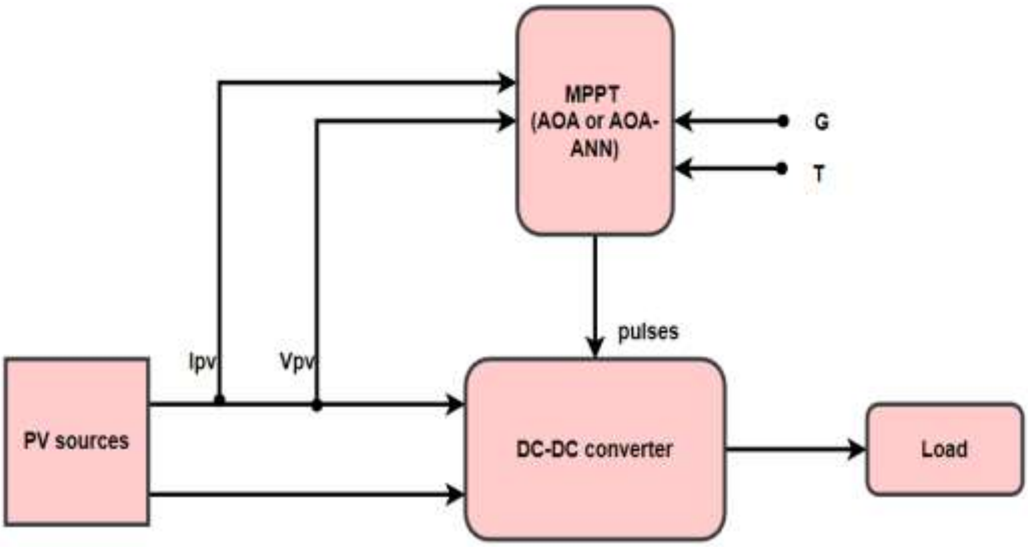


Figure 17. Proposed system configuration.

Table 3. The electrical parameters Aavid solar ASMS-185M PV panel at STC conditions.

Parameter	Value
P_{mp}	$185W$
V_{oc}	$45\ V$
V_{mp}	$36\ V$
I_{sc}	$5.55\ A$
I_{mp}	$5.13\ A$
K_i	$0.038973\ A/K$
K_v	$-0.36486V/K$
N_s	72
R_{sh}	$274.186\ \Omega$
R_s	$0.68311\ \Omega$

3.5. Design of PV Panel using MATLAB/Simulink

The block design of the PV panel is built based on the previous equation in Chapter two based on the schematic in figure 3.2. Figure 3.3 (a) shows the SIMULINK of the PV cell and (b) shows the Simulink block diagram of the photocurrent source model. Figure 3.2(c) presents the Simulink model of the reverse saturation current. In addition, the saturation diode current is presented. The PV panel's inputs are solar irradiance (G) and temperature (T), and its output is PV current.

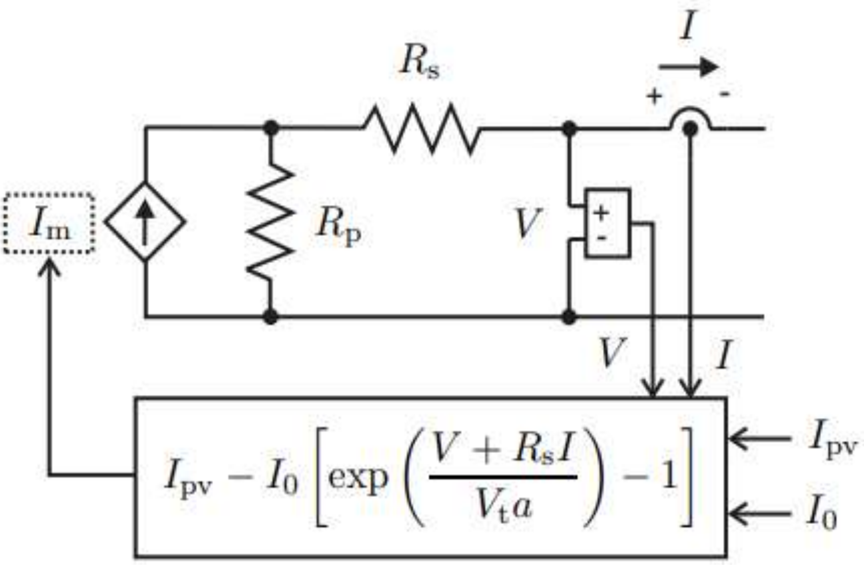
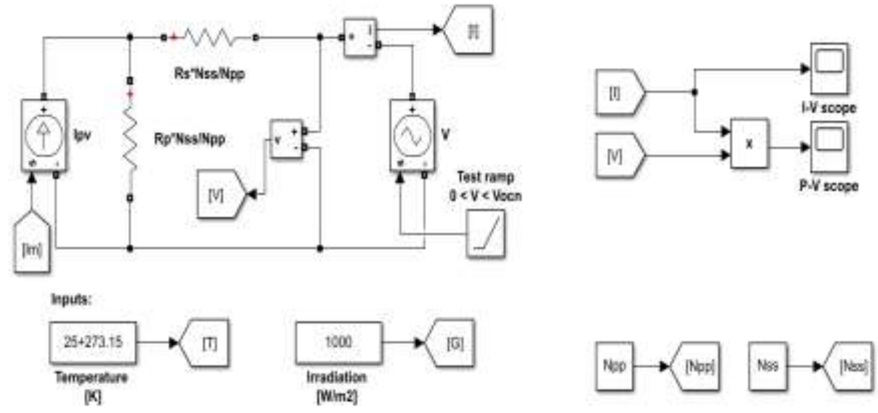
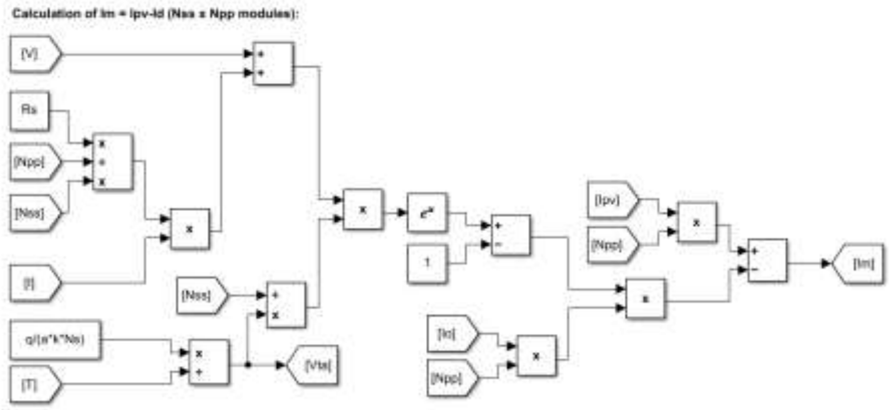


Figure 18. Schematic of the solar cell.



(a)



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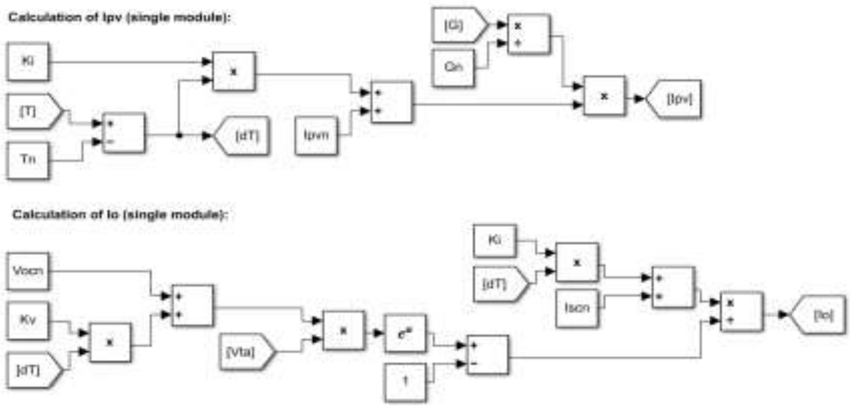


(c)

Figure 19. Model of Photovoltaic circuit using MATLAB/SIMULINK, (a) solar PV cell, (b) Photocurrent model under MATLAB/Simulink, (c) the Simulink model of the diode reverse saturation current, and the Simulink model of the diode saturation.

3.6 DC/DC Boost Converter

In order to boost the output voltage of PV system from 144V to 220V, the boost converter is used in this thesis. The MPPT's purpose is to link the PV module to the output load through a DC/DC boost converter *Masri, S. (2010).* As a result, the matching between the PV module and the load is determined by the load impedance, which is given as follows,

$$Z_{Load} = \frac{V_o}{I_o} \tag{3.4}$$

Were V_o, I_o are the voltage and current at the load side, respectively. Based on this mechanism, the MPP point is achieved when the input impedance equals the output impedance. As a result, the optimal impedance for the PV operation is defined as follows:

$$Z_{opt} = \frac{V_{MPP}}{I_{MPP}} \tag{3.5}$$

Where $V_{MPP.}$ and I_{MPP} are the maximum PV voltage and current values, respectively.

The DC/DC boost converter is commonly employed in PV applications such as MPPT controllers. Figure 3.4 depicts the boost converter's electrical circuit, which includes an inductor, a single diode, semiconductor switches such as a MOSFET or IGBT, and the capacitors at the input and output sides. The waveforms of a boost converter triggered by a PWM signal are shown in Fig.3.5.

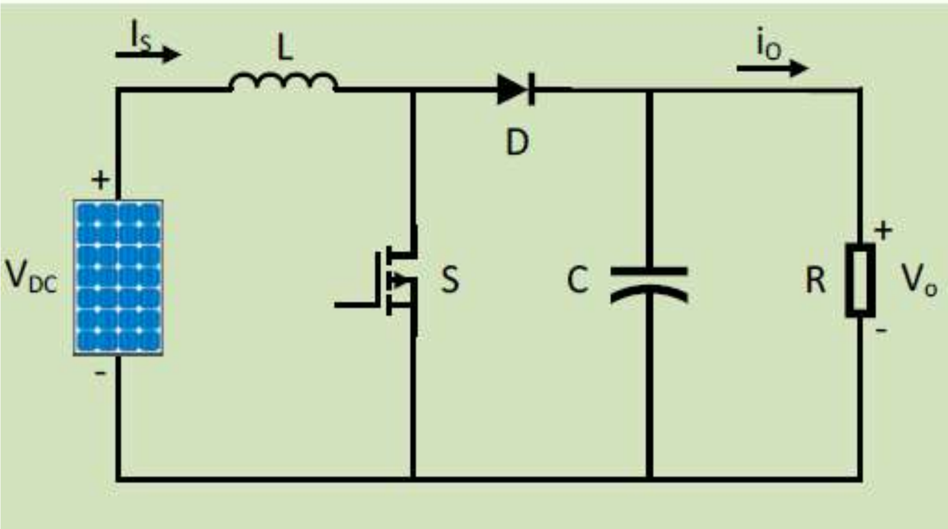


Figure 20. Electrical circuit of the boost converter

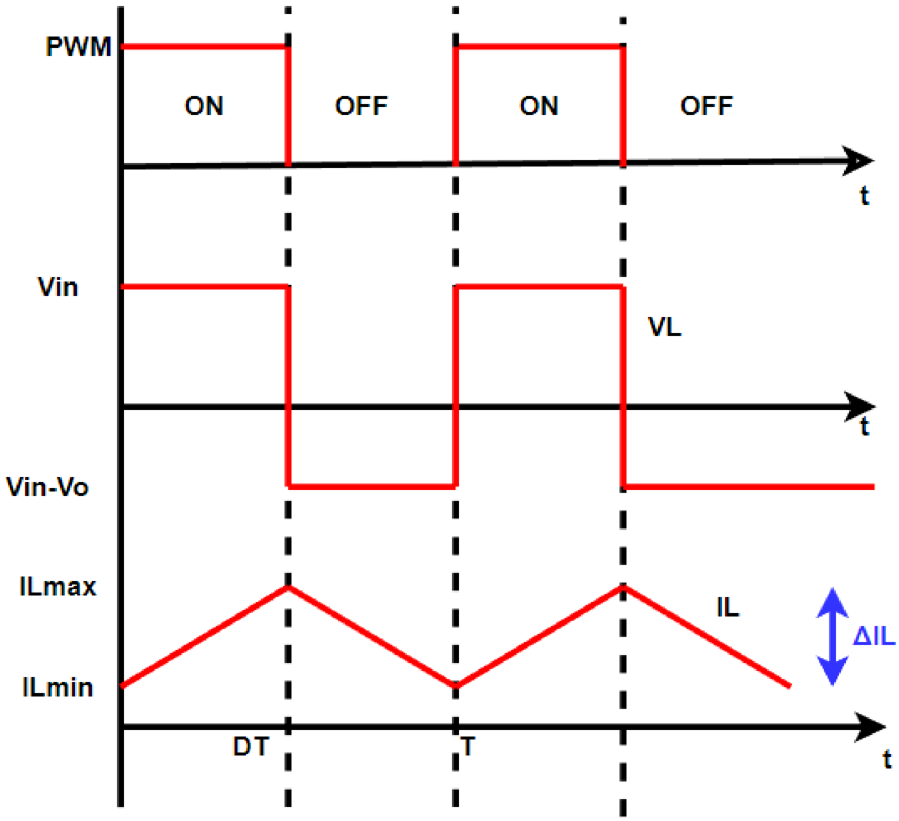


Figure 21. PWM waveforms of boost circuit during CCM mode.

The output voltage for the boost converter is denoted by,

$$V_o = \frac{1}{1-d} V_{in} \tag{3.6}$$

In order to reach a suitable design for the boost converter, the efficiency of the converter is assumed to be 95%, and if it cannot take into account the losses, the $P_o = P_{in}$. The input current can be calculated as follows:

$$I_O = \eta I_{in} \ (1 - d\ ) \tag{3.7}$$

Where $I_{in} = I_L$ and $\eta = \frac{P_o}{P_{in}}$ is the efficiency of the boost converter. The duty cycle can be written based on equation (3.6):

$$d = 1 - \frac{\eta \times V_{in}}{V_o} \tag{3.8}$$

Equation 2.9 should be examined in order to compute the parameters of the boost converter in CCM mode,

$$L = \frac{V_{in}\ d}{f_s\ \Delta I_L} \quad (3.9)$$

Where f_s is the switching frequency, and $\Delta I_L = 0.3 I_L$.

The following equation may be used to calculate the output capacitor:

$$C_O = \frac{I_o\ d}{f_s\ \Delta V_o} \quad (3.10)$$

Where $\Delta V_o = r \times V_O$ and $r = 0.5\%$. As a result, C_o must be greater than the calculated value to ensure that the boost converter's output voltage ripple remains within the specified range. Also, because the input capacitor is critical for decoupling the PV power and reducing harmonics in its voltage, it may be computed using the following equation.

$$C_{in} = \frac{d \times V_{in}}{8 \times {f_s}^2 \times L \times \Delta V_C} \quad (3.11)$$

Where $\Delta V_c = r \times V_{in}$ and $r = 1\%$.

Finally, the circuit parameters of the boost converter are extracted based on Eqs. (3.6 -3.11) for four PV panel, Aavid solar ASMS-185M, that was defined in this chapter. The total number of the panel is equal to 16, divided into 4 panels connected in series and 4 in parallel. The power is 2960W with a PV voltage equal to 144V. The design of each boost converter according to the above given is listed in table 3.3.

Table 4: Simulation parameters of the boost circuit.

Parameters	Value	Unit
L	1800	μH
$\mathbf{C_{out}}$	925.16	μF
$\mathbf{f_s}$	5	kHz
$\mathbf{C_{in}}$	107	μF
$\mathbf{d_{min}}$	0. 3782	-
$\mathbf{d_{max}}$	0.5	

3.7. Artificial Neural Network MPPT Technique

Nowadays, ANN is used in various systems and MPPT algorithms for estimating and controlling. For computations involving nonlinear systems, ANN is a common technique. It is characterized by the characteristics of biological neurons, which include the utilization of weighted connections to transmit information. The training procedure's learning rule determines the input values' weights. Figure 3.6 displays the suggested architecture of the ANN used in this thesis; it consists of two inputs: irradiance and temperature, 10 neurons, and a single output, the predicted voltage of the PV system.

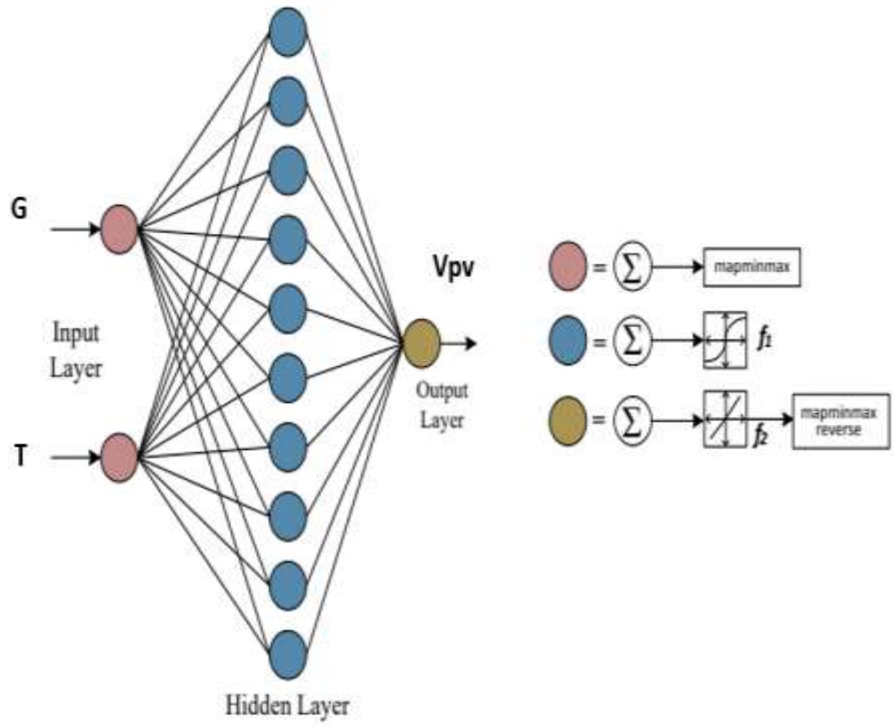


Figure 22. The proposed structure of the ANN MPPT algorithm.

Figure 3.6 demonstrates how the ANN structure uses the mapminmax function to standardize input values. The activation function in the hidden layer was the tansig function, as expressed in Equation 3.15. Using the mapminmax reverse function in Equation 3.16, normalized values are converted back to their original values.

$$\text{mapminmax} = \frac{(x-x_{min})(x_{max}-x_{min})}{(y_{max}-y_{min})} + y_{min} \tag{3.15}$$

$$tansig = \frac{2}{1+e^{-2x}} - 1 \tag{3.16}$$

$$\text{mapminmax\_rever} = \frac{(x-y_{min})(x_{max}-x_{min})}{(y_{max}-y_{min})} + x_{min} \tag{3.17}$$

Where x is, the input signal and y is the output signal, either maximum or minimum. To obtain the output neuron, we multiply each input signal by the corresponding connection weights, as shown in Equation 18.

$$\mathrm{y_j} = \mathrm{f}\left(\sum w_{ij}x_i + b\right) \tag{3.18}$$

Where xi is the input signal, b is the deviation value, w_{ij} is the connection weight, f is the activation function, and y_j is the output neuron. Equation 3.19 shows the sum of the deviation between the expected and actual output values *ÇELİKEL, Reşat (2020)*.

$$E = \frac{1}{2}\sum j\left(y_{dj} - y_j\right)^2 \tag{3.19}$$

Where y_{dj} Refers to the intended output value; the MATLAB/Simulink environment was used to collect the necessary data for ANN training in this investigation. The number of data retrieved for each input was 25, and 10 were put through their paces in a testing environment, leaving 15 for actual training. These include Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR), all of which were employed as training techniques. Mean square error (MSE) and regression coefficient (R^2) was used to evaluate the performance of the ANN. Formulas 3.20 and 3.21 detailed these performance standards *ÇELİKEL, Reşat (2020)*.

$$MSE = \frac{\sum_{i=1}^{n}\left(y_{p,i}-y_i\right)^2}{n} \tag{3.20}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{p,i}-y_i\right)^2}{\sum_{i=1}^{n}\left(y_{m,i}\right)^2} \tag{3.21}$$

Where n is the number of samples, y_p is the predicted value, y_m is the actual value, and y_i is the value of the data randomly selected for analysis. Using the

Levenberg-Marquardt algorithm yielded the best outcomes. The results showed an MSE of 0.22781 and an R^2 of 0.9993.

Figure 3.7 depicts the view of the structure of ANN. The best training for the proposed ANN MPPT is demonstrated in figure 3.8. at the same time, the training parameter for evaluated performances is depicted in figure 3.8. The combining Simulink part is shown in figure 3.9.

Finally, based on the fractional PI controller, the proposed ANN used to regulate the boost by the duty cycle to reach the maximum power from the PV system minimizes the discrepancy between the estimated and measured PV voltages.

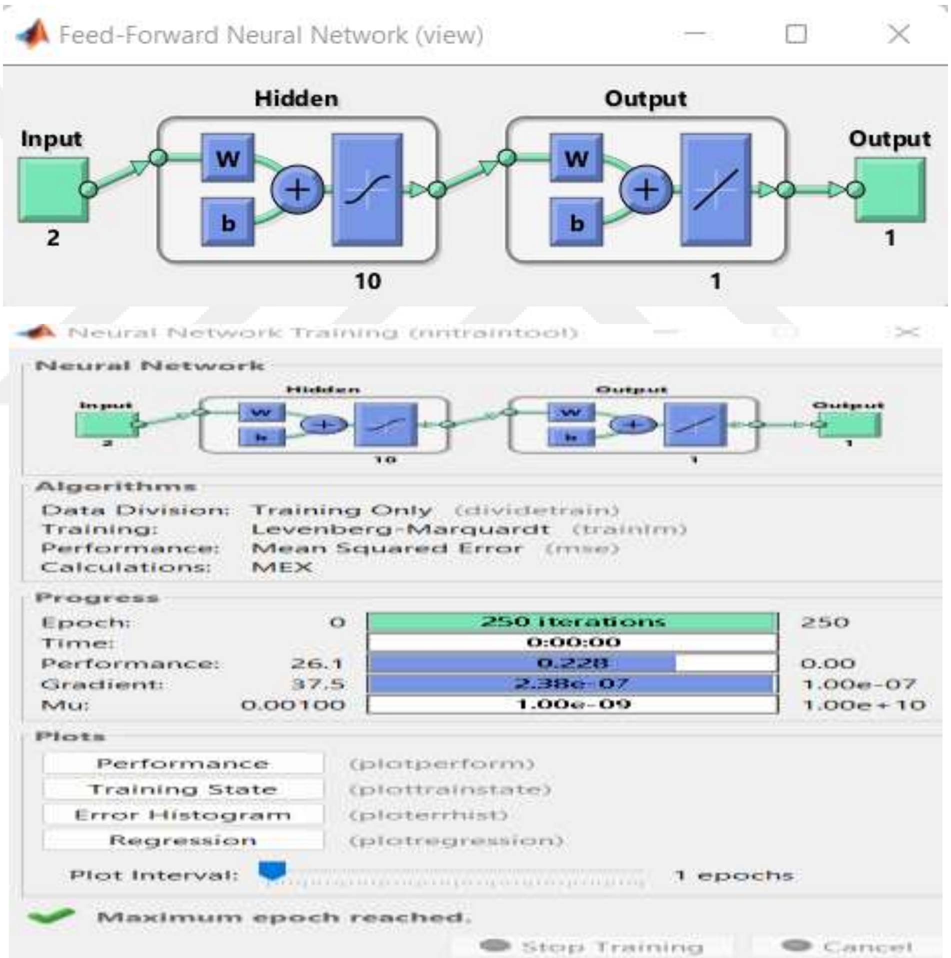


Figure 23. View of ANN MPPT.

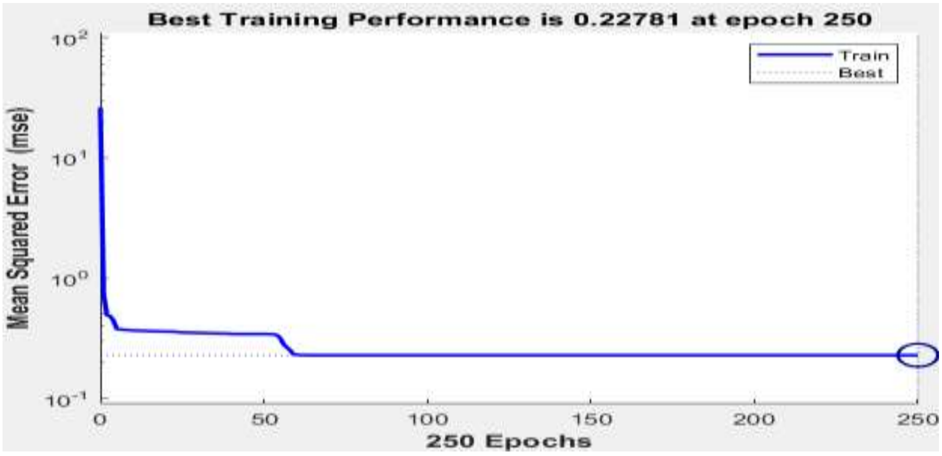
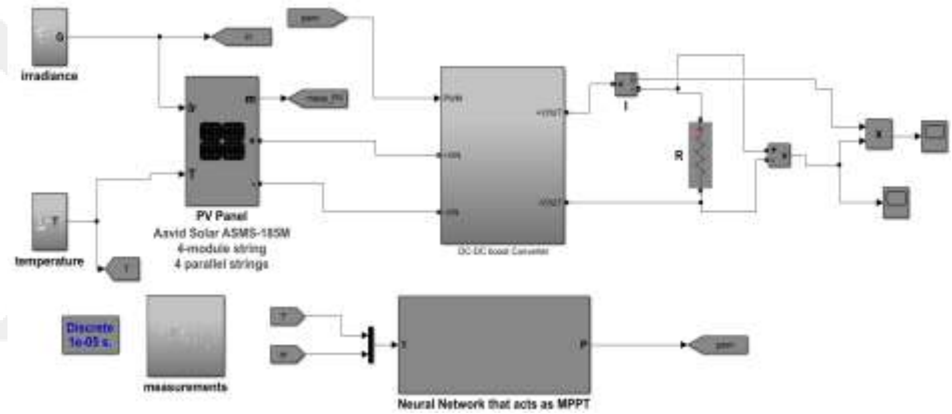
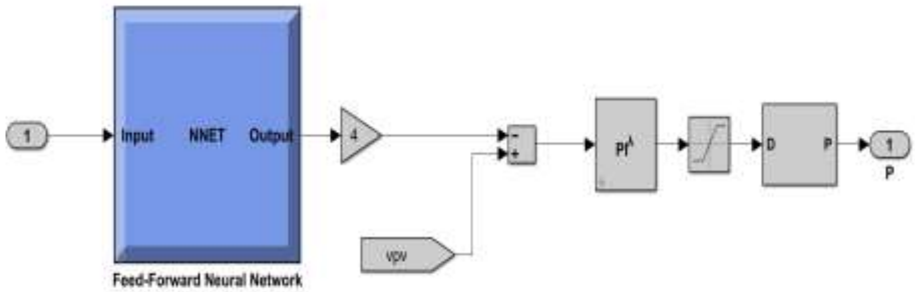


Figure 24. Shows the validation of 250 epochs, with the best fit occurring at epoch 250, which is 0. 22781.



(a)

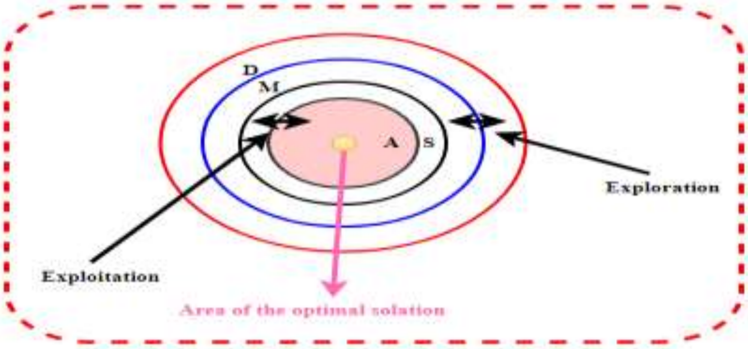


(b)

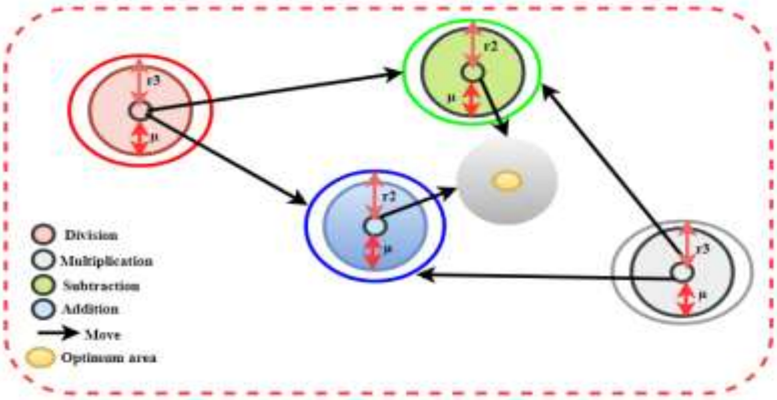
Figure 25. PV Simulink system based ANN MPPT (a) overall system, (b) proposed ANN MPPT.

3.8. Arithmetic Optimization Algorithm

The essential parts of numerical theory and one of the primary aspects of contemporary mathematics are geometry, algebra, and analysis. The core mathematical measurements for data analysis are arithmetic operators (Multiplication, Division, Subtraction, and Addition). The arithmetic optimization algorithm (AOA) *Abualigah, Laith (2020)* is a newly created optimization approach based on the proven rules of arithmetic operations. Exploration and exploitation are the two steps of the AOA optimization process. In order to solve Arithmetic issues, the proposed Arithmetic Optimization Algorithm (AOA) draws its inspiration from the employment of Arithmetic operators in the first place. The behaviour of arithmetic operators (multiplication, division, subtraction, and addition) and their effect on the proposed technique will be examined in further detail in the subsequent subsections of this section. Illustration of the hierarchy of Arithmetic operators and their dominance from the outside to the inside, as seen in Figure 3.10 *Abualigah, Laith (2020).*



(a)



(b)

Figure 26. (a) Hierarchy of Arithmetic operators, (b) Mathematical model AOA operators to the optimal location.

A. Initialization phase

According to Eq. (3.22), AOA's optimization process begins with a random set of candidate solutions (x). The candidate solution that performs best in each iteration is deemed the best or near optimum solution.

$$X = \begin{bmatrix} x_{1,1} & \cdots & \cdots & x_{1,j} & & x_{1,n-1} & \cdots & x_{1,n} \\ x_{2,1} & & & x_{2,j} & \cdots & \vdots & & x_{2,n} \\ \cdots & \cdots & \cdots & \cdots & & \cdots & \cdots & \cdots \\ \vdots & \cdot\cdot & \cdots & \vdots & & \vdots & \cdots & \vdots \\ \vdots & & & \vdots & & \vdots & & \vdots \\ x_{N-1,1} & \cdots & \cdots & x_{N-1,j} & & \cdots & & x_{N-1,n} \\ x_{N,1} & & & x_{N,j} & & x_{N,n-1} & \cdots & x_{N,n} \end{bmatrix} \tag{3.22}$$

The AOA should choose the search phase before beginning its job (i.e., exploration or exploitation). As a result, the Math Optimizer Accelerated (M O A) function is a coefficient derived using Eq. (3.23) applied in the subsequent search phrases.

$$M\ O\ A(C\_Iter) = Min + C\_Iter \times \left(\frac{Max - Min}{M\_Iter}\right) \tag{3.23}$$

$M\ O\ A(C_Iter)$Denotes the function value at the t^{th} iteration, as determined by Eq (3.23). C_Iter is the current iteration, which is between 1 and the maximum number of iterations, denoted by (M_Iter). Min and Max denote the accelerated function's lowest and maximum values.

B. Exploration phase

This section discusses the inquiring nature of the AOA. According to the Arithmetic operators, mathematical processes involving Division (D) or even Multiplication (M) produced values or judgments that were excessively distributed. AOA exploration operators hunt for better answers using two primary search techniques (the Division (D) search strategy and the Multiplication search strategy), which they choose randomly from a pool of possibilities. This phase of searching (exploration search by running D or M, as seen in Fig. 3.10(a)) is constrained by the constraint of r1 > MOA, which is met by the Math Optimizer accelerated (MOA) function (see Eq. (3.23)). (r1 is a random integer). As seen in Fig. 3.10(b), the operators being utilized converge in the vicinity of the ideal region. When the first operator (D) completes its current task (as determined by the first rule in Eq. (3.23)), the other operator (M) is neglected until the first operator (D) completes its next job. If this occurs, the second operator (M) will be assigned to complete the present assignment in place of the first operator (D). (r2 is an entirely arbitrary number.) When looking at the element, it is essential to consider the stochastic scaling coefficient to develop additional diversification courses and research other parts of the search space. To imitate the behaviour of Arithmetic operators, the most straightforward rule was utilized to simulate their behaviour. This section contains the location updating equations for the exploratory components that are as follows:

$$x_{i,j}(C_{Iter}+1)=\begin{cases} best(x_j)\div(M\ O\ P+\epsilon)\times\left((UB_j-LB_j)\times\mu+LB_j\right), r_2<0.5 \\ best(x_j)\times M\ O\ P\times\left((UB_j-LB_j)\times\mu+LB_j\right), otherwise \end{cases} \tag{3.23}$$

where $x_{i,j}(C_{Iter}+1)$refers to the ith solution in the next iteration, $x_{i,j}(C_{Iter})$refers to the jth position of the ith solution in the current iteration, and $best(x_j)$refers to the jth place in the best-obtained solution thus far. UB_j and LB_j Signify the upper and lower bound values of the jth positions, respectively. ϵ is a tiny integer number according to the tests in this study, μ is a control parameter for adjusting the search process, which is set at 0.5.

$$M\ O\ P(C\_Iter)=1-\frac{C\_Iter^{1/\alpha}}{M\_Iter^{1/\alpha}} \tag{3.24}$$

where $M\ O\ P(C\_Iter)$ This means the function value at the tth iteration, C_Iter denotes the current iteration, and (M_Iter) signifies the maximum number of iterations, and $M\ O\ P(C\_Iter)$ Denotes the function value at the tth iteration. According to the studies in this study, it is a crucial parameter that defines the exploitation accuracy across iterations and is set at 5 *Abualigah, Laith (2020).*

C. Exploitation phase

The AOA exploitation strategy is explained to round out the concept of this algorithm. According to the Arithmetic operators, mathematical calculations using Subtraction (S) or Addition (A) yielded high-density outputs. Due to their low dispersion, these operators (S and A) may reach the target more rapidly than other operators.

For this phase of searching, the MOA function value for the condition of r1 is not greater than the current $M\ O\ A(C\_Iter)$ Value (see Eq. (3.22)) is conditioned (exploitation search by executing S or A). The AOA exploitation operators (Subtraction (S) and Addition (A)) thoroughly study the search region in different dense areas and try to find a better solution using two primary search techniques (Subtraction (S) and Addition (A)) as shown in Eq (3.25).

$$x_{i,j}(C_{Iter}+1)=\begin{cases}\mathrm{best}(x_j)-M\ O\ P\times\left((UB_j-LB_j)\times\mu+LB_j\right), r_3<0.5\\ \mathrm{best}(x_j)+M\ O\ P\times\left((UB_j-LB_j)\times\mu+LB_j\right), \text{otherwise}\end{cases} \quad (3.25)$$

This phase takes advantage of the search space by doing a deep search. The first operator (S) is conditioned by $r_3 < 0.5$in this phase (the first rule in Eq. (3.25), while the other operator (A) is ignored until the present work of this operator is completed, and the other operator (B) is respected. If this occurs, the second operator (A) will be used to complete the current operation instead of the S to complete the current operation. The same processes for partitioning used in the previous phase are used. On the other hand, exploitation search operators (S and A) make every effort to remain as far away from the local search area as possible. In order to select the best response while keeping the number of candidate answers as low as feasible, this strategy works in conjunction with exploratory search strategies. Our settings were carefully chosen to generate a different random result at each iteration, allowing discovery to continue not only during the initial iteration but also throughout the subsequent iterations and beyond. This search component is advantageous in local optima stagnation, especially in the last rounds of the search process.

Figure 3.11 illustrates how a search solution changes its variables (positions) in a two-dimensional search space in response to the variables D, M, S, and A. Because of this, it is possible that the final location reached will fall within a stochastic range given by the locations of the letters D, M, S, and A in the search scope. Among the ideas, D, M, S, and A are responsible for estimating the location of the near-optimal solution, while other solutions change their locations stochastically around the area of the near-optimal solution.

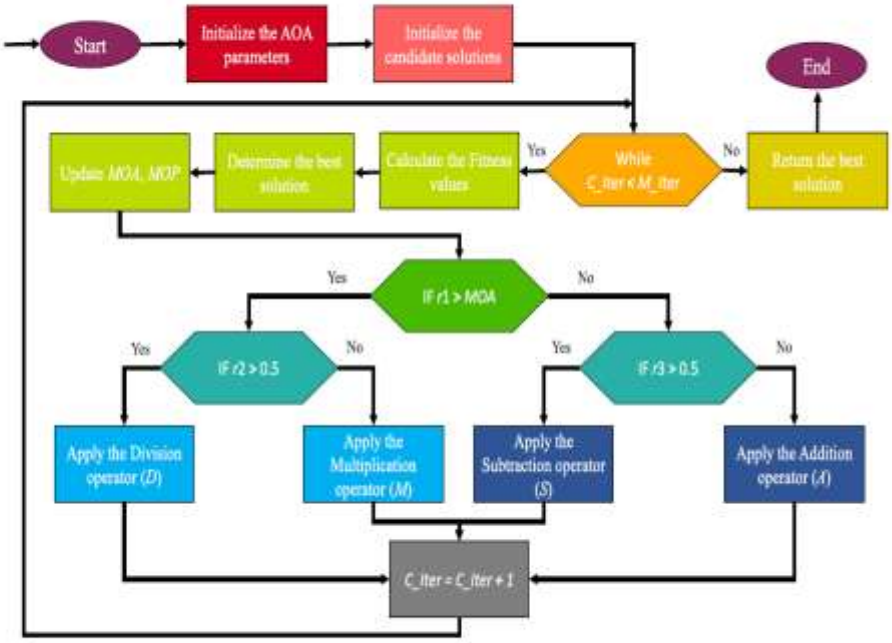


Figure 27. The flowchart of AOA to demonstrate the process of reaching the best solution.

3.9. Design of Proposed MPPT Based on AOA Algorithm

This work combines Incremental Conductance (IC) MPPT algorithm-based grey wolf optimizer. This section discusses a metaheuristic method of Modified IC MPPT algorithm-based arithmetic optimization algorithm (AOA) controller that is used to propose a suitable duty cycle for the switch of DC-DC converter under rapid change conditions, as well as to overcome the demerit of the IC method under non-uniform irradiation such as fluctuating around MPP and address the issue of fixed step size. This work of a modified IC MPPT algorithm-based AOA controller is done by developing and modifying the traditional IC-based AOA and teak the simplicity of IC considered by its condition ($\frac{I}{v} + \frac{dI}{dv} = 0$) and make it a fitness function for the AOA algorithm and adders the issue of fixed step size of IC employed the AOA method to propose ΔDaccording to equation (3.26).

The position of the AOA acts as the duty ratio so that when the updated position represents the suitable duty cycle achieved by the algorithm as in the equation below:

$$D_{i+1} = D_i \pm \Delta D \tag{3.26}$$

Where D_{i+1} acts the new duty cycle; ΔD represents the position that gives accurate duty in each iteration; D_iIt acts as the duty cycle at each iteration.

The fitness function used with all proposed MPPTs, which turns to adjust the parameters of the FOPI controller, is Integral Time Absolute Error (ITAE). The ITAE can be expressed by equation (3.27):

$$j_{min} = \int_0^t t \times \left(\left| 0 - \frac{\mathrm{i_{PV}}}{\mathrm{v_{PV}}} + \frac{\mathrm{di_{PV}}}{\mathrm{dv_{PV}}} \right| \right) dt \quad (3.27)$$

Where $j_{min} is\ the\ minimum\ fitness$ and t is the simulation error.

The proposed AOA for each boost converter connected with the inverter based on the droop control strategy is depicted in figure 3.12.

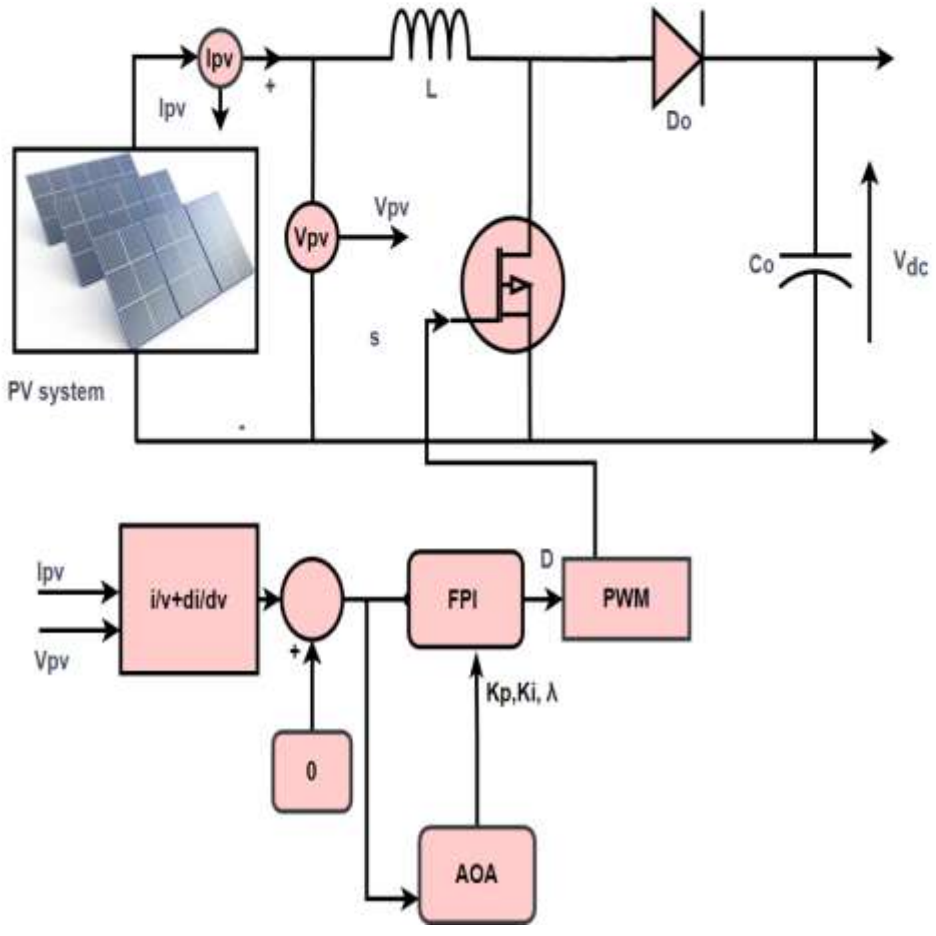


Figure 28. Proposed MPPT based on AOA strategy.

The merits of this hybrid are fast response, lower ripple, zero oscillation, ease of implementation, and higher efficiency of more than 99.55%, according to the equation:

$$\eta_{mppt} = \frac{\int_0^{tm} p_{dc}(t).\,dt}{\int_0^{tm} p_{\mathrm{PV}}(t).dt} \quad (3.28)$$

3.10. Proposed MPPT Based on Hybrid AOA with ANN Strategy

In this section, the hybrid MPPT is presented. The hybrid MPPT depends on the weather conditions such as temperature and irradiance and the temperature in addition to the PV voltage of the output PV system, as depicted in figure 3.13.

It can be observed from figure 3.13 that the ANN is employed to predict the PV voltage based on weather conditions, and the output of the ANN is the PV voltage compared with the measured PV voltage. The comparison output is entered into the fractional PI controller to suggest a suitable duty cycle for the DC-DC converter. In order to reach the optimal performance of this hybrid, the AOA is used to adjust the FPI parameters based on the finiteness equation presented in equation (3.27). The simulation results present the optimized parameters of FPI controllers in chapter four.

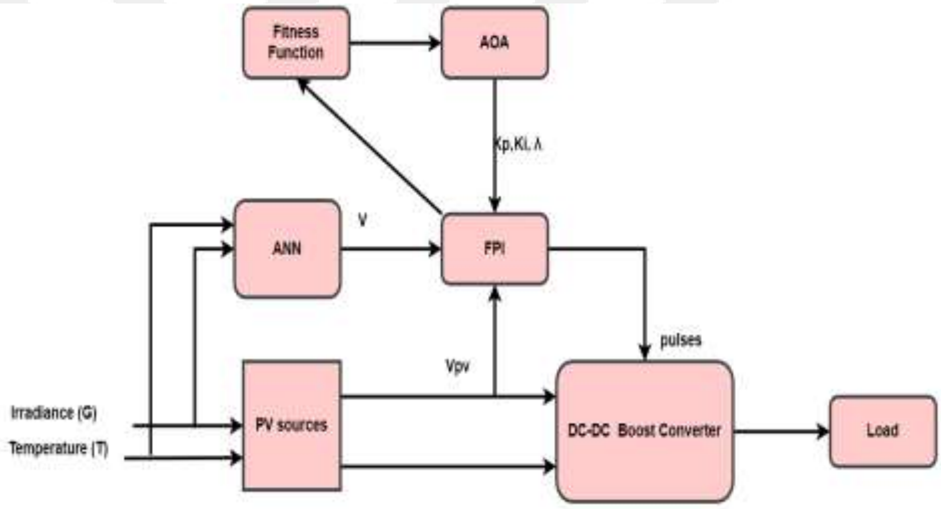


Figure 29. Proposes a hybrid MPPT based on AOA and ANN.

3.11. Summary

The PV module's overall power was initially designed based on load consumption. Following the introduction of the boost DC/DC converter design, the two proposed designs based on MPPT have been thoroughly explained and discussed. MATLAB/Simulink R2021 is used to verify the presented methods for a solar system's MPPT. In chapter four, the simulation results are mentioned. The robustness and steady-state power tracking effectiveness of the proposed hybrid ANN with the AOA-based MPPT control method set it apart from competing systems.

CHAPTER FOUR

ANALYSIS AND DISCUSSION OF SIMULATION RESULTS

4.1. Introduction

This chapter discusses the outcomes of proposed optimization MPPTs: predictive artificial neural network(ANN) and arithmetic optimization algorithm (AOA) and hybrid AOA-ANN-based principle of MPPT algorithm. In addition, these MPPT compares them to show the effectiveness and suitability of PV systems under various critical weather conditions. This chapter offers a Matlab Simulink of the proposed MPPT and an examination of the influence of irradiance and temperature.

4.2. The Influence of Irradiance and Temperature on PV Properties

In order to validate the robustness and ensure the system has high performance, test the system with a standard test condition which means both irradiation and temperature are uniform. The irradiation G=1000 W/m^2 and the temperature T= 25 ℃ at time $t = 1.5$ sec.

From the current-time curve, as indicated in figure (4.1), the overshoot of the IC strategy is very high compared to the AOA, ANN and AOA-ANN methods. The voltage-time curve, as depicted in figure (4.2) shows that the IC is a high ripple and oscillation while the AOA-ANN method has less ripple and zero oscillation, so these merits make the PV system more stable.

The power-time curve shows that the IC is a higher steady-state error and low response than the AOA, ANN and AOA-ANN techniques, as shown in figure (4.3). The predictive voltage based on ANN under uniform conditions shows the AOA-ANN captures maximum power point faster than the ANN method, as in figure (4.4).

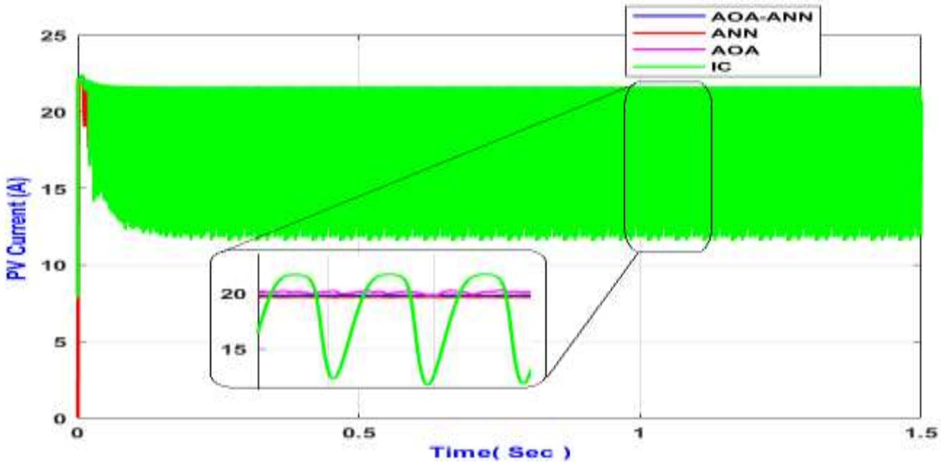


Figure 30. PV current under STC.

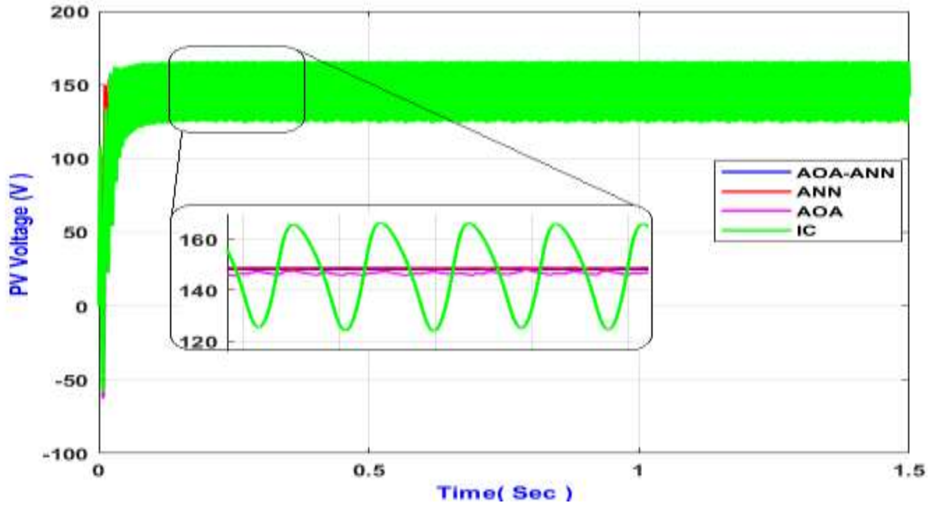


Figure 31. PV voltage under STC.

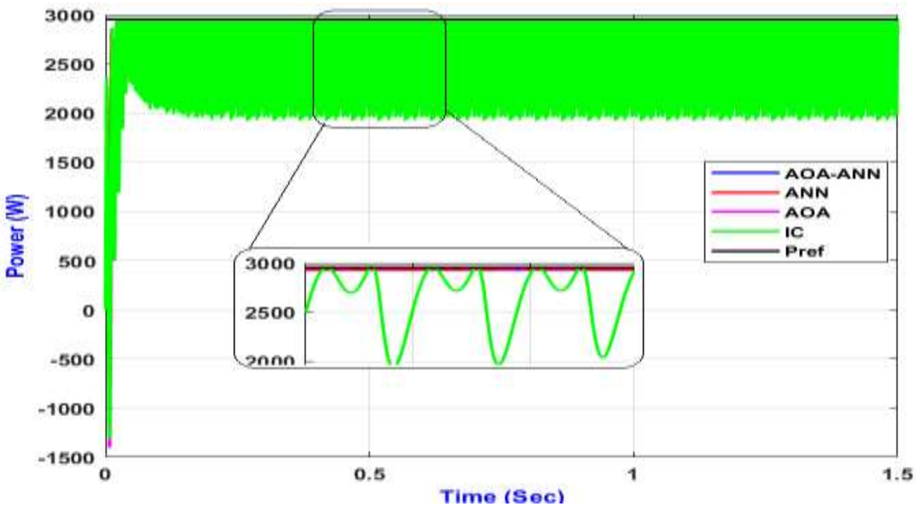


Figure 32. PV power response under STC.

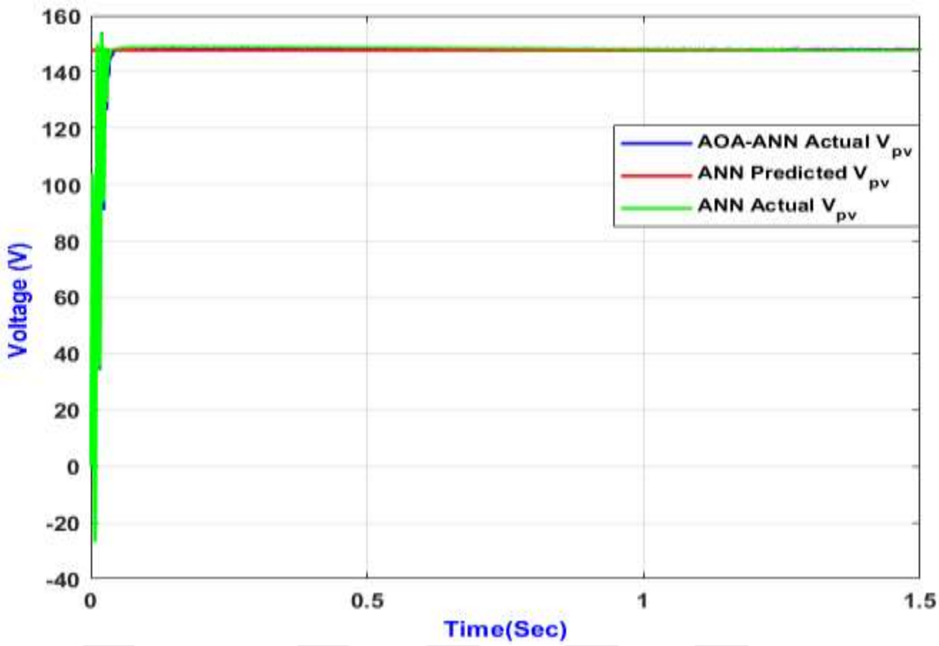


Figure 33. predictive voltage based on ANN.

4.3. Test the Proposed MPPT Strategies Under Critical Conditions

4.3.1. Performance under Nonlinear Values of Irradiance

The nonlinear change in solar irradiance G is employed with constant temperature T=25°C to test the MPPT approaches' performance. As shown in Fig.4.5, the solar irradiance is altered from a lower level value of $G = 500W/m^2$to a higher level value of $G = 1000W/m^2$ at $t = 0.2sec.$, and decrease to the value of $G = 800W/m^2$ at for period $t = 0.6sec.$ in this scenario, the proposed MPPT technique is tested and compared among them, and then the output current, voltage, and power of the 16 PV panel is trucked according to its theoretical maximum value, as seen in Figures 3.6, 3.7, and 3.8, respectively. The PV power is less than the maximum value and oscillates around the MPP point based on the IC algorithm, leading to decreased system efficiency. In the IC technique, the tracking power reaches its maximum after $t = 0.02sec$. Therefore, huge oscillations arise in INC-MPPT, indicating a slow reaction speed. While the AOA-ANN MPPT has superiority over MPPT-based ANN, AOA techniques and traditional IC MPPT in terms of fast reach to steady state at 0.00124sec and without overshoot and oscillation, as demonstrated in a zoomed section of figures 3.6-3.8, respectively.

As discussed above, the studied MPPT techniques are validated under different solar irradiance values. According to the theoretical power of the PV system, the best performance is attained by utilizing the ANN-MPPT approach by predicting the PV voltage and correcting the steady state error by the PI controller, as shown in figure 4.9.

Finally, this test is considered normal and can the traditional algorithm reach maximum power for slight oscillations. In order to call the AOA-ANN outstanding from the other techniques, the next test depends on the sawtooth and sinusoidal test and simultaneously changes the profile of temperature and irradiance.

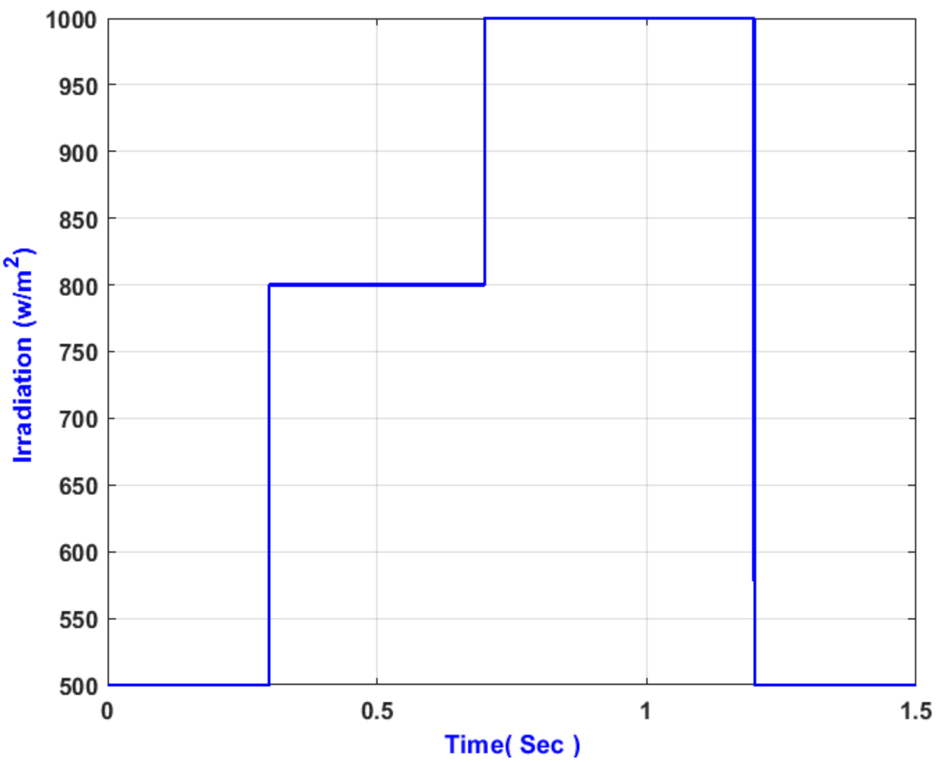


Figure 34. Irradiance profile.

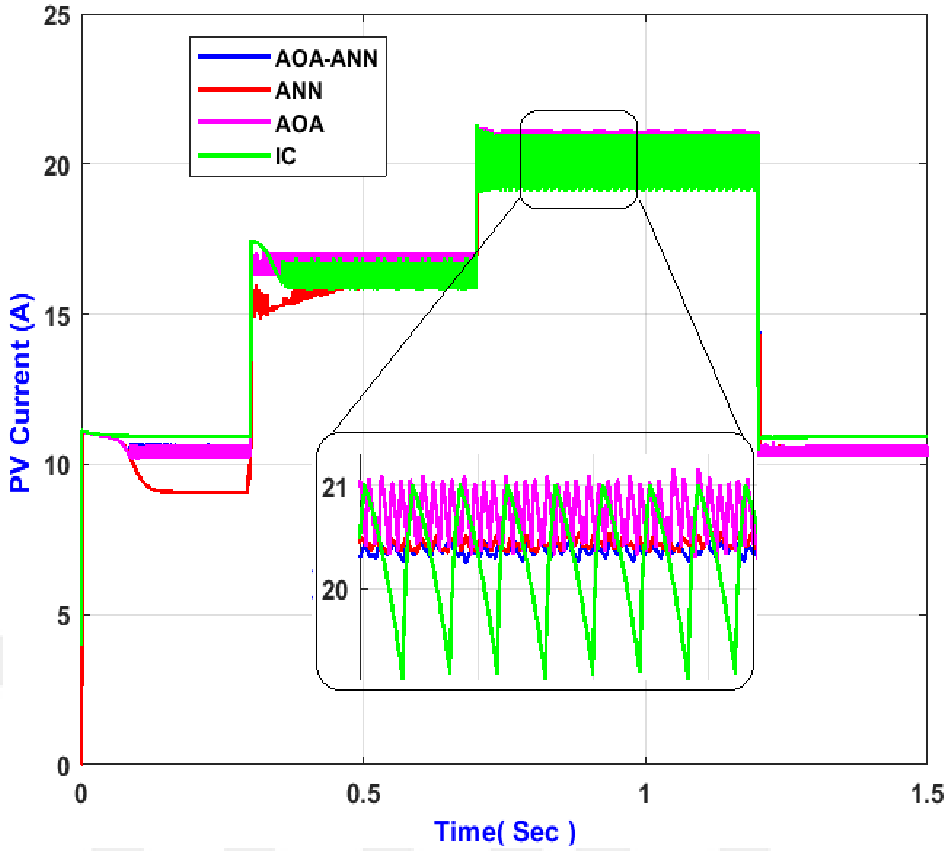


Figure 35. Dynamic response of PV current.

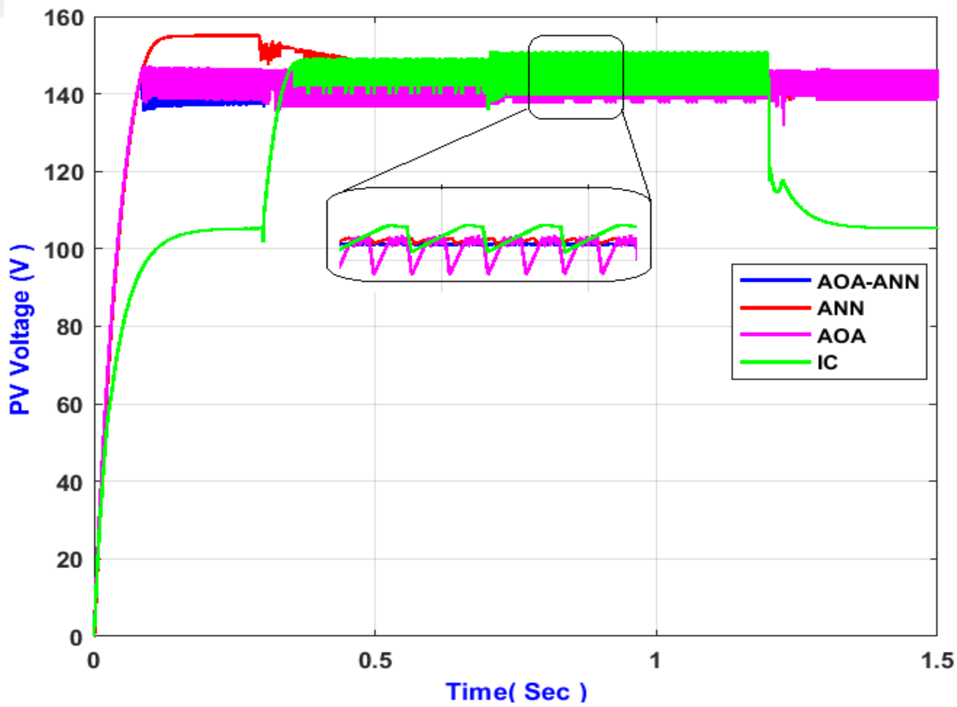


Figure 36. Dynamic response of PV voltage.

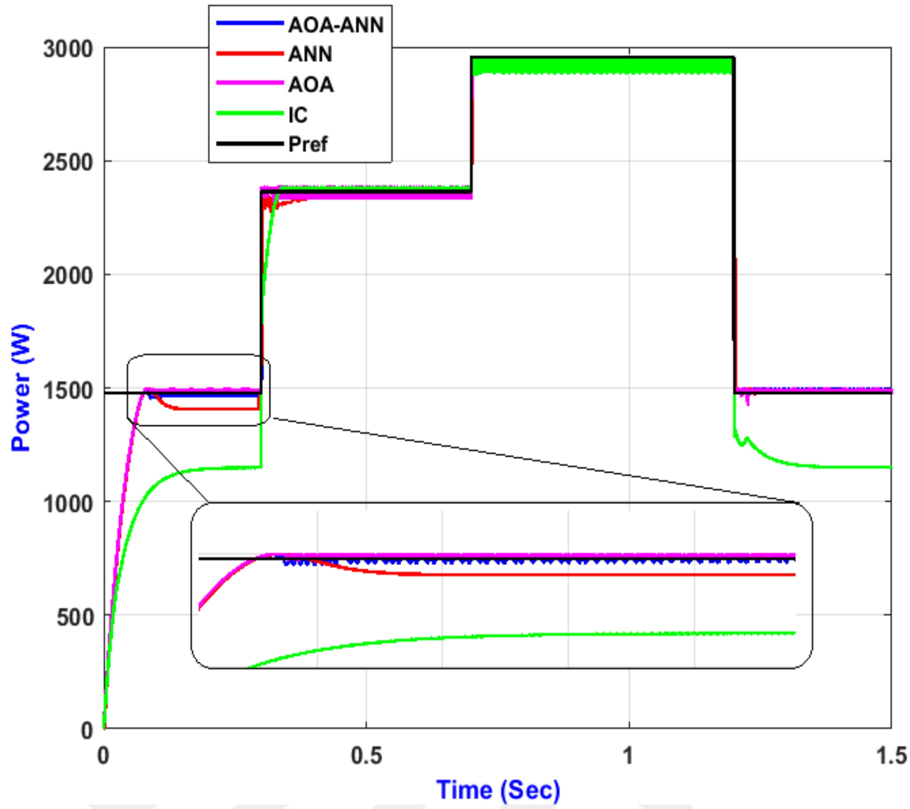


Figure 37. Dynamic response of PV power.

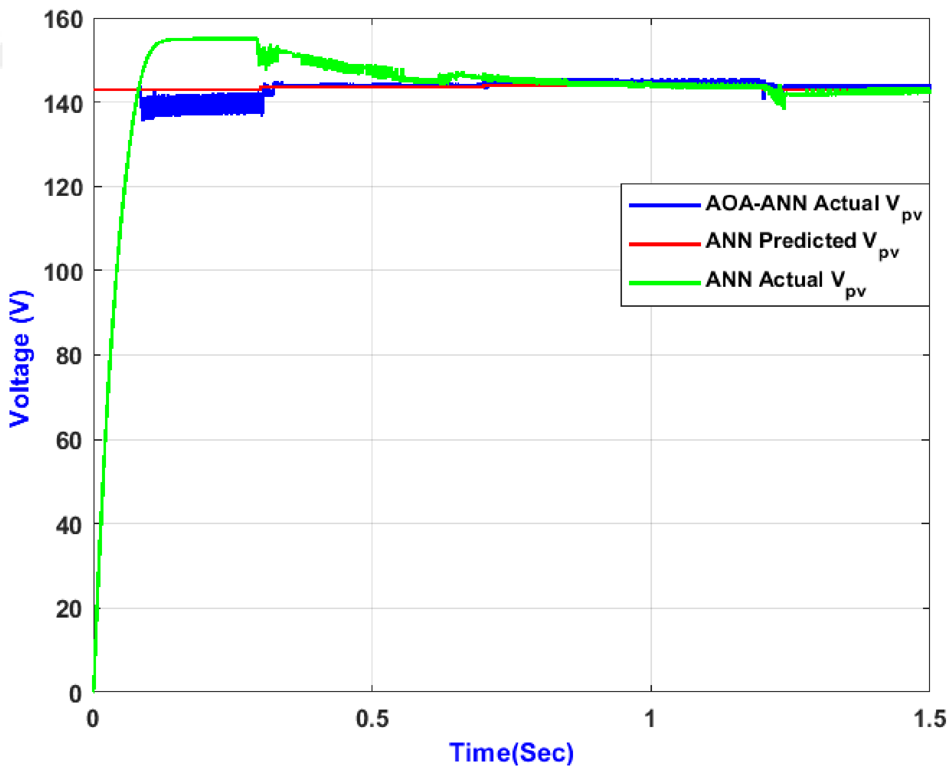


Figure 38. Predictive PV voltage-based ANN technique.

4.3.2 Performance under Sawtooth Waveform of Irradiance

The sawtooth test is considered a criterion for testing the performance of any proposed MPPT. The irradiance profile of the sawtooth is demonstrated in figure 4.10.

The simulation results obtained using the IC, AOA-MPPT, ANN, and AOA-ANN-MPPT techniques are reported in Figures 3.11-3.13, respectively. Figure 3.13 shows the obtained PV power compared to the maximum ideal values for the fast change in the irradiance. A more stable and fast response in achieving the maximum power is reached quickly based on AOA-ANN-MPPT compared with AOA, ANN and IC algorithms. Also, the oscillation power based on ANN techniques is near zero, leading to higher efficiency and reducing the loss of power while tracking the MPPT for different solar characteristics. The zoomed sections of figures 4.10-4.13 demonstrate that the AOA-ANN has no ripple, zero steady-state error, and no overshoot compared to ANN and IC techniques. Finally, the predictive PV and actual voltage are indicated in figure 4.14. It can be seen from this figure that the AOA-ANN has higher accuracy for predictive PV under the fast change in irradiance with tiny variation and agrees with the theoretical results.

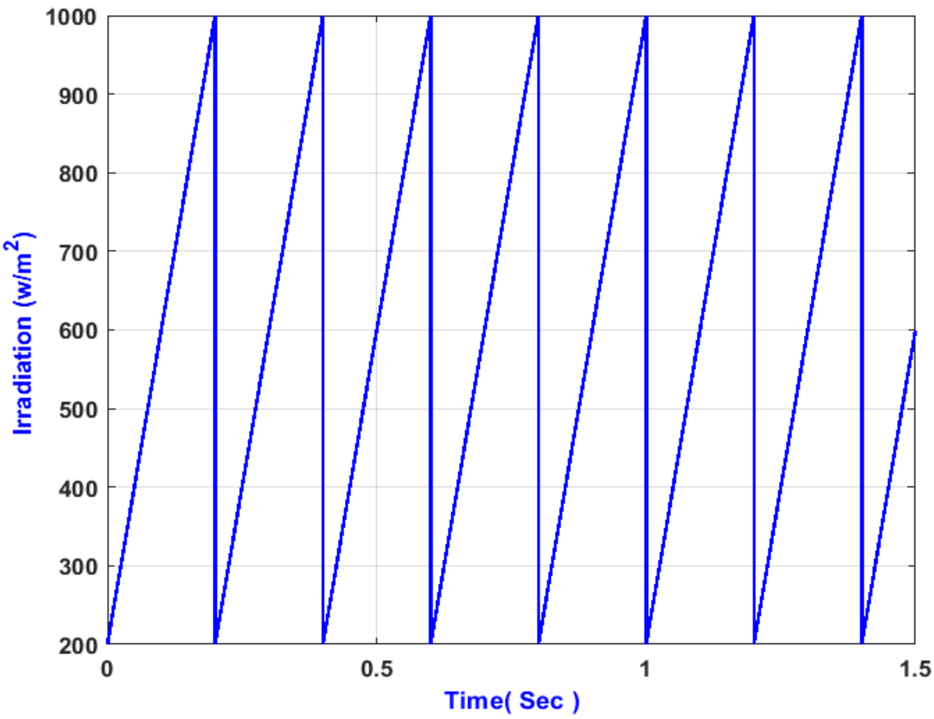


Figure 39. Irradiance profile under Sawtooth waveform.

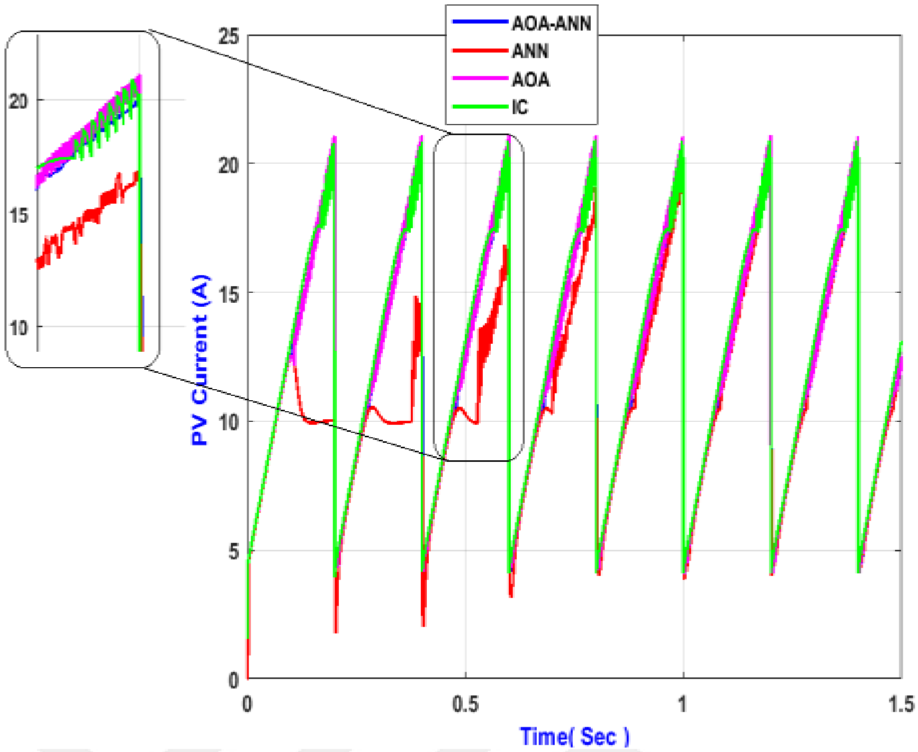


Figure 40. Dynamic response of PV current under Sawtooth waveform.

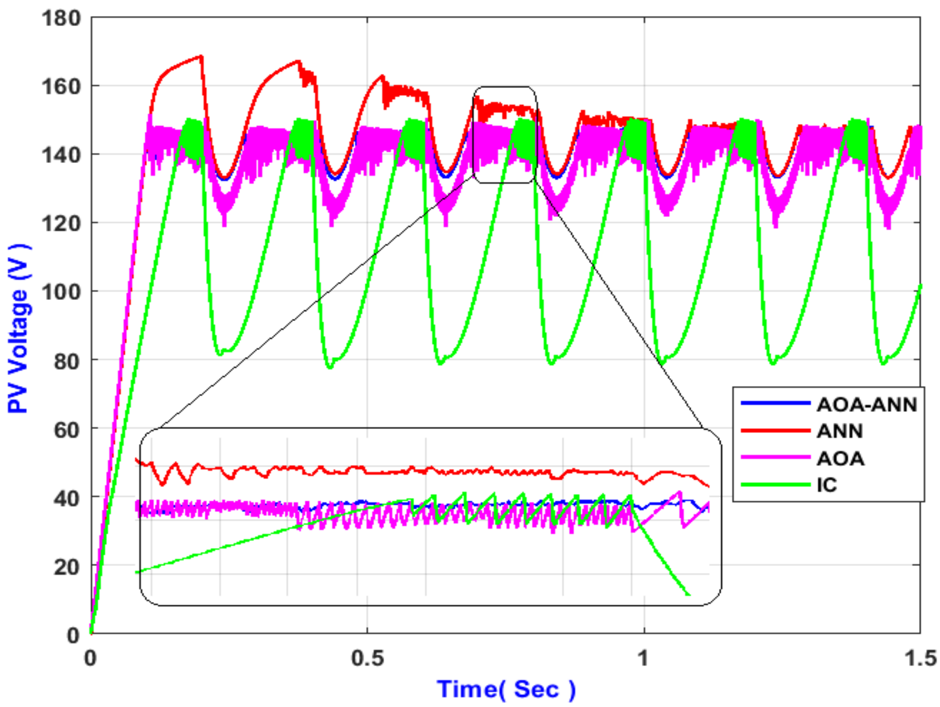


Figure 41. Dynamic response of PV voltage under Sawtooth waveform.

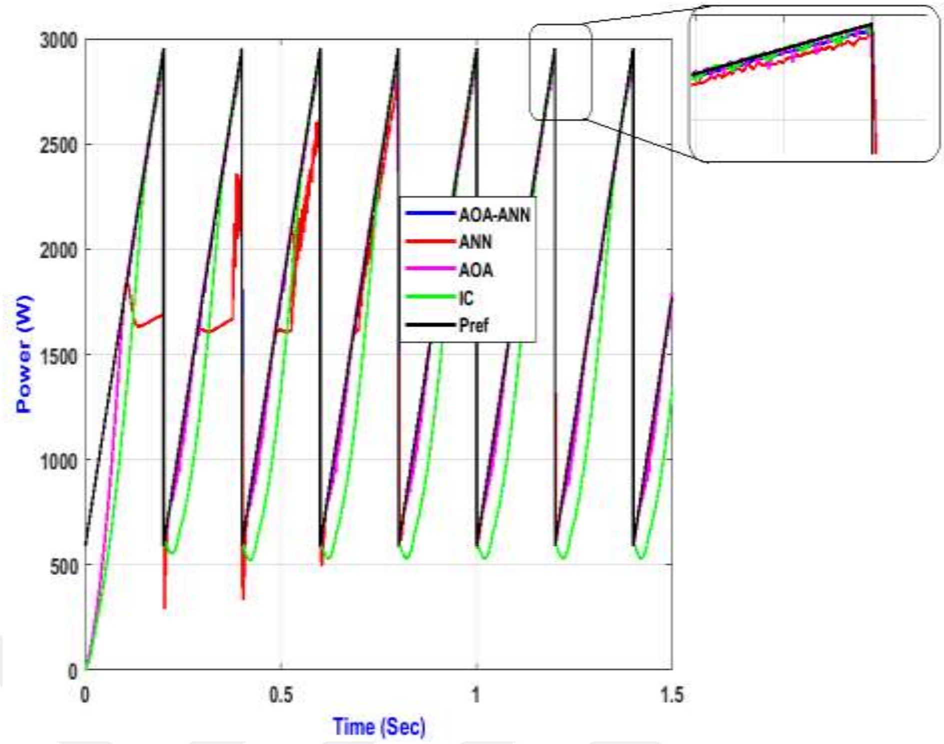


Figure 42. Dynamic response of PV power under Sawtooth waveform.

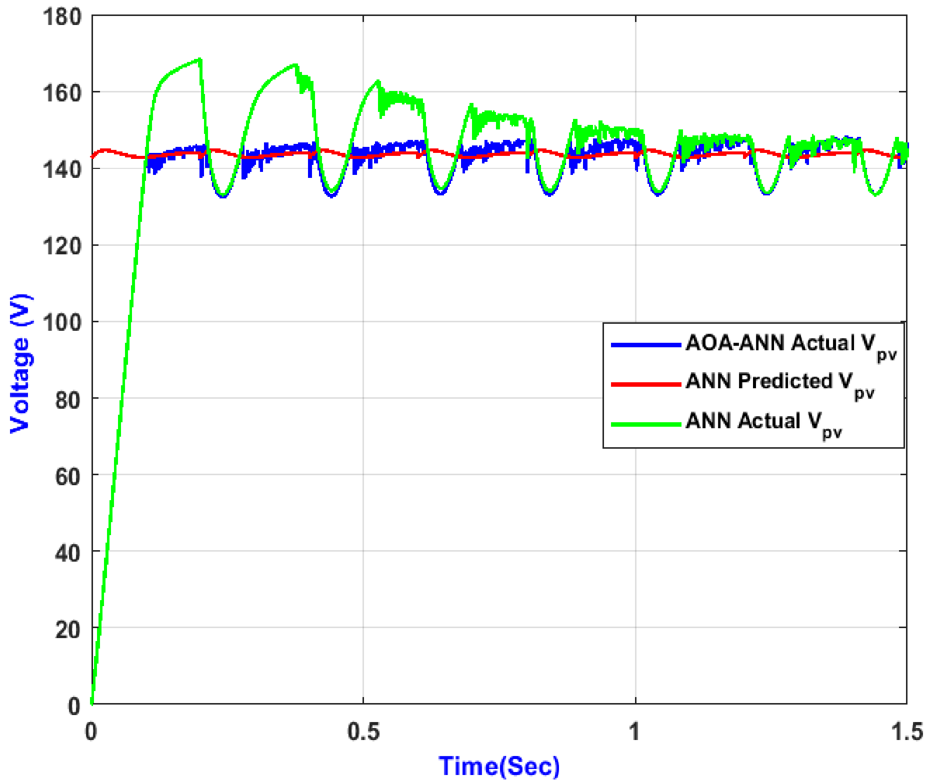


Figure 43. Predictive PV voltage under Sawtooth waveform.

4.3.3. Performance under Sinusoidal Waveform of Irradiance

Figure 4.15 shows the base irradiation profile. Because highly transient environmental changes cause rapid irradiance variations, the variation occurs within a narrow irradiation band of 800 W/m^2 to 1000 W/m^2, as indicated in this figure for the sinusoidal test. The proposed AOA-ANN-MPPT is compared with AOA, ANN MPPT and IC algorithms. During irradiation variations, T= 25°C is maintained.

As previously mentioned, most conventional and intelligent MPPT controllers cannot measure success in these scenarios. However, the traditional IC method does not follow the target power according to the input irradiance when subjected to the sinusoidal test. The ANN-MPPT remains the best technique in this scenario by monitoring the system's response and ensuring that it does not deviate from the set point, as shown in figures 4.16-4.18. The suggested AOA-ANN-MPPT transitions smoothly from high to low power without ripple, overshoot, or oscillation. Figure 4.16 depicts the PV array's voltage response, and as seen from the figure, the voltage response is constant because of the physical behaviour of the PV system. While this is the case, the PV array voltage response is presented.

Finally, to prove that the ANN strategy is suitable for all critical conditions, the predictive and actual voltage of PV voltage based on temperature and irradiance are plotted in figure 4.19. from this figure, the ANN based on the controller has higher tracking and predictability for the variations with little steady-state error.

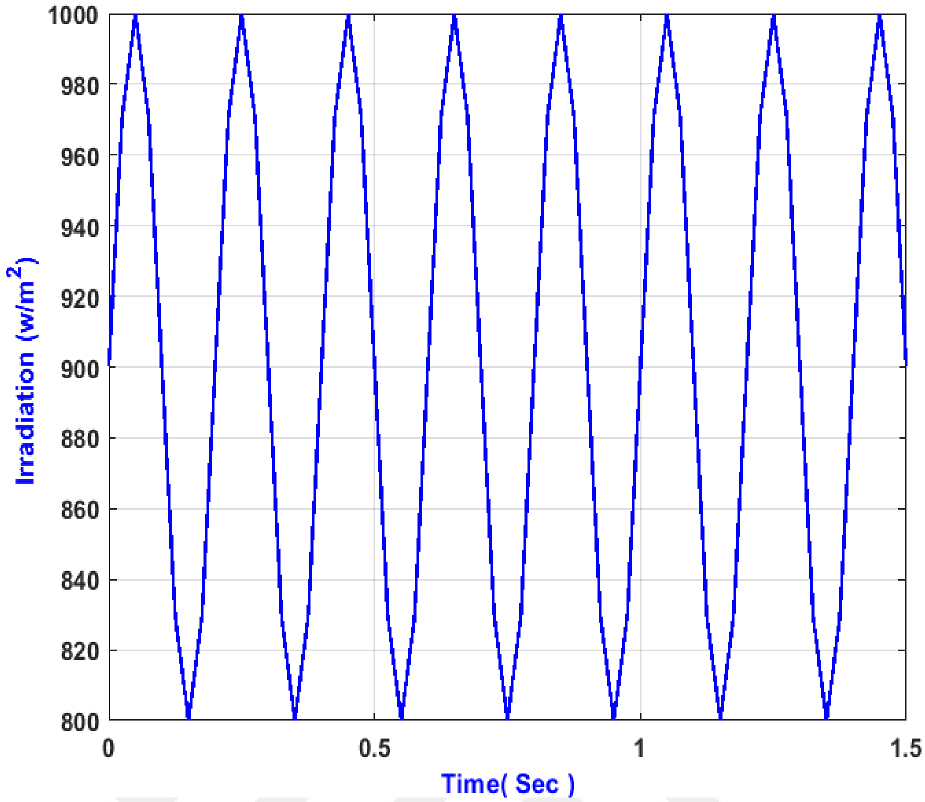


Figure 44. Irradiance profile under sinusoidal waveform.

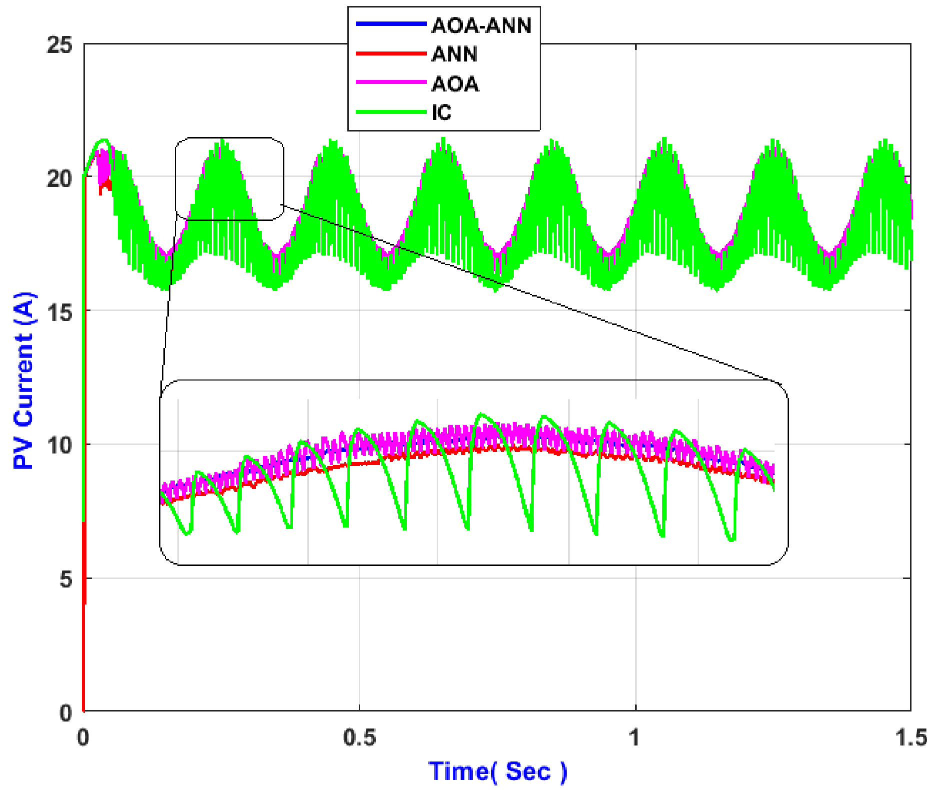


Figure 45. Dynamic response of PV current under sinusoidal waveform.

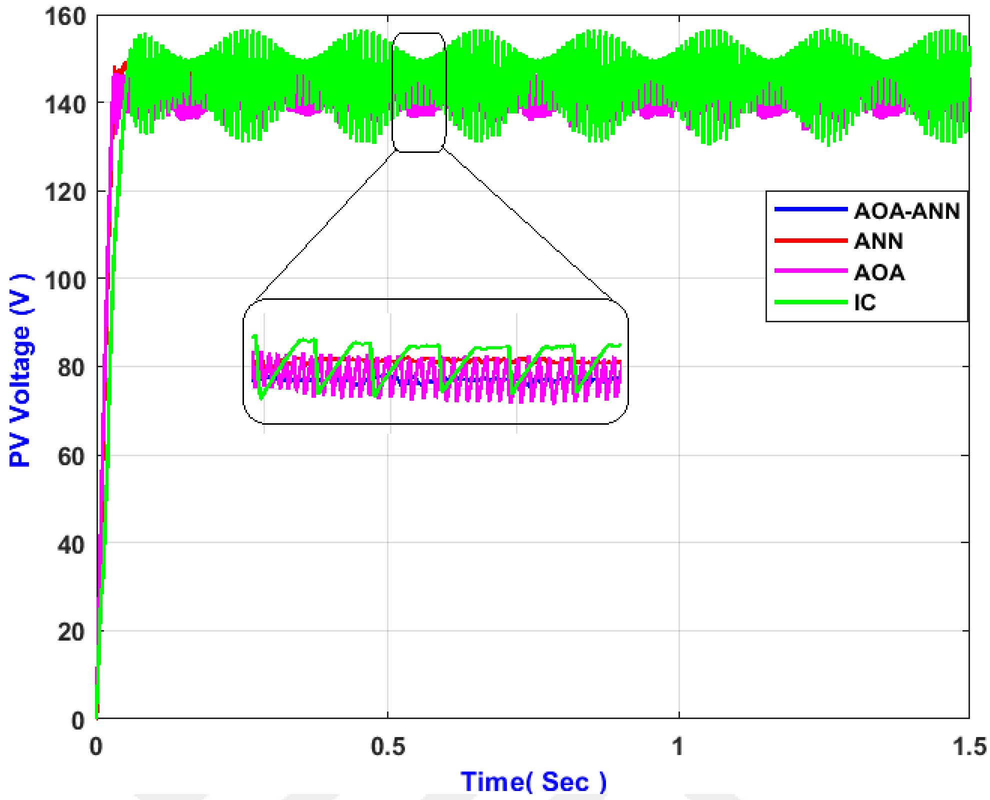


Figure 46. Dynamic response of PV voltage under sinusoidal waveform.

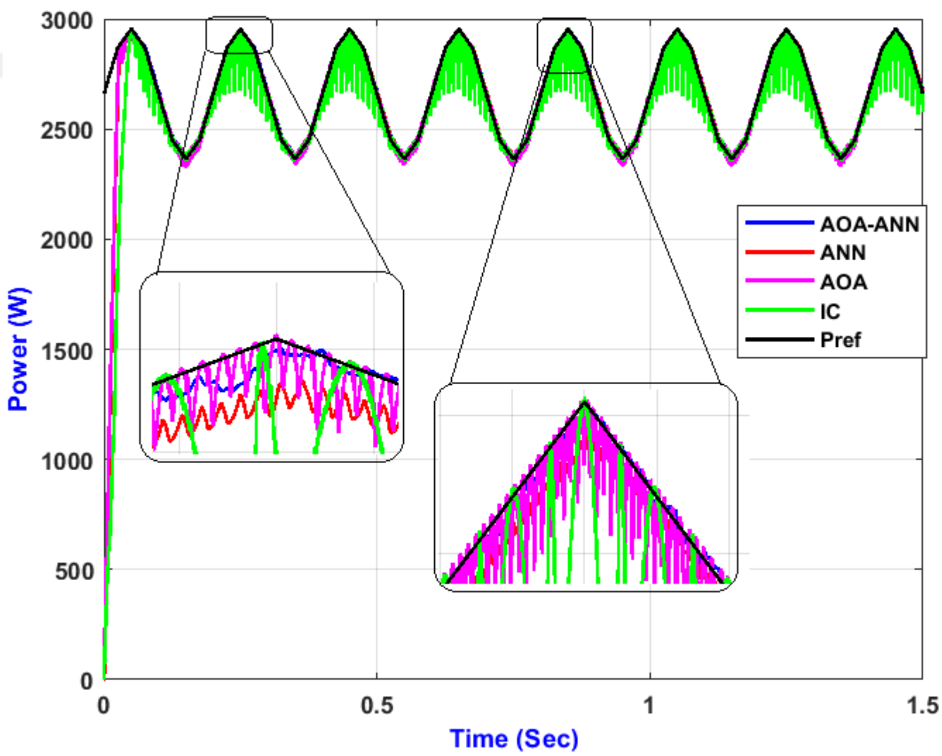


Figure 47. Dynamic response of PV power under sinusoidal waveform.

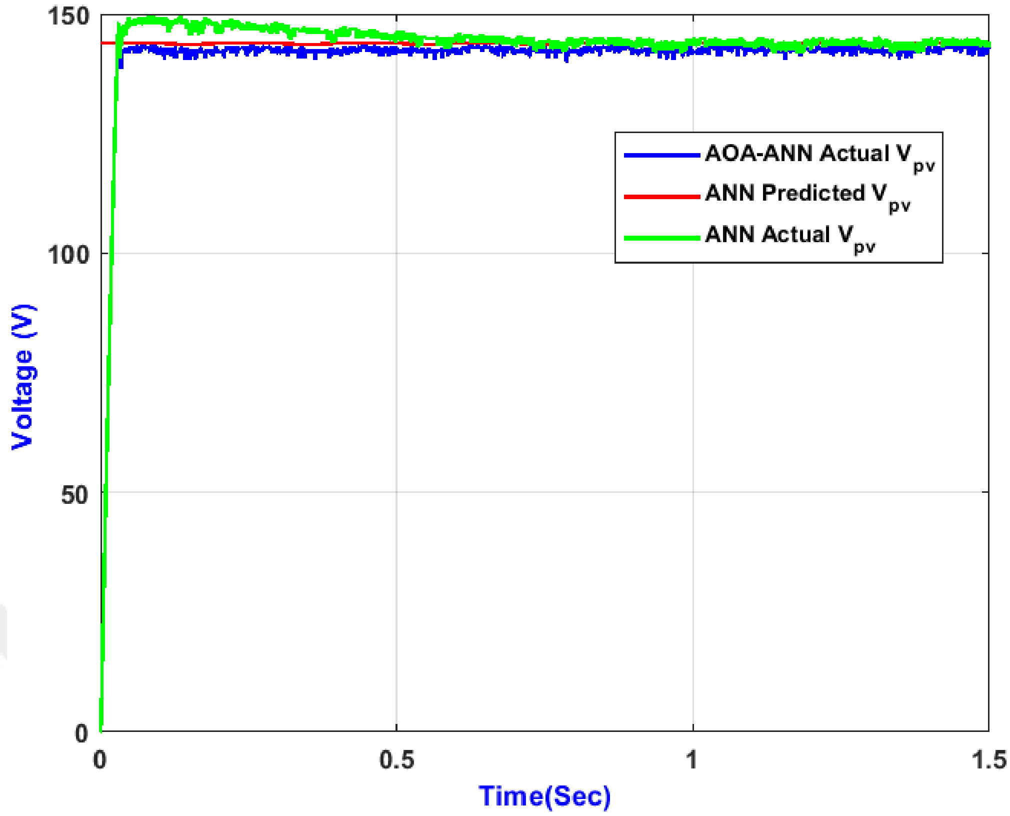


Figure 48. Predictive PV voltage under sinusoidal waveform.

4.3.4 Performance under simultaneous variation of temperature and irradiance

In order to determine whether or not a vital requirement has been met, irradiance and temperature changes are combined in one test. The profile employed is shown in figures 4.20 and 4.21, respectively. These figures show that it comprises abrupt and gradual temperature variations and irradiation levels. The photovoltaic system might be expected to operate abruptly and unpredictably.

The behaviours of the MPPT to variations in temperature and irradiance for PV current, PV voltage, and PV power are depicted in Figures 4.22 through 4.23 and 4.24, respectively. Figures 4.22 and 4.23 demonstrate that the MPPT-based AOA-ANN-MPPT is still the optimum strategy for all tested conditions with no overshoot and ripples compared to AOA-MPPT and the quickest tracking to rapid changes in temperature and irradiance.

It was clear that from zoomed sections of figures 4.25-4.27, the ANN-based MPPT controller had a tiny steady-state error compared to the other MPPT, confirmed by figure 4.28. this figure shows the effectiveness of predicting the optimum value of PV voltage under critical conditions.

Finally, the ANN-MPPT approach is the optimum solution for a PV system with no oscillation and a fast-speed reaction. The ANN-MPPT is used with the proposed seven-level inverter in AC simulation results.

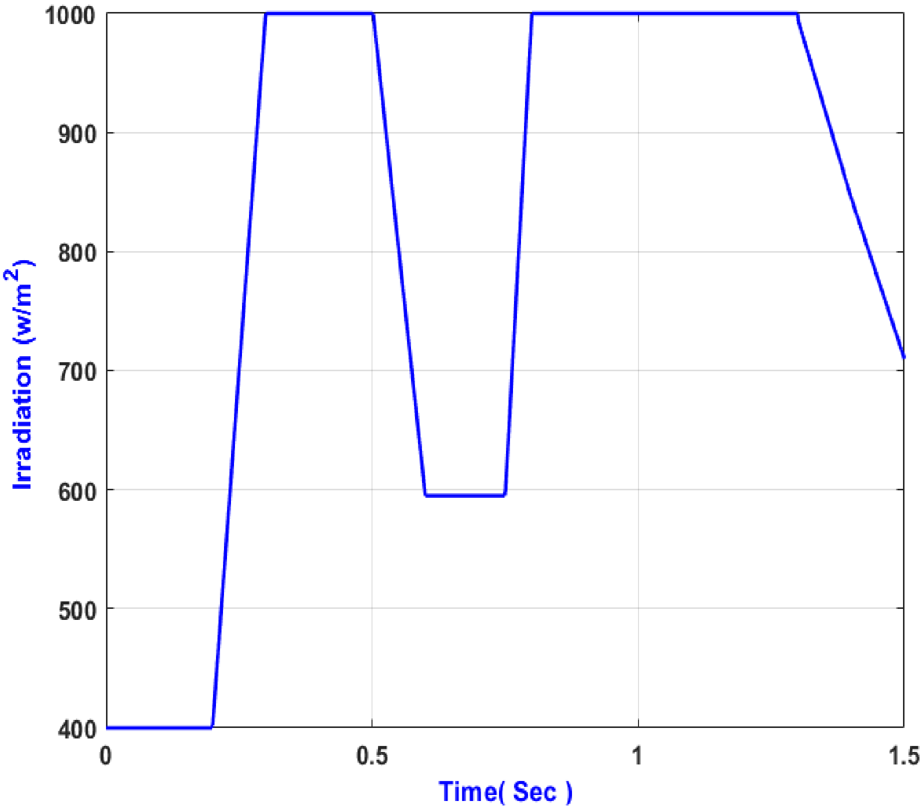


Figure 49. Irradiance profile.

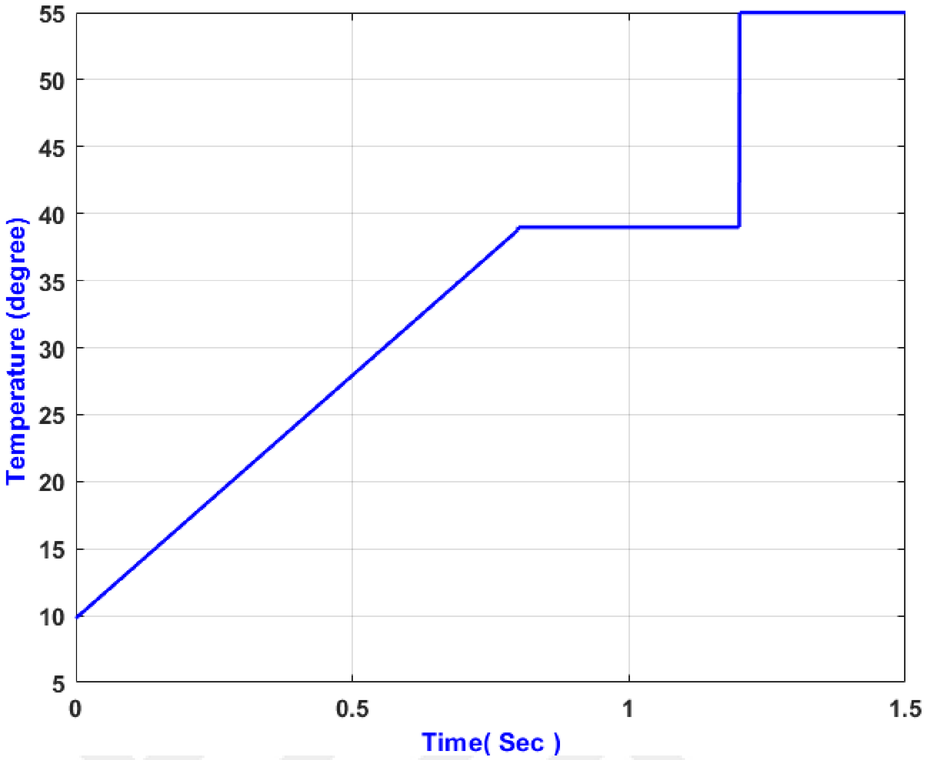


Figure 50. Temperature profile.

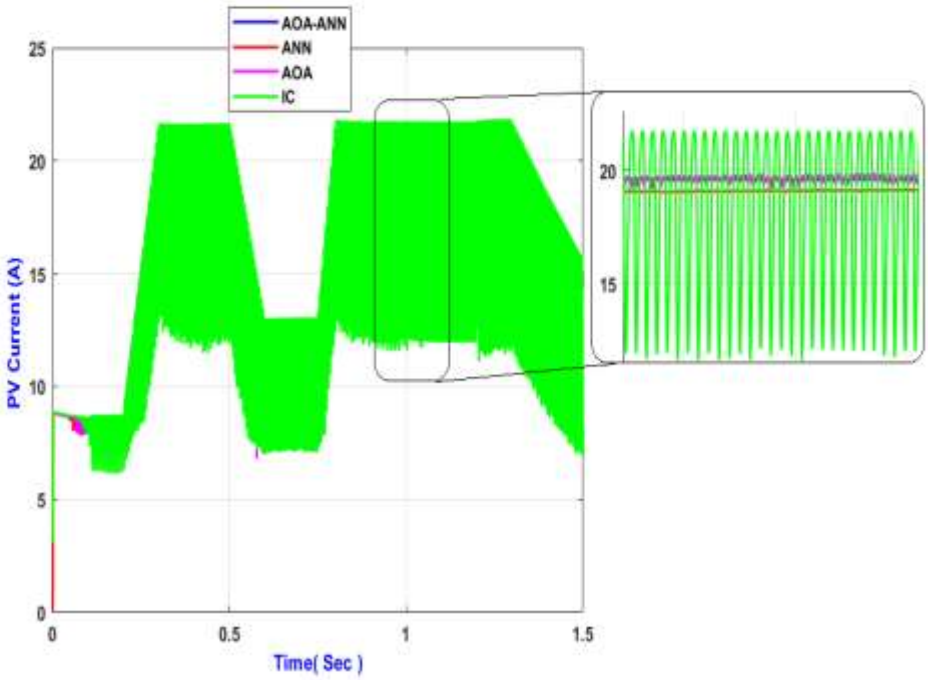


Figure 51. Dynamic response of PV current.

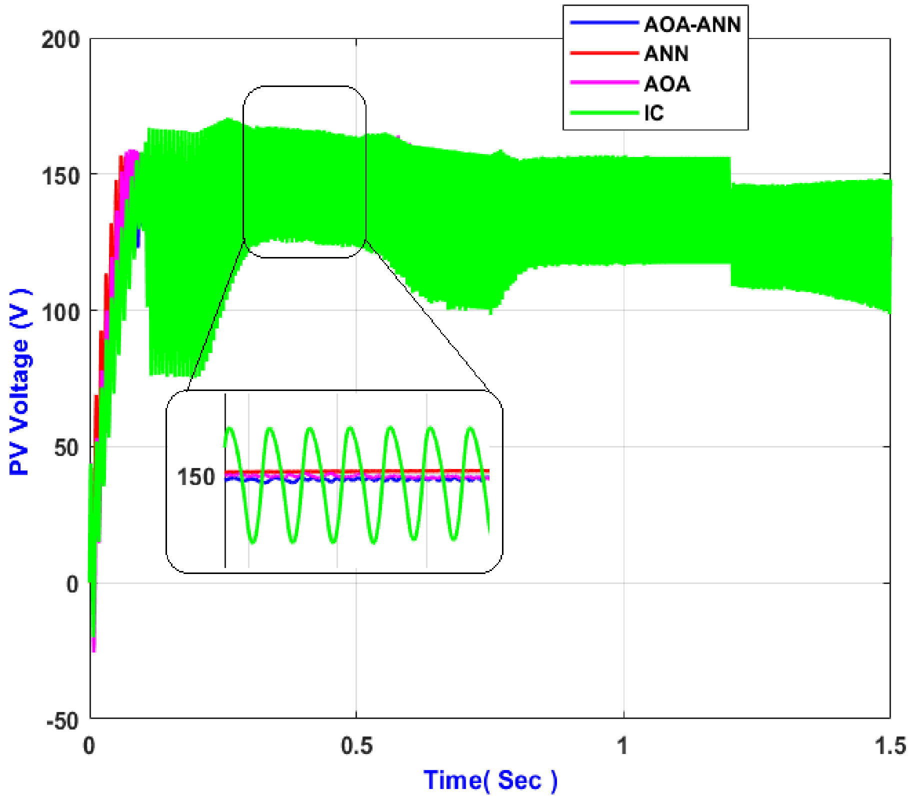


Figure 52. Dynamic response of PV voltage.

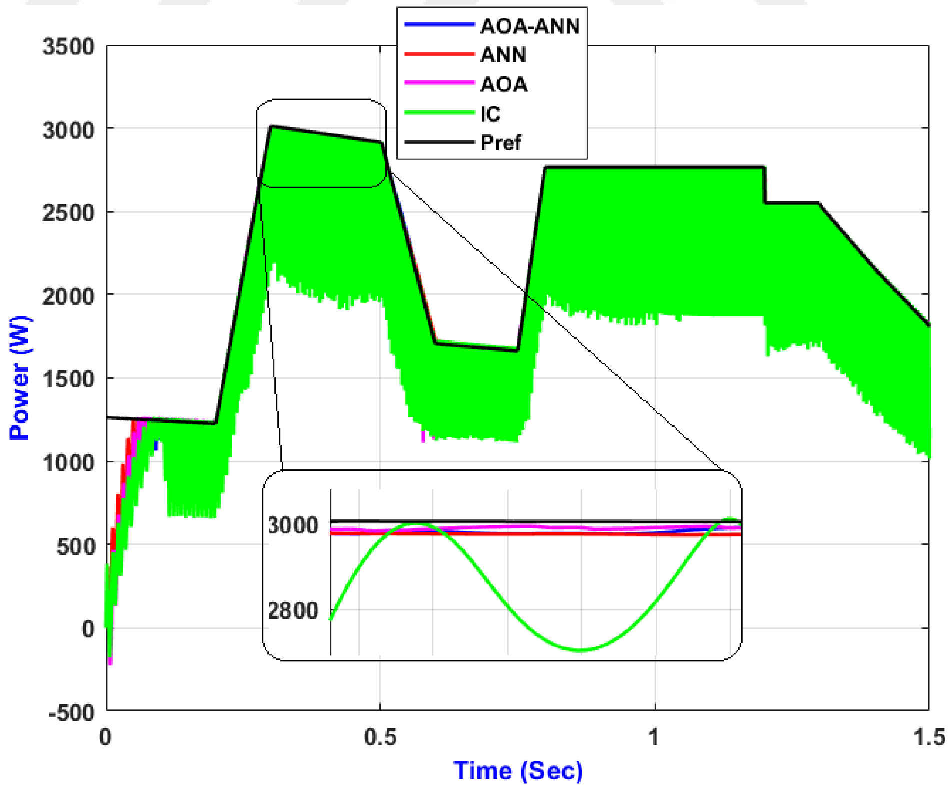


Figure 53. Dynamic response of PV power.

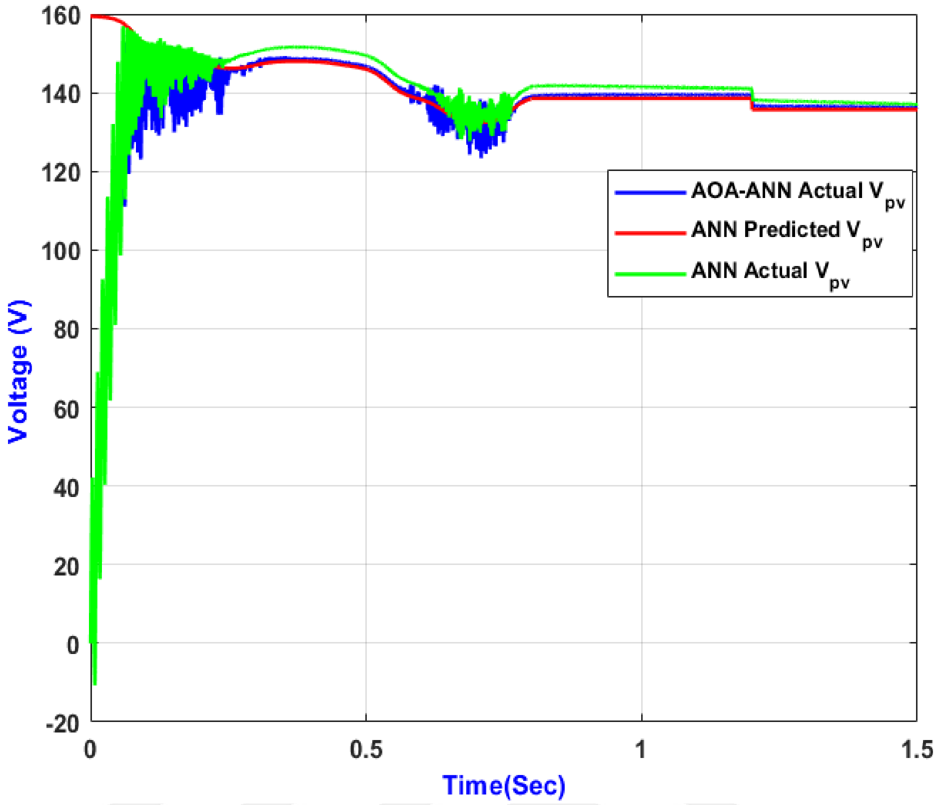


Figure 54. Predictive PV voltage under irradiance and temperature variation.

In summary, as seen above, the proposed AOA and ANN techniques provided acceptable results in terms of power oscillation compared to the conventional IC method. However, it was considered less efficient in responding to the load changing. The AOA-ANN-MPPT presents good results with slight power loss, no oscillation, and fast trucking speed, which is considered the best choice for the MPPT under different load conditions.

CHAPTER FIVE
CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

5.1 Conclusions

The demand for energy and environmental concerns are increasing daily in the current situation. Natural energy sources have largely replaced conventional energy sources. The sun's abundant energy can effectively generate electricity using a PV array. Temperature, sun angle, intensity, and I-V operating point variations affect solar panel efficiency differently. The maximum power point tracking (MPPT) technique is required to maximize the output power of a PV array. This study proposes a hybrid Arithmetic Optimization Algorithm (AOA) based on an incremental conductance algorithm and fractional PI controller to improve a PV system's performance and efficiency. Another goal was to improve the consistency and dependability of photovoltaic power conversion, especially during a rapid change in weather conditions; the new hybrid based on AOA and artificial neural network (ANN) is proposed in this thesis.

This thesis deals with two algorithms to accomplish the goal of this work, which are arranged as follows:

1. The first approach proposed MPPT based on AOA with IC algorithm. The simulation results demonstrated that the system is stable and resistant to abrupt changes in the input parameters. The duty cycle variation also varies quickly as the error rises, deviating from the MPPT.
2. In order to mitigate the limitations in the proposed approach, MPPT, the second approach, uses feedforward artificial neural networks (FANNs) based on their two inputs: irradiance and temperature, to predict the PV voltage and hybrid it with AOA to reach fast tracking to the MPP under rapid change and improve the efficiency of the PV system. The findings demonstrate that the effectiveness depends on the number of input patterns. The prediction time increases along with the number of hidden units. The resulting duty cycle was unable to monitor MPP.

3. Finally, various circumstances tested the suggested MPPTs performance using Matlab/Simulink. According to the simulation findings, the suggested strategies investigate the goal of this thesis by success in each critical test of weather conditions . According to the EN50530 standard test, the AOA based on an incremental conductance algorithm and fractional PI controller technique achieves an average tracking efficiency of around 99.3%. The proposed hybrid AOA-ANN MPPT control system stands out for its efficiency of up to 99.55%, in addition to its ease of implementation, reliability, and steady-state power tracking.

5. 2. Recommendations for Future Work

Proposals can be implemented to solve some of the problems that may arise in this thesis in the future. In brief, the suggestions for future works are as follows:

1. This thesis proposed a small-scale standalone PV system. For more contribution, a large PV system should install to increase the output power.
2. Monitoring the PV system using the internet of things (IoT) to detect faults or issues is critical to the scope of this work. The IoT technique is appropriate for completing this work in all aspects.
3. To be more evaluated and to select the appropriate MPPT with the grid-connected system, test the proposed MPPT strategies with the grid-connected.

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APPENDIXES

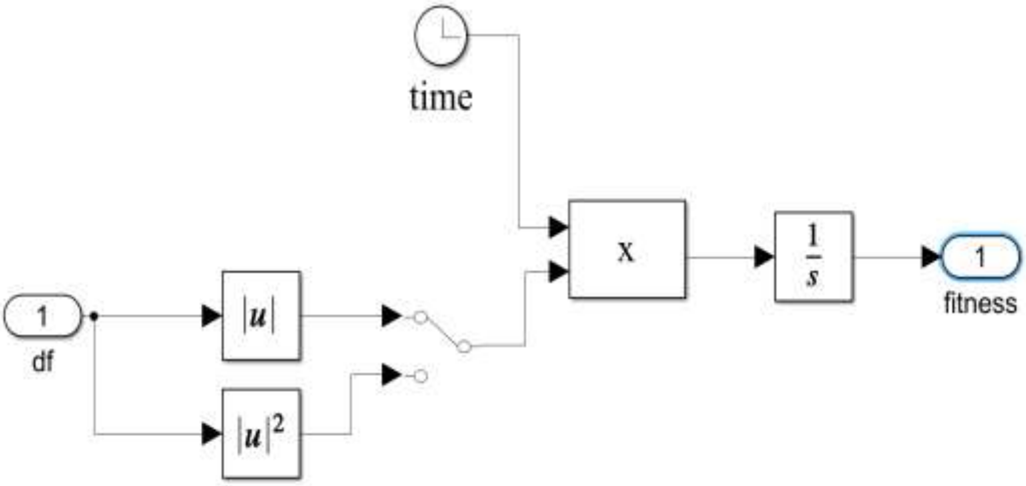
Appendix A: M.File for boost Design

boost.m

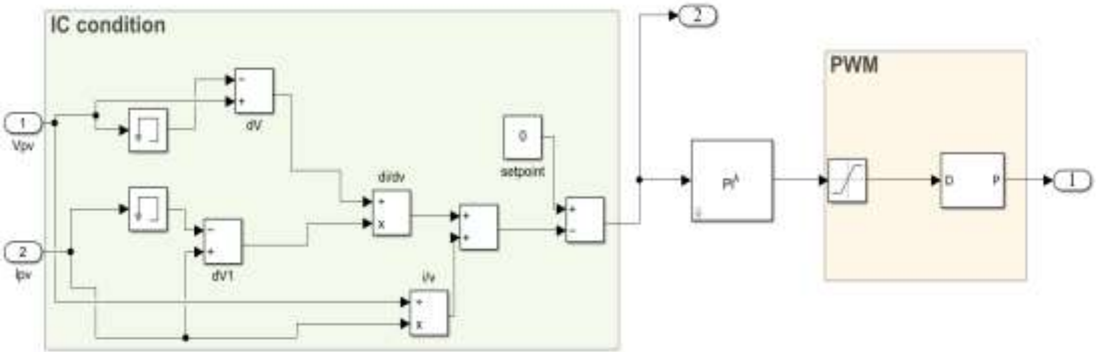
```
clc
clear all
Vinmin=144; % minimum out voltage available at PV output
Vout=220;  % DC-DC converters output
Po=2960;  % The power rating of the DC-DC converter
% The switching frequency (fs)
fs=5000;
% The efficiency(n) of the DC-DC converter
n=0.95;
 D=(1-(Vinmin*n)/Vout) % D is the dutycycle of the DC-DC boost converter
Io=Po/Vout ;
Iin=((1)/(1-D))*Io
% input current ripple (dI)
Ioriple=0.3; % 20%-40% of the output current
dI=Ioriple*Io*(Vout/Vinmin)
RL=(Vout/Io)

%dI=Ioriple*Iin;
% Output voltage ripple(dV)
```

```
% I am considering 0.5% voltage variations in output voltage,
% standard is 0.5%-1%.
dV= Vout*0.5/100;
dVc= Vinmin*1/100;
% the inductance value (L)
Lmin=(Vinmin*D)/(dI*fs);
L=1*Lmin
% the capacitance value (C)
Co=(Io*D)/(fs*dV)
Cin=(Vinmin*D)/(8*fs*fs*L*dVc)
% Minimum load to be applied more then of
RL=(Vout/Io)
RL=((Vout*Vout)/Po)
```

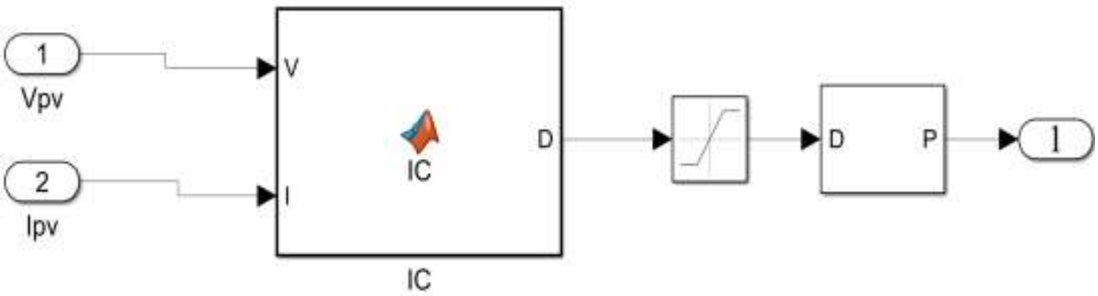
Appendix B: Simulink of Fitness Functions for AOA Tuner



Appendix C: Simulink of AOA based on IC Algorithm



Appendix D: Incremental conductance (IC) based MPPT



```
function D  = IC(V, I)


Dinit = 0.35;  %Initial value for D output
Dmax = 0.65;   %Maximum value for D
Dmin = 0.05;   %Minimum value for D
deltaD = 0.003; %Increment value used to increase/decrease the duty cycle D


persistent Vold Pold Dold Iold M;

dataType = 'double';

if isempty(Vold)
    Vold=36;
    Pold=185;
    Iold=0;
    Dold=Dinit;
    M=1;
end
P= V*I;
dV= V - Vold;
dP= P - Pold;
dI= I - Iold;
M=abs(dP);

if M < 0.005
    D=Dold;
```

```
else
    if dV == 0
        if dI == 0
            D=Dold;
        elseif dI>0
            D=Dold - (M*deltaD);
        else
            D=Dold + (M*deltaD);
        end
    else
        if dI/dV == -I/V
            D=Dold;
        elseif dI/dV>-I/V
           D=Dold - (M*deltaD);
        else
           D=Dold + (M*deltaD);
        end
    end
end

if D >= Dmax | D<= Dmin
    D=Dold;
end

Dold=D;
Vold=V;
Pold=P;
Iold=I;
```