ACE-ESD
AFRICAN CENTER OF
EXCELLENCE IN ENERGY FOR
SUSTAINABLE DEVELOPMENT

COLLEGE OF SCIENCE AND TECHNOLOGY

MASTER OF SCIENCE IN RENEWABLE ENERGY ENGINEERING.

ACADEMIC YEAR 2024-2025.

FINAL YEAR RESEARCH PROJECT.

Project Title: **“Design and Performance Analysis of Solar Charging Stations Using Artificial Neural Network (ANN) Control Methods”.**

The Thesis has been submitted to the African Center of Excellence in Energy Studies for Sustainable Development (ACE-ESD) In Partial fulfillment of the requirements for the degree of MASTER OF SCIENCE IN RENEWABLE ENERGY.

Done by:

Student name: NSENGIYUMVA Claver

Student Registration Number: 217030386

Supervisor: Dr. Innocent NKURIKIYIMFURA

DECLARATION

I Claver NSENGIYUMVA, the undersigned, declare that this is my original work, and has not been presented for a degree at the University of Rwanda or any other university. All sources of material that will be used for the thesis work will have been fully acknowledged.

Names:

NSENGIYUMVA Claver.

Ref no. 217030386. **Signature**

APPROVAL

Submission Date: **24 February 2025.**

This Thesis has been submitted for examination with my approval as a university advisor.

Dr. Innocent MKURIKIYIMFURA

Thesis Advisor **Signature.**

ABSTRACT

The increasing demand for sustainable energy solutions, particularly in the transport sector, highlights the critical need for innovative approaches to energy management. This research focuses on the design and performance analysis of solar charging stations utilizing ANN control methods. It aims to address the challenges posed by the rising use of Electric Vehicles (EVs) especially motorcycles in Rwanda, particularly in urban areas such as Kigali, where rapid urbanization elevates energy needs. This study proposes to build a Matlab Simulink model that leverages ANN to optimize solar energy capture and charging efficiency. Through a comparative analysis of Maximum Power Point Tracking (MPPT) methods, specifically the Perturb and Observe (P&O) and ANN control techniques, the research evaluates their effectiveness in varying environmental conditions. Data was collected from weather stations and charging stations across Kigali to inform model design and simulation. Key findings demonstrate that ANN significantly enhances energy extraction efficiency and charging performance, showcasing the viability of solar-powered EV charging solutions as an environmentally sustainable alternative to fossil fuels. The outcomes of this research contribute to the development of scalable solar charging station technologies, addressing energy scarcity in both urban and rural settings. By promoting the integration of renewable energy in the EV sector, this project not only supports Rwanda's energy transition goals but also aims to mitigate environmental challenges associated with traditional fuel sources. The insights gained from this work pave the way for future advancements in sustainable transportation infrastructure.

LIST OF ABBREVIATION

Table 1-1 Shows the list of important abbreviations used in this thesis.

Table 1-1: List of Abbreviations used with their meaning.

Abbreviations	**Meaning of Abbreviations**
UR-ACEESD	University of Rwanda-African Center of Excellence in Energy Sustainable Development
MPPT	Maximum Power Point Tracking
ANN	Artificial Neural Network
P&O	Perturb and Observation
EVs	Electric Vehicles.
IoT	Internet of Things.
PSO	Particle Swarm Optimization.
GA	Genetic Algorithm.
SNO	Social Network Optimization.
GIS	Geographic Information System
MCDM	Multi-Criteria Decision Making.
LPSP	Loss of power supply probability.
PVEVCS	Photovoltaic Electric Vehicle Charging Station.
OC	Operational Cost.
CVaR	Conditional value at risk.
SOC	State of charge.
DOD	Depth of discharge of the battery.
EMS	Energy Management system.
EVCSs	Electric vehicle charging stations.
SCS	Solar Charging Station.
BESS	Battery Energy Storage System.

Table of Contents

LIST OF FIGURES.

LIST OF TABLES.

ACKNOWLEDGEMENTS

First and foremost, I am profoundly grateful to the Almighty God for granting me strength, wisdom, and resilience throughout my academic journey. I would like to express my deepest appreciation to my academic supervisor, Dr Innocent NKURIKIYIMFURA, for his invaluable guidance, insightful feedback, and continuous support throughout the research process. Your mentorship has been pivoted in shaping the success of this thesis.

I extend my sincere gratitude to the faculty and staff of the University of Rwanda-African Center of Excellence of Excellence in Energy for Sustainable Development (UR-ACEESD) for creating a conducive learning environment and providing the resources essential for my research. Also, heartfelt thanks to the professionals and stakeholders at the charging stations in Kigali for their cooperation and assistance in data collection, which was crucial for the development of this work.

To my family, I am eternally grateful for your unconditional love, encouragement, and prayers. You have been my foundation and source of strength every step of the way. Finally, I wish to acknowledge my friends and classmates for their support, collaboration, and motivation throughout this journey. This work would not have been possible without the contributions of all these incredible individuals and institutions.

“May God bless all of you”

DEDICATION

This work is truly dedicated to my beloved family, and cherished brothers and sisters who are unwavering support and encouragement have been my guiding light throughout this academic journey. To my parents especially my mother, for instilling in me the values of hard work and perseverance; to my siblings for their constant motivation; and to my friends for their most encouragement. Most importantly, I dedicate this work to my future spouse, whose love and understanding have been a source of strength as I pursued this academic milestone. Lastly, I extend this dedication to the renewable energy community, whose passion and innovations inspired me to contribute to sustainable development through this research on solar charging stations.

CHAPTER 1 . INTRODUCTION

1.1 Background

African countries, especially Rwanda, are experiencing rapid urbanization and an increasing energy demand, especially in the transportation sector, for instance, the rise of Electric Vehicles (EVs). Rwanda's geographical location near the equator provides abundant solar energy potential which makes it an ideal candidate for solar energy projects. Addressing energy scarcity and reducing dependence on non-renewable energy sources can be achieved by helping with this harness potential of solar energy. We have different designs and development of EV charging stations and the role of incorporating Technology like PV-based multi-mode Converters with enhanced Artificial Neural network (ANN), and smart networks like the Internet of Things **(IoT).** [1]**[2]**.

This research project aims to design and analyze the performance of solar charging stations: by building a general case Matlab Simu-link model and the project will focus on sustainable design and cost-effective solutions to meet the growing demand for renewable energy in both rural and urban settings**.** We have focused on harvesting maximum solar irradiance, maximum power point tracking, and the most important elements of the solar charging stations including Load analysis, PV solar panels, Battery storage (Battery banks), DC-to-DC booster converter, Bidirectional DC-DC Converter, MPPT P&O (Maximum Power Point Tracking perturb and Observation) controller, Artificial Neural Network (ANN) controller, Back booster converters[3]. We also considered the case that if the power source is limited, we can set a strategy to prioritize **EV** charging from a single network, especially in the case of renewable energy helped with the design and development of the solar charger model. This project also demonstrated the economic viability and renewable energy-powered EV charging, potentially leading to widespread adoption and development in urban and rural areas alike[4]**.** Then, thesis writing outlines the contained chapters like Introduction, Literature review, Methodologies used, Result and Discussion, Recommendation, and Conclusion.

1.2 PROBLEM STATEMENT.

The demand for sustainable energy solutions is growing worldwide, with solar energy emerging as a viable alternative to fossil fuels. Rwanda is a country where the level of transport is rising through using fuel and this fuel contributes to environmental pollution and climate change. Nowadays, Rwanda is putting too much effort into moving from fuel transport to EV transport for example at the end of 2024 the government of Rwanda announced a law banning new fuel-powered motorcycles in Kigali city and this law started to be implemented from the beginning of 2025[5]. Despite the government of Rwanda's doing this, the location of EVs is concentrated in cities like Kigali and other sub-cities of Rwanda like MUSANZE, MUHANGA, RUBAVU, HUYE, KIBUYE(KARONGI), RWAMAGANA AND NYAMATA where there is availability of electricity, then too much use of EVs in these cities can cause national electrical network (grid) instability especially during the Peak period (the time of high demand of electrical energy). Also, there is still a long journey of using EVs in rural areas where there is no availability of electrical energy infrastructures. The use of electric vehicles in different means of transportation is a key solution and also it is rising to replace the existing way of transportation in many like Rwanda, which is non-renewable means, but the primary challenge in solar charging stations is to optimize the maximum solar energy capture (tracking of the maximum solar irradiance), storage of solar energy, long charging period, and distribution to ensure high efficiency and reliability in varying environmental conditions. However, while EV adoption offers environmental benefits, the increased demand for electricity due to widespread EV charging could lead to grid instability and inefficiencies. Solar charging stations integrated with efficient control methods, such as Artificial Neural Networks (ANN), offer a promising solution to alleviate grid pressure by harnessing renewable energy and optimizing charging operations [6]**,** this model will also increase the use of electric motorcycles especially in rural areas when there is not enough electricity. Addressing this problem is critical to enhancing developing countries' sustainable energy infrastructure, improving the maximum solar irradiance as well as increasing maximum power point tracking, this will reduce reliance on fossil fuels, and improve economic outcomes for users and providers of solar energy**.** In addition, this research project focuses on modeling and performance analysis of Solar charging stations using an Artificial Neural Network (ANN) control method to address the dual challenge of supporting developing countries' growing Electric Vehicles (EV) ecosystem while ensuring grid stability and sustainable energy utilization.

1.3 RESEARCH OBJECTIVES.

1.3.1 Main objective.

The main objective of this research project is to Design (building a Matlab model) and Perform an Analysis of the Solar Charging Stations model using the Artificial Neural Network **(ANN)** Control Method. This will be done based on improving the way to maximize solar irradiance tracking by comparing two ways of control which are MPPT and ANN control according to available variable environmental conditions.

1.3.2 Specific Objective.

To achieve the main objective above, there are 4 specific objectives to follow and achieve which are listed below:

1. To Collect data from the meteorological station (Meteo Rwanda) and data from different sampled electric charging stations using Questionnaires.
2. To Build the MATLAB Simulink model of a solar charging station that can work on the variable Solar irradiance and simulate this model by using MATLAB Simulink.
3. To Validate a solar charging Simulink model using a comparative performance analysis method to interpret the results for evaluating power extraction efficiency, and ANN control method accuracy.

1.4 Research Problem Justification.

The utilization of electric vehicles (EVs) like electric motorcycles in Rwanda, particularly in the sub-cities said above presents a significant shift toward sustainable transportation. However, this transition introduces challenges, including increased pressure on the national grid during peak periods as said. Grid instability risks could hinder the widespread adoption of EVs, particularly in rural regions where energy infrastructure remains underdeveloped. Given Rwanda's advantageous geographical location near the equator, solar energy offers an abundant renewable solution to address this issue. Despite the potential, solar charging stations face key operational challenges, such as maximizing solar irradiance capture, efficient energy storage, and long charging periods under variable environmental conditions. Integrating Artificial Neural Networks (ANN) control methods can optimize Maximum Power Point Tracking (MPPT), improving energy efficiency and reliability. This research justifies its focus on addressing these challenges to ensure a sustainable EV ecosystem and enhance Rwanda's clean energy infrastructure.

1.5 Scope of the Research Study.

This research focuses on modeling and analyzing a solar charging station for EVs using an ANN control method. The key components addressed include: the MATLAB/Simulink model which can work on variable environmental conditions (irradiance), comparing 2 ways of control which are MPPT and ANN control for solar energy optimization, evaluating performance indicators such as Power extraction efficiency and charging time under simulated conditions and investigating how the proposed model supports EV adoption in cities and rural areas without stable grid infrastructure[7]. The purpose of this research study is to emphasize sustainability and to demonstrate the viability of renewable energy-powered EV charging systems in both urban and rural settings. The scope of this study also is limited to MATLAB/Simulink only and there is no physical model due to financial constraints.

1.6 Thesis Organization.

Chapter 1 Introduction; comprises: a general introduction, objectives (main and specific objectives), research problem justification, Scope of the research study, and conceptual framework. Chapter.2 Literature review: it shows the previous work and similar works of solar charging station technologies, MPPT methods, and ANN applications. Chapter.3 Methodology: it comprises Data collection methods, MATLAB model design, MPPT, and ANN integration. Chapter 4 Results and Discussion: Model performance analysis, comparative evaluation of ANN and MPPT methods, and Model Validation by using 3 different types of PV panels. Chapter.5 Conclusion and Recommendations: the key findings, implications, and future research directions are points discussed in this chapter.

1.7 Contribution and Significance of the Study

The first thing is technological innovation where the research introduces SNN-based optimization for MPP which demonstrates its superiority in improving solar charging station performance compared to traditional P&O methods. The second is Practical Application where the proposed model provides a scalable solution for sustainable EV charging stations in Rwanda, particularly in rural regions with limited grid access. Thirdly is the environmental impact where the adoption of renewable energy-powered EV stations can reduce reliance on fossil fuels, contributing to environmental conservation and climate change mitigation. Last but not least are the economic benefits whereby enhancing solar energy utilization, the model offers a cost-effective solution for EV users and energy providers, encouraging EV adoption.

CHAPTER 2 . LITERATURE REVIEW.

2.1 Introduction.

The current research in solar charging stations primarily focuses on individual components such as PV panels, battery storage, inverters, and grid integration. The study has demonstrated the potential of advanced PV technologies like bifacial panels and concerned photovoltaics to improve energy capture. Similarly, advancements in battery storage technologies, including lithium-ion and solid-state batteries, offer promising solutions for efficient energy storage. Smart grid technologies, including demand response and real-time energy management, have shown potential in optimizing energy distribution. Based on the solar charging station for electric vehicles, there are 3 types of electric vehicle charging stations namely; rapid, slow, and fast charging stations, depending on the speed, and power output available to charge the electric vehicle, in the quickest way, the rapid charging is used. There are different ways of rating the levels of the charging system associated with their components[8][4]In this chapter, we shall focus on reviewing the existing literature on solar energy technologies, solar charging station designs, the mode of charging used on the different charging stations, and case studies of similar implementations in rural and urban settings. It will address the gaps in current research and establish the theoretical framework for the proposed study.

2.2 Algorithms adopted in the optimization of Electric vehicles.

In 2021, Alessandro Niccolai, Leonard Bettini, and Riccardo Zich published a paper titled" Optimization of Electric Vehicles Charging Station Deployment Evolutionary Algorithms". The project aimed to address the issue of deploying electric vehicle (EV) charging stations (CS) in urban environments. With the increasing adoption of EVs, efficiently locating charging stations to meet demand while considering various performances. These researchers have aimed to develop a flexible and effective approach to optimize the deployment of these charging stations using Evolutionary Algorithms (EAs)[9]. This study introduces a novel approach that leverages evolutionary algorithms to solve the charging station (CS) deployment problem and the key steps in the methodology include Design variables Selection by defining variables that influence the deployment of charging stations, Feasibility Function by establishing criteria to assess the feasibility of proposed solutions, Weighting Maps by introducing maps to incorporate different social and quality of service requirements into the optimization process. The methodology was tested using the 4 Different Evolutionary Algorithms (EAs) Biogeography-Based Optimization (BBO), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Social Network Optimization (SNO). The results obtained were analyzed from the Optimization process using those four algorithms were compared to a greedy optimization method the performance of each algorithm was evaluated based on average cost, standard deviation, average distance, and maximum distance, and the key findings were: SNO Performance where it demonstrated superior performance with the lowest average cost and standard deviation as well as the shortest average and maximum distances, Comparison with Greedy approach: SNO output performed the greedy approach in all tested scenarios, demonstrating higher reliability and efficiency[10].

Also, Mr. Imran Ullah published a similar paper titled" Optimal Deployment of Electric Vehicle' Fast-charging" in 2023, but the main purpose was to address the critical issue of optimizing the deployment of fast-charging stations for electric vehicles (EVs). With the increasing adoption of EVs, there is a growing demand for a well-distributed network of charging stations to support long-distance travel and reduce range anxiety (worry). The problem involves determining the optimal locations for these charging stations to maximize accessibility and efficiency while minimizing costs and environmental impacts. Some methodology used is Geographic Information System (GIS) analysis which is used to analyze spatial data and identify optimal locations based on various criteria such as traffic density, proximity to the existing, infrastructure, and land use patterns[11]. Multi-Criteria Decision Making (MCDM) method involves evaluating potential sites based on multiple criteria, including economic, social, and environmental factors. The study utilizes the Analytic Hierarchy Process (AHP) to weigh these criteria and rank the potential sites. The optimization Algorithms method is used to study the implementations of genetic algorithms (GA) to solve the optimization problem of locating the charging stations efficiently. Then, the model used in this study integrates GIS data with MCDM and GA. The GA data provides spatial information, while the AHP method helps in prioritizing the criteria for site selection. The GA is then used to find the optimal configuration of charging stations that satisfies the defined objectives. The study results indicate that the integrated approach effectively identifies optimal locations for EV fast-charging stations[10]. The GIS analysis helps narrow potential sites, while the MCDM framework ensures that the selected sites align with economic, social, and environmental goals. The genetic algorithm successfully optimizes the placement of these stations, balancing the trade-offs between various criteria. The analysis shows that the proposed method can significantly improve the accessibility and convenience of EV charging infrastructure, promoting electric vehicle adoption. The results also highlight the importance of considering multiple criteria in the decision-making process to ensure sustainable and efficient development[12].

2.3 Design and sizing Photovoltaic Systems.

The paper titled **“Design and Sizing of Solar Photovoltaic Systems”** by **A. Bhatia, published** by Continuing Education and Development focuses on providing comprehensive guidance on designing photovoltaic (PV) systems. The primary objective of this paper is to present a structured approach to designing and sizing solar photovoltaic systems for both standalone and grid-connected applications. The research aims to equip engineers, energy professionals, and stakeholders with technical knowledge for building sustainable and efficient solar PV systems. Some methodologies like **Data Analysis** which examine environmental factors such as solar irradiance, temperature, and site location for optimizing PV system design; **Component Selection** detailed guidelines for selecting system components, including PV panels, inverters, charge controllers, and batteries; **System Configuration** which is explanation of configuration for standalone, grid-connected, and hybrid PV systems; Sizing Calculation where the step-by-step calculations for PV array sizing, battery sizing, inverter selection, and cable sizing to match specific energy requirements. The **results obtained** for this system's efficiency and performance are: PV systems designed with proper sizing and efficient components can yield substantial energy savings, Environmental factors such as temperature and shading significantly impact system performance requiring careful site evaluation, The proper integration of components like MPPT controllers enhances energy output by optimizing the operating point of PV systems, and Comparative analysis shows grid-connected systems are cost-effective in urban areas while standalone systems are better suited for rural off-grid locations. The researcher proposed some recommendations **Battery Usage** to minimize the batteries in grid-connected systems to reduce maintenance and efficiency losses; **shading Avoidance** to ensure PV modules are placed to minimize shading and maximize solar exposure; **The system Efficiency** to incorporate MPPT controllers and inverters with high efficiency to improve energy conversion rates; **The Site Selection** to conduct detailed site assessments considering factors such as orientation, tilt angles, and local insolation data; **Monitoring Systems** to implement monitoring solutions to track system performance and optimize energy output over time [17]**.**

In 2024, Mr. Aimable Ngendahayo from the University of Rwanda-College of Science and Technology, Adrià Junyent-Ferré, Joan Marc Rodriguez Bernuz, Elizabeth Nyeko, and Etienne Ntagwirumugara published a research paper titled **“Sizing Requirements of the Photovoltaic Charging Station for Small Electrical Cables”** in the international journal of Renewable Energy Development. The study aimed to design and optimize a photovoltaic (PV) charging station to support the growing adoption of small-sized electric vehicles (EVs) in Rwanda, particularly by leveraging solar energy resources to reduce dependence on fossil fuels and alleviate grid congestion. The research developed a tool using

MATLAB’s EventSim to simulate the discrete events associated with EV charging stations, such as customer arrivals and continuous charging processes. The study modeled solar resources using data from Renewables. They employed a Poison distribution to predict customer arrival patterns and battery discharge levels at the station. Sensitivity analysis was conducted by varying system parameters such as the number of PV panels and battery storage capacity by ±25% to evaluate their impact on blackout periods, waiting queues, and energy management. The results demonstrated that increasing the number of PV panels by 25% reduced the blackout period by 2.12% while decreasing the panels by 25% led to a 2.18% increase in blackout time. Additionally, using an Energy Management System (EMS) reduced customer waiting times by 8% and blackout periods by 3.23%. The EMS adjusted the state of charge (SOC) to limit energy usage during high-demand periods, enhancing system performance. These researchers recommended carefully balancing PV panel sizing and battery storage capacity to minimize construction costs while maintaining energy availability. They also emphasized the importance of EMS to optimize system efficiency and customer satisfaction. The study’s findings offer valuable insights for developing sustainable EV charging infrastructure in Rwanda and other regions with similar renewable energy potential.

2.4 Standalone PV Electric Vehicle Charging Station.

In 2023 also, the researchers Zhendong Chen, Aritra Ghosh, and Neil Stephen A. Lopez wrote a paper titled “Optimization of a standalone photovoltaic electric vehicle charging station using the loss of power supply probability” to address the challenge of ensuring reliable and efficient charging for electric vehicles (EVs) using standalone photovoltaic (PV) systems. This challenge is particularly relevant given the UK’s plan to ban the sale of fuel vehicles by 2035, which will significantly increase the demand for EV charging. The authors aim to optimize the reliability of a 2MW standalone Photovoltaic Electric Vehicle Charging Station (PVEVCS) by analyzing the loss of power supply probability (LPSP). The methodology utilized by these researchers was a simulation-based approach to model the PVEVCS, the system comprises three main components: a PV generation system, a battery energy storage system (BESS), and the charging station (CS). They employed climate data from Camborne, UK, which was categorized into high and low irradiation sections. Four different charging demand profiles were used to test the models’ LPSP. These profiles were then optimized using various combinations of PV systems, BESS, and CS capacities[13]. Then, the model used in this study integrates the PV system, BESS, and CS into a standalone PVEVCS. The authors employed the Loss of Power Supply Probability (LPSP) as a key metric to evaluate the reliability of the system under different configurations and demand profiles. The results obtained indicated that solar irradiation levels significantly affect the LPSP. Specifically, higher PV capacity positively impacts reducing daytime LPSP, while higher BESS capacity is more effective in lowering nighttime LPSP. The optimized configurations demonstrated improvements in reliability for each of the four demand profiles analyzed[14].

2.5 Grid-connected solar charging stations.

Mr. Pharma and R. Chinnappa Naidu wrote a paper in 2023 and it was talking about "Optimization Techniques for Grid-connected PV with Retired EV Batteries in Centralized Charging Station with Challenges and Future Possibilities" talking about the challenge of optimizing grid-connected photovoltaic (PV) systems integrated with retired Electric Vehicle (EV) batteries in centralized charging stations. The problem focuses on improving the efficiency and economic viability of these systems while considering various operational and technical constraints. These authors reviewed various optimization techniques and algorithms applied to enhance the performance of Grid-connected PV systems with retired EV batteries. The Paper extensively discusses Single Objective Optimization Algorithms which address individual objectives such as Operational Cost (OC) conditional value at risk (CVaR) and multi-objective optimization algorithms simultaneously tackle multiple objectives, enhancing the overall system performance. Regarding the model used, the review does not focus on a single model but rather evaluates various model and their applications in optimizing PV systems with retired EV batteries[15]. One of the key models reviewed includes Mathematical models for cost functions and efficiency calculations and Simulation models implemented in software like MATLAB and HOMER. The results analysis done on different optimization techniques and their effectiveness in improving the performance of PV systems with retired EV batteries and the key findings include the DSPBO Algorithm where it was showed significant improvements in operational cost (OLCC), loss of load probability (LOLP), and Levelized Cost of Energy (LCOE) when compared to traditional algorithms like WCA, GA, FA, GWO, and MFO. MD-NSGA-II Algorithm demonstrated better results in managing charging costs, power load profiles, and battery degradation compared to the standard (NSGA-II)[16].

In 2023, the researchers Abhishek Mane, Pranav Chavan, Aniket Patil, Karan Khochare, Siddarth Katagde, and Shagufta Mestri published a research paper titled **"Solar Based EV Charging Station"** in the Journal of Recent Trends in Electrical Power System[18][10]. The study aimed to explore a powered electric vehicle (EV) charging station, positioning it as a sustainable solution for clean energy and carbon emission reduction in the transportation sector. The primary objective of their research was to design a solar-based EV charging station capable of reducing dependence on the traditional power grid and mitigating environmental pollution. The authors sought to demonstrate how such stations could provide a reliable and sustainable energy solution for EV owners, particularly in remote or off-grid areas. To achieve these objectives, the methodology involved designing an EV charging system comprising photovoltaic (PV) solar panels, inverters to convert DC to AC, and batteries to store excess energy for use during periods without sunlight. The system also incorporated different charging technologies, including Level 1, Level 2, and DC fast charging, to accommodate diverse EV models. Also, the researchers highlighted the importance of site selection, system design, installation, and operation monitoring in successfully deploying solar-based EV charging stations. The results showed that solar-based EV charging stations significantly reduce carbon emissions and promote clean energy usage.[19] The research demonstrated the feasibility of functioning independently of the traditional grid, thus offering stable power even during grid outages. Additionally, it emphasized the economic advantage of selling excess solar energy back to the grid to offset installation costs. These researchers recommended implementing these charging stations in public transportation hubs, commercial buildings, residential areas, tourist spots, and along highways. They emphasized the importance of community participation and education to promote EV adoption. Furthermore, they suggested continuous monitoring and maintenance of charging stations to maximize system efficiency and reliability. And, this study underscores the potential for solar-powered EV charging stations to contribute to a cleaner and more sustainable transportation system, offering a viable alternative to traditional fossil fuel-dependent infrastructure[4].

2.6 Electric Vehicle charging stations design.

In the research conducted by T.S. Geetha, V. Amudha, and C. Chellaswamy, published in 2022, titled “A Novel Dynamic Capacity Expansion Framework Includes Renewable Energy Sources for an Electric Vehicle Charging Station,” the authors aimed to develop a comprehensive framework for capacity expansion planning of electric vehicle charging stations (EVCSs). The Primary objective was to address the increasing energy demand from EVs while incorporating renewable energy sources such as solar and wind power within a microgrid setup. The methodology utilized involved a dual approach, addressing both short-term operational decisions and long-term strategic planning. The framework leveraged stochastic modeling to accommodate the inherent uncertainties in power demand and resource availability, optimizing the hourly operation of resources over a five-year planning horizon. This optimization focused on enhancing the capacity of key resources such as solar panels, energy storage systems, and wind turbines. The researchers also set up a comparison of their proposed method with three existing algorithms to demonstrate its efficacy. Results indicated that the proposed capacity expansion framework significantly improved the overall system performance by efficiently integrating various renewable resources and managing the EV charging demand. The model heighted the system's ability to adapt to fluctuations in power availability and demand, showcasing its potential as a robust solution for future EVCS implementations. The researchers also recommended further research into refining this framework and extending its application to larger-scale systems. This work suggests that implementing such renewable energy frameworks can lead to more sustainable and reliable electric vehicle charging infrastructure, emphasizing the importance of innovative energy solutions in addressing future transportation needs. By integrating cutting-edge technologies and methodologies, their research provides a strong foundation for advancing the role of renewable energy in the expansion of electric vehicle charging capabilities, moving towards a greener future in transportation and consumption[20].

The study on the optimal development of electric vehicle fast-charging stations, while comprehensive, identifies several gaps that require further exploration. One key area is the need for Real-Time Data Integration[3]**;** the current model relies on static data (data that is collected and remains unchanged throughout the study), and incorporating dynamic factors like traffic conditions and energy pricing could enhance site selection accuracy. Another gap is the model's Scalability and Adaptability; it needs testing across different geographical and socio-economic contexts to ensure it can be effectively scaled. Further research is also needed in User Behavior Analysis to integrate these insights into the optimization model. Addressing these gaps could refine the deployment strategies for EV fast-charging stations[11]. Additionally, in optimizing standalone photovoltaic electric vehicle charging stations (PVEVCS), the study highlights the need for integrating economic and environmental assessments with technical optimization. The reliance on climate data from a single location underscores the necessity for validation across various regions. Increasing PV and Battery Energy Storage System (BESS) capacities is recommended to enhance reliability, particularly in areas with variable solar conditions[2][1]. Moreover, in optimizing grid-connected PV systems with retired EV batteries, gaps such as the lack of Real-World Validation and challenges in the Integration of renewable sources remain significant, alongside the need to understand the Long-Term Performance of retired batteries[15][9][21]. This review emphasizes the potential and challenges of optimizing such systems. However, there is still a need to extend these methods to large urban areas, integrate real-time data, and refine user behavior models. Furthermore, current research has not sufficiently addressed ways to minimize start-up costs for fast-charging stations or clarified aspects of the control system, such as the use of Arduino Nano controllers. Finally, there is a lack of statistical data from MATLAB simulations to compare with case study results, and a deeper exploration of grid frequency and voltage control is needed.

CHAPTER 3 . RESEARCH METHODOLOGY.

3.1 Path of designing Solar charging station model.

The Figure 3-1 below is the flow path used in designing EV solar charging model.

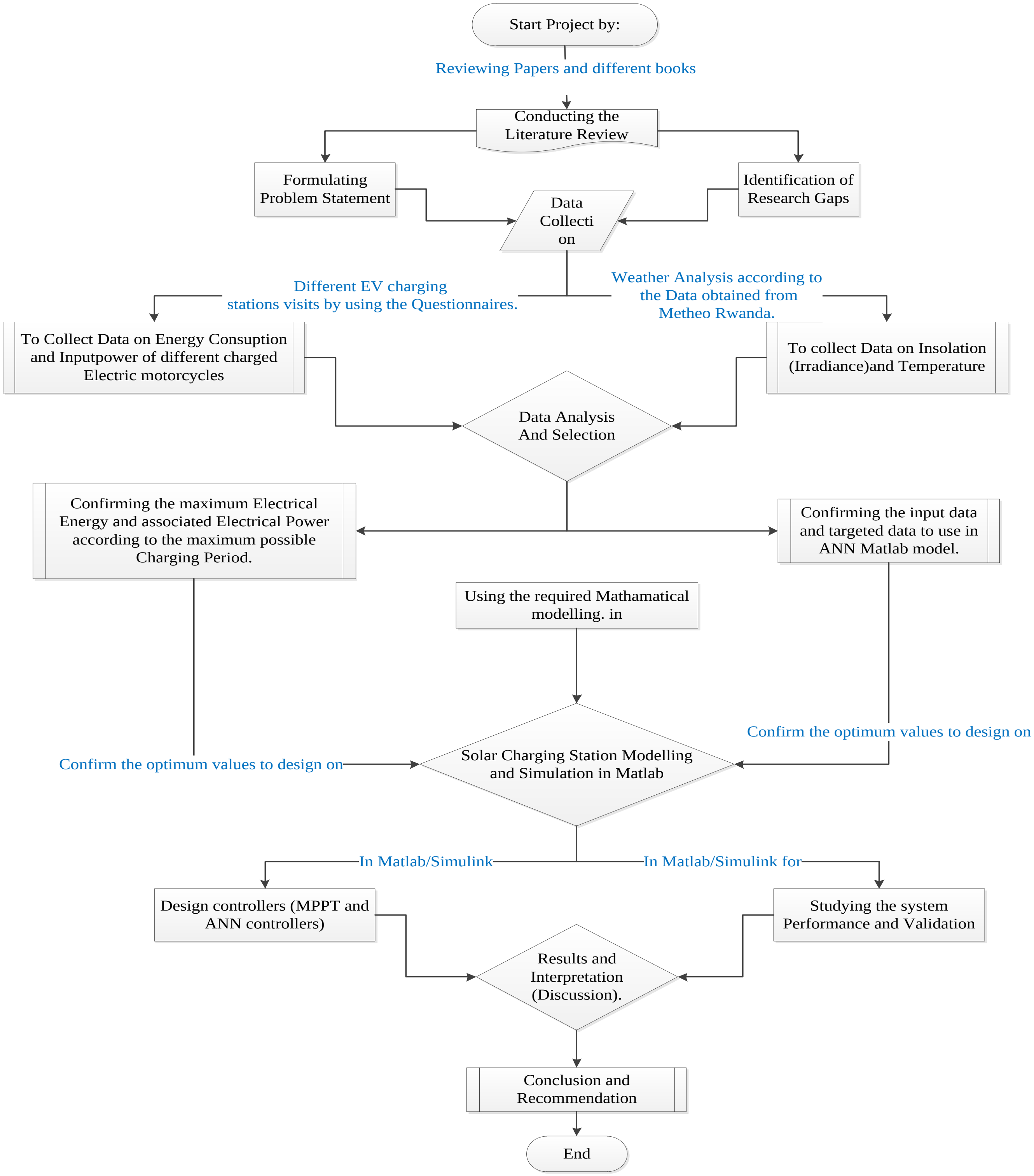


Figure 3-1: The flow chart of the solar charging station model research design.

As shown on the above flow chart, the methodologies in design and performance analysis of solar charging stations using Artificial Neural Networks (ANN) for Maximum Power Point Tracking (MPPT). The chapter covers the data collecting process, MATLAB-Simulink model design, and the integration of MPPT and ANN.

3.2 Data Collection Methods

The success of the proposed solar charging station model depends significantly on accurate and comprehensive data collection, below there are key collection methods that were employed:

3.2.1 Meteorological Data.

Historical data on solar irradiance and temperature trends were obtained from meteorological departments and energy until utility reports in Rwanda. The values presented on solar irradiance are based on historical data and studies conducted in Rwanda. The country's average daily solar irradiance ranges between 4.3 and 5.2 kWh/m²/day, with variations depending on the region and time of year. The average ambient temperatures are derived from historical weather data for Rwanda. Temperatures are relatively stable throughout the year, with minor fluctuations between months. The

Table 3-1 below is the list of data obtained from **1st** January **2024** to **31st** December **2024** from Metheo-Rwanda.

Table 3-1: Average monthly insolation and ambient temperature from Metheo-Rwanda.

MONTHS	Average Monthly Insolation **(kWh/m^2).**	Average maximum Solar Irradiance **(W/m^2).**	Ambient Temperature **(^{0}C)**	Maximum Average Ambient Temperature on a day (^{o}C)
January	5.8	650	22.2	29.5
February	5.9	670	22.8	30.0
March	5.8	660	22.2	29.0
April	5.3	610	21.1	27.5
May	5.5	620	21.7	27.0
June	5.9	680	22.2	28.5
July	6.2	700	22.5	28.8

August	6.3	710	22.8	29.2
September	6.1	690	22.8	29.0
October	5.6	640	22.2	28.0
November	5.4	620	21.7	27.5
December	5.6	650	22.2	28.5

3.2.2 Site Selection and Survey.

The primary data was gathered from existing Kigali-Rwanda charging stations, including grid-based stations by using the Questionnaire, and the Metheo-Rwanda Site. The data collected are includes: Solar irradiance variation levels, Ambient temperature, Station capacity and energy consumption patterns, Load Profile for charging electric motorcycle. Data collected from sampled existing charging stations.

Using the questionnaire with key stakeholders, including station operators and EV (electric motorcycles) users, provided insights into charging behavior, energy efficiency challenges, and performance expectations. The Table 3-2: Data collected from 3 sampled charging stations in Kigali. below are the important parameters of all data collected from three sampled electric charging stations.

Table 3-2: Data collected from 3 sampled charging stations in Kigali.

Focused parameters	**Gisimenti Station**	**Kacyiru Station**	**Kinamba station**
Location of Stations	Gasabo	Gasabo district	Nyarugenge
Station type (Solar, Grid, Hybrid)	Grid Connected	Grid Connected	Grid Connected
Year of Establishment	2019	2024	2019
Number of Charging Ports	15	20	8
Charging Technology (Slow, or Fast)	Fast by battery Swapping	Fast by Automated Battery swapping	Fast by Battery Swapping
Battery Types Supported (Lithium-ion, Lead-acid, or other)	Lithium-ion	Lithium-ion	Lithium-ion
Battery Capacity (kWh)	3.5	5	3.5
Charging Capacity per Session (kWh)	3.5	5	3.5
Average Charging Time per motorcycle	Approximately 2 minutes (battery swap)	Approximately 2 minutes (battery swap)	Approximately 2 minutes (battery swap)
Number of Motorcycles Charged Daily	200	300	200

3.3 MATLAB Model Design

MATLAB was chosen as the primary simulation tool due to its powerful capabilities in modeling and analyzing renewable energy systems. The following steps were undertaken to design the model for system components, system equations, and parameters:

3.3.1 Load Profile Analysis.

Representing EV charging demand patterns. Design an Off-Grid Solar PV System for a charging station. The typical range of the existing electric motorcycles is between 1.5 kWh - 10 kWh, to means that the smaller motorcycles' capacities (1.5-3 kWh) per single charge are common for urban motorcycles and scooters, the medium range between 3-5kWh while higher capacities (6-10 kWh) are used for long-range or performance models and specific uses like in military and police services. We sized a PV solar charging system for motorcycles at a maximum medium range of energy consumption of 3-6kWh at 6kWh on a station [22]**.** We designed an off-grid charging station model that can charge at least 5 motorcycles that consume 30kWh in total, the Figure 3-2 shows the type of electrical load that we are dealing with and it was picked from designed solar charging model.

Figure 3-2: Electric motorcycles as our loads of concern.

3.3.2 Calculating of total daily energy consumed by 5 motorcycles.

If one motorcycle in the medium range of energy consumption consumes 6kWh, then 5 motorcycles will consume 30kWh as the total load that we need to design for. The maximum charging time one motorcycle can take for a single charge is 1hr hours, then input power to load when all 5 motorcycles are connected will be calculated as follows:

$$\text{Input power to the Loads} = \frac{Total\ Energy\ Consumption\ \ by\ the\ load}{Maximum\ charging\ time} \ldots\ldots\ldots\ldots\ldots\ldots.. \ Eqn(1)$$

But the standard solar charging station uses 1hr for fast charging which means on 30 000Wh we can connect a load of 30kW.

3.3.3 Estimation of Daily energy generation Required with losses.

Solar PV systems have losses from wiring, shading, temperature, and inverter efficiency, and if we add up all these losses range between 15% to 30% but we designed 15% as an evitable loss, which means the system efficiency is 85% or 0.85.

$$\text{Daily required PV energy output} = \frac{Daily\ Energy\ Consumption}{(1 - System\ Loss\ Factor) or\ system\ efficiency}$$

$$= \frac{Daily\ Energy\ Consumption}{System\ Efficiency} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \text{ Eqn (2).}$$

3.3.4 Estimation of Solar Photovoltaic (PV) Array.

Simulated based on real-world specifications to capture the impact of varying solar irradiance and temperature. Sizing the PV Array by determining the total Solar Panel Capacity. We can implement the project by using Monocrystalline Silicon (Mono-Si) Panels because it is best for High-efficiency applications and limited space and it has an efficiency range between **20-23%** with a capacity range of **300W** to 7**00W** which varies by size and brand. Some of its most advantages are: high efficiency and performance in low-light conditions, a long life span of **25-30 years** with minimal degradation and it has a compact design; ideal for limited space but it possesses some disadvantages like high cost compared to the other types and energy-intensive manufacturing process which can be avoided according to the rapid grow of the nowadays modern technology[23]. **Figure 3-3** shows how the PV array was installed in the designed Solar charging model.

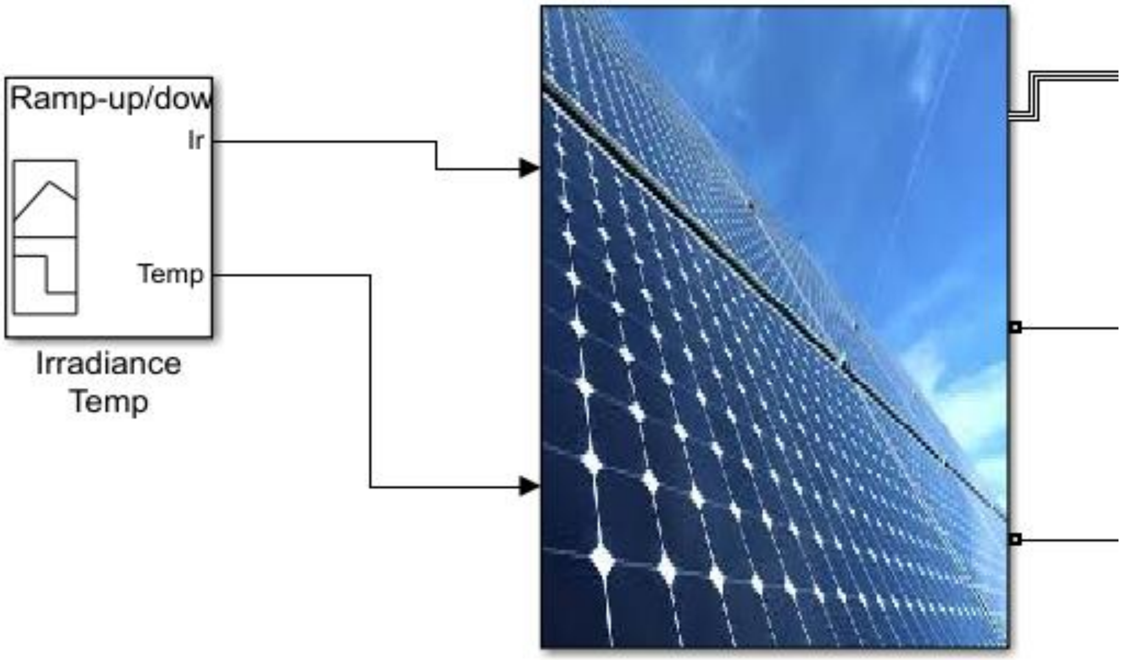


Figure 3-3: The PV array and its Input ambient temperature and solar Irradiance.

i. Specifications of used PV panel.

In the simulated model, we have chosen a solar panel which is **Boviet Solar Technology Co. Ltd BVM6612M-375 from** Matlab-Simulink, **Table 3-3** below is showing the specifications of this PV Panel.

Table 3-3: Specification of the Selected Boviet Solar Technology Co. Ltd BVM6612M-375 PV panel.

Parameters	Values
Rated Power (P_R)	375W
Open circuit Voltage (V_{oc})	48V
Short Circuit Current (I_{sc})	10.11A
PV cell dimensions:	
PV Length	1.75m
PV Width	1.05m
PV surface area	1.8375m^2
Panel Efficiency regarded to its dimensions	20.04%

ii. **Determining the total Solar Panel capacity.**

The total energy requirement is to be provided by the PV panels, considering the solar irradiance at the given location. The common Peak Sun Hour (PSH) for Kigali is around 5 hours per day.

Required PV Capacity=$\frac{Adjusted\ Energy\ \ Requirement\ from\ the\ system}{Peak\ Sun\ Hour\ (PSH)}$……………………Eqn (3)

iii. **Number of Panels needed**

Concerning the above specification of the PV Panel, each panel has a rated power of 375W.

Number of PV Panels=$\frac{Total\ PV\ Capacity}{Panel\ Rated\ Power}$………………………………Eqn (4)

Based on this equation, we will need to use only 20 panels of 375W for each, and 10 are connected in parallel while 2 are connected in series and all panels will have 36.75m^2 as total area.

3.3.5 Battery Storage System

Sizing the battery Bank Integrated to store excess energy for later use. For Rwanda's weather, 2 days of autonomy is recommended for a grid system to ensure reliable power even during rainy spells, the **Figure 3-4** shows the battery banks used in the designed solar charging station model.

Figure 3-4: Battery bank used for Solar Charging station model.

The best battery banks which are on the market are Lithium type ($LiFePO_4$) which have the following specifications shown in the Table 3-4 shows the characteristics and specifications of the battery bank used in the SCS model:

Table 3-4: Battery Characteristics and Specifications

Battery Characteristics	**Specifications**
Rated Voltage, V_R	48V
Battery Rating	200Ah
Battery DOD (Depths of Discharge)	80%
Battery Efficiency	85%

i. Calculations of Battery Energy Storage.

Our daily consumption is 30 000Wh in large installations and its corresponding system voltage is 48V,

Battery Energy Storage= $\frac{Daily\ Energy\ Consumption\ x\ days\ of\ Autonomy}{Battery\ Depth\ of\ Discharge\ (D.O.D)}$ **…………………**Eqn(5).

ii. Calculation of the battery bank capacity.

Battery bank capacity=$\frac{Daily\ consumption*days\ of\ autonomy}{D.O.D*system\ voltage*Battery\ Efficiency} = \frac{Battery\ Enery\ Storage\ in\ Wh}{System\ Voltage\ in\ V*Battery\ Efficiency}$

……………………………. Eqn (6).

iii. Calculation of the number of battery strings.

Number of batteries string= $\frac{Total\ Battery\ capacity}{Battery\ rating}$……………………… Eqn (7).

From these equations, the selected battery capacity is 1839Ah at 48V, and it is configured with 10, 48V, and 200Ah batteries connected in Parallel to meet the capacity.

3.3.6 DC-DC Booster Converter.

The DC-DC booster converter used in designing a solar charging model is built with some electrical components such as inductor boost, capacitor boost, IGBT boost, and diode boost as shown on the **Figure** 3-5 below and it was picked from the MATLAB Simulink SCS model.

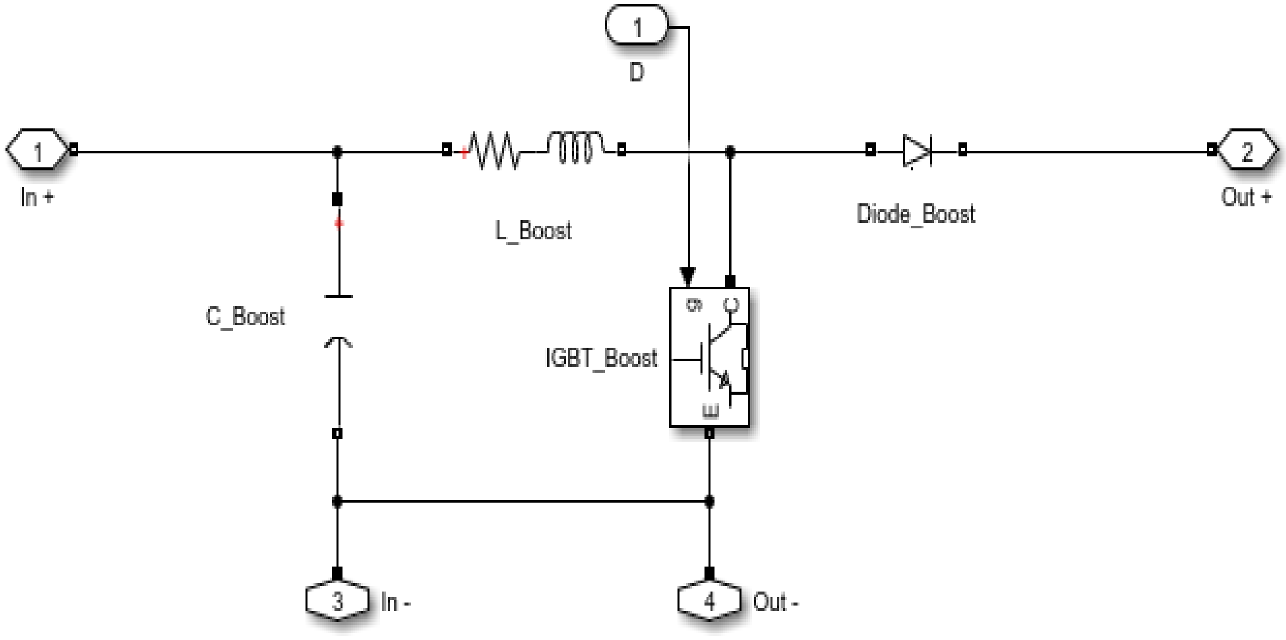


Figure 3-5: DC-to-DC back booster converter used in our SCS model.

Designed a boost converter using an IGBT for the solar PV charging system. It was modeled to regulate the power output from the PV array, the **Table 3-5** below are the Parameters and specifications of the DC-to-DC booster converter.

Table 3-5: Parameters used to design DC to DC booster converter and Specification.

Parameters used to design DC to DC booster converter	Specifications
Input voltage ranges from PV panels:	
Minimum voltage input, V_{in}	96V approximately.
Nominal voltage, $V_{in\text{-}nominal}$	96V approximately.
Battery Bank Voltage, Vout	48V
Power Requirement:	
Maximum Load Power, Pload	30 kW
Converter Efficiency (η) is assumed to be;	95%.
Input Power: $P_{in} = \frac{P_{load}}{\eta}$	$31.359kW.$
Recommended Switching Frequency for IGBT-based converters.	10 kHz to 25 kHz.

i. Key Components Calculations

1. Inductor Calculation

The inductor value for a boost converter is given by: $L = \frac{V_{in}*(V_{out}-V_{in})}{f_s*I_{out}*V_{out}}$ ……...Eqn (8), Where: V_{in}= 96 is the normal input voltage, V_{out}= 48V, Switching frequency f_s= 20kHz. Nominal output current I_{out}=$\frac{30\ 000W}{48v}$= 625 A.

2. Capacitor Calculation

The output capacitor value for maintaining voltage ripples is given by: C=$\frac{I_{out}}{f_s*\Delta V_{out}}$.……...Eqn (9), where: I_{out}= 625A, Ripple voltage ΔV_{out}=5%*48=2.4V and switching frequency f_s=20 000Hz. Substitute these values: $C = \frac{625}{20\ 000*2.4}$= 0.013F (13 000μF).

3. IGBT Selection

We choose IGBTs with the following specifications: Voltage rating: $V_{ce} = 1.5 * V_{in-max}$=150V…Eqn (10) and Current rating: $I_C = 2 * I_{out} = 1250A$……Eqn (11), for safe operation. We recommended IGBT models: Infineon FZ1500R33HE3 or Mitsubishi CM600HA.

4. Diode Selection

The fast recovery diode for high-efficiency diode for high efficiency, voltage rating $V_{diode}>V_{out}$, and Current rating $I_{diode}>I_{out}$.

3.4 Matlab-Simulink Model with MPPT Controller.

The MATLAB Simulink model comprises with main parts explained above of the SCS model and subsystem before integrating the ANN controller given Figure 3-1 below.

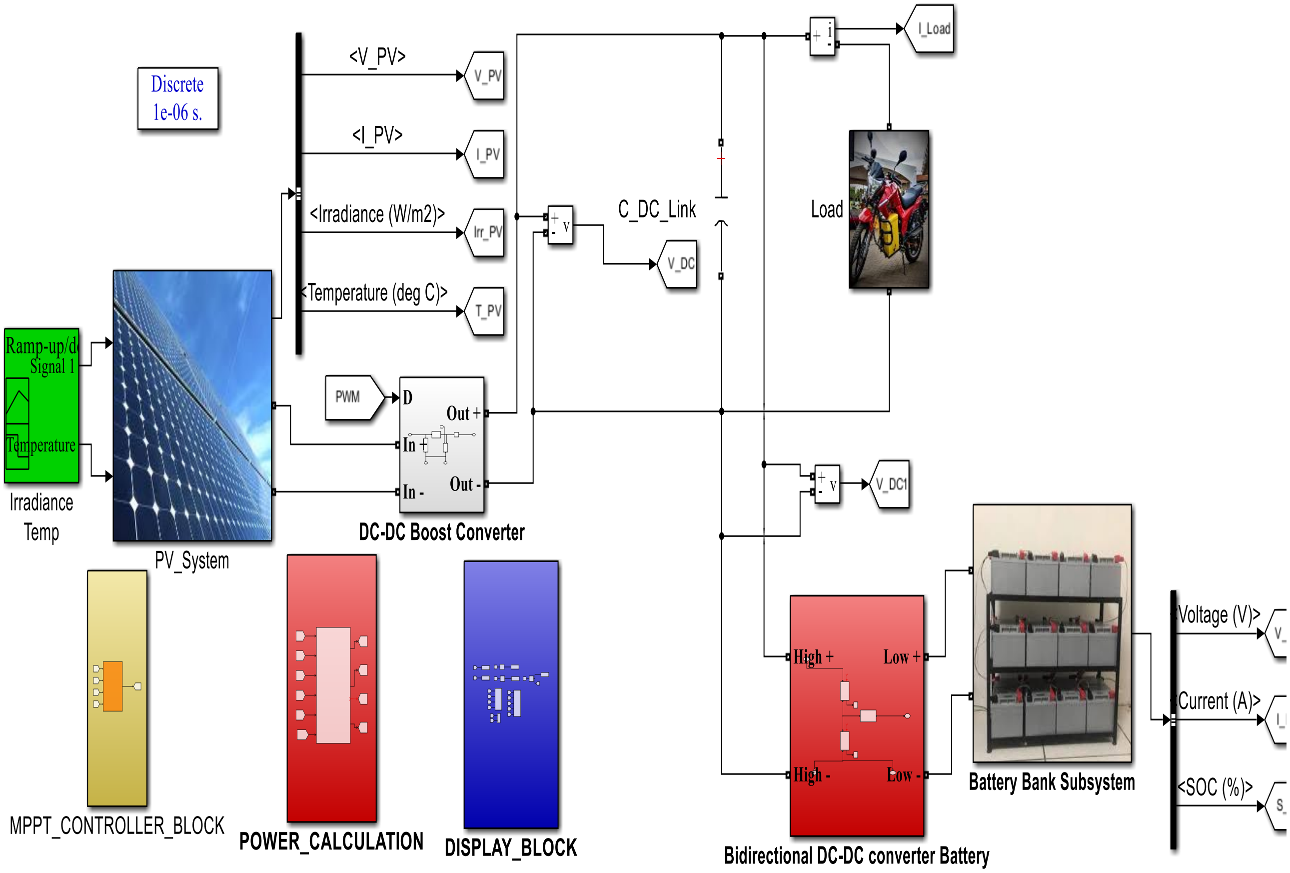


Figure 3-6: The SCS Matlab Simulink Model which uses the MPPT Controller

The Figure 3-6 represents a solar-powered charging system for an electric motor vehicle with power flow management between a photovoltaic (PV) system, battery storage, and the load. In the paragraphs below interpret each component in detail.

PV System (Solar Panel): it generates electricity based on irradiance (W/m^2) and temperature (^{o}C), the Maximum Power Point Tracking (MPPT) controller optimizes power output from the PV system, The DC-DC boost converter increases the voltage level of the PV output to ensure efficient energy transfer.

Battery Storage System: This is a bidirectional DC-DC converter that manages power flow between the battery bank and the DC link, its Charging mode: Excess solar energy charges the battery, and in its Discharge Mode: the battery provides power when solar energy is insufficient. The battery bank subsystem consists of multiple batteries connected and the battery's state is monitored with Voltage (V_Bat); Current (I_Bat) and State of Charge (SOC%).

Power Calculations and Display Blocks: The power Calculation Block computes electrical parameters such as power output, efficiency, and system performance. The display block visually represents system parameters.

Overall Functionality:

From the above calculations, the power generated from PV panel is distributed between the battery storage and the load, the system performance is monitored via power calculation and display units. The **Table 3-6** shows the main parts of SCS model and their functions

Table 3-6: The main parts of SCS model and their functions.

Main parts	**Functions**
PV panel (solar Panel)	Generate power.
MPPT Controller	Ensures optimal power extraction.
DC-DC Boost Converter	Regulates and steps up the voltage
Bidirectional DC-DC Converter	Manages energy flow to and from the battery

3.5 Process of Artificial Neural Network (ANN) Integration

Artificial Neural Networks were integrated to enhance the performance of the MPPT system and improve overall efficiency. The collected data used to train ANN to harvest maximum solar irradiance and the **Table 3-6** below shows monthly Solar Irradiance, Ambient Temperature, and PV Module Voltage data used to train ANN for harvesting maximum Solar irradiance[24].

Table 3-6: Monthly Solar Irradiance, Ambient Temperature, and PV Module Voltage data used to train ANN for harvesting maximum Solar irradiance.

Months	**Average solar irradiance (W/m^2)**	**Average Ambient Temperature**	**Maximum output Voltage of PV (V)**
JANUARY	980	21.1	47.9
FEBRUARY	990	21.7	47.7
MARCH	970	20.0	47.5
APRIL	930	21.7	46
MAY	880	21.9	47
JUNE	980	22.5	48
JULY	970	21.9	48
AUGUST	980	23.7	48
SEPTEMBER	870	21.4	47.4
OCTOBER	860	21.4	47.3
NOVEMBER	940	21.9	47
DECEMBER	1000	20	48

3.5.1 ANN Architecture.

In optimizing maximum solar irradiance tracking the above data were used to train ANN and the ANN model was designed by a two-layer feedforwards network with sigmoid hidden neurons and linear output neurons, suitable for regression tasks and the **Figure 3-7** represents a simple Artificial Neural Network (ANN) architecture used for training.

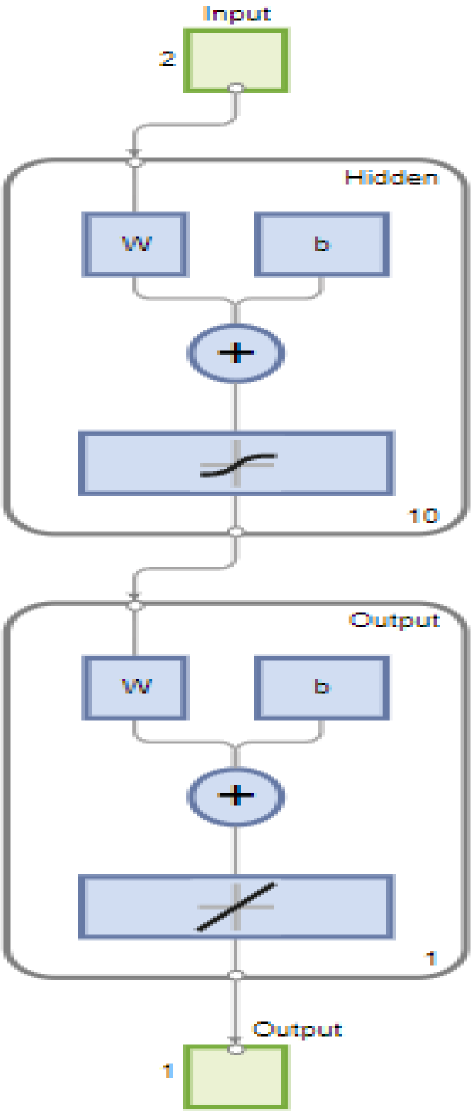


Figure 3-7: The structure of layers that make ANN Algorithm.

3.5.2 THE STRUCTURE INTERPRETATION.

INPUT LAYER: the network takes an input with 2 features (as indicated by the number “2” inside the input block). Hidden layer: it consists of 10 neurons as indicated by the number “10” at the bottom of the hidden layer block. **This hidden layer has: Weights (W)** which is a matrix connecting the input layer to the hidden neurons, **Biased (b)** which is added to the weighted sum before activation and Summation (+) where the inputs are multiplied by weights, added to biases, and then passed through an activation function represented by the curved symbol.

OUTPUT LAYER: This layer consists of **1 neuron** as indicated by the number “1” at the bottom of the output layer block. Similar to the hidden layer, it has: **Weights (W)** and **Biases (b), Summation (+)** operation, Activation **function** represented by the curved symbol and the final output is 1-dimensional which suggesting either regression or binary classification.

3.5.3 FUNCTIONAL INTERPRETATION

Feedforward process: the 2-dimensional input is fed into the hidden layer where it processes the input using learned weights and biases, applies an activation function, and passes the result to the output layer. The output layer performs another weighted summation, applies an activation function, and generates the final output.

Possible Activation functions: the hidden layer likely uses a nonlinear activation function like ReLU, Sigmoid, or Tanh to introduce complexity. The output layer might use; **Sigmoid** for binary classification, **SoftMax** for multi-class classification and **Linear** activation for regression.

3.5.4 Training of ANN

Train a neural network to map predictors to continuous responses. **Hidden Layers:** Two hidden layers with Re LU activation functions.

Data.

Predictors: Input_train_ANN- [2x12 double], included solar irradiance, and ambient temperature. **Inputdata_for_training_ANN:** Double array of 12 observations with 2 features. **Responses:**

Outputdata_training_ANN- [1x12 double]. **Output_for_training_ANN:** Double array of 12 observations with 1 feature, provided the optimal duty cycle for the DC-DC boost converter.

ANN Algorithm

Data division: Random, Training algorithm: Lenberg-Marquardt as it is very accurate and fast in training and Performance: Mean Square Error (MSE).

3.6 Model with ANN Integration.

The trained ANN was integrated into the MPPT system to provide real-time control decisions to harvest maximum solar irradiance and get the maximum possible output power. The **Figure 3-8** shows ANN block diagram used in SCS Simulink model.

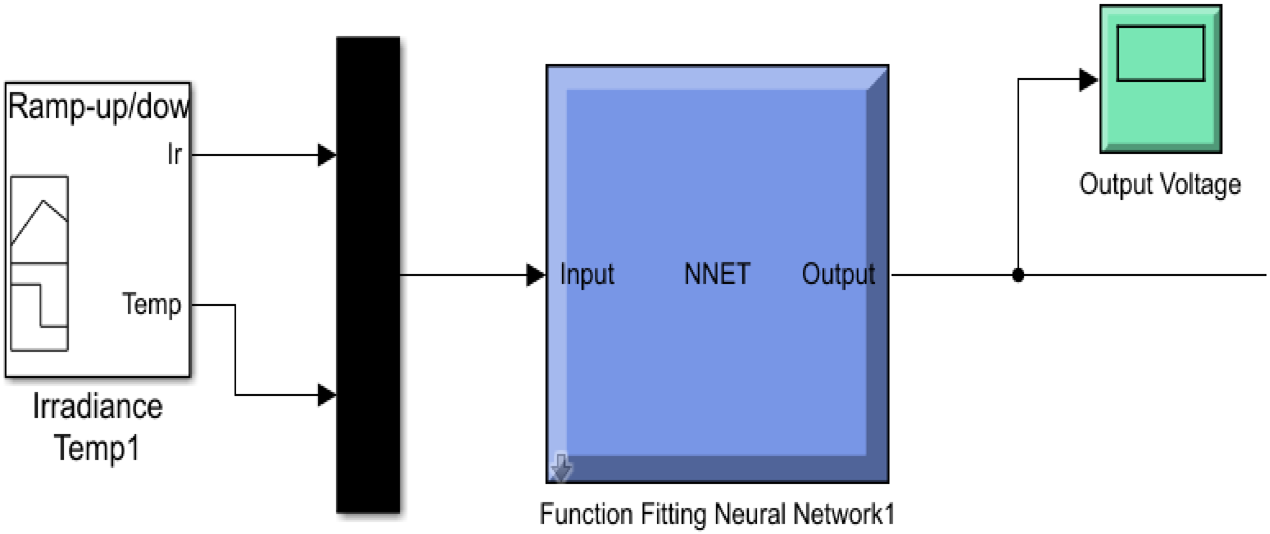


Figure 3-8: The ANN block diagram used in designed SCS MATLAB model.

The Figure 3-9 below represents a solar- powered electric motorcycles charging system with an Artificial Neural Network (ANN) control strategy. It appears to be a Simulink block diagram showing the flowchart of power and control signals. In this model, MPPT (Maximum Power Point Tracking) was replaced by ANN (Artificial Neural Network) is used to optimize power extraction from the PV system and this enhance efficient power extraction of SCS model.

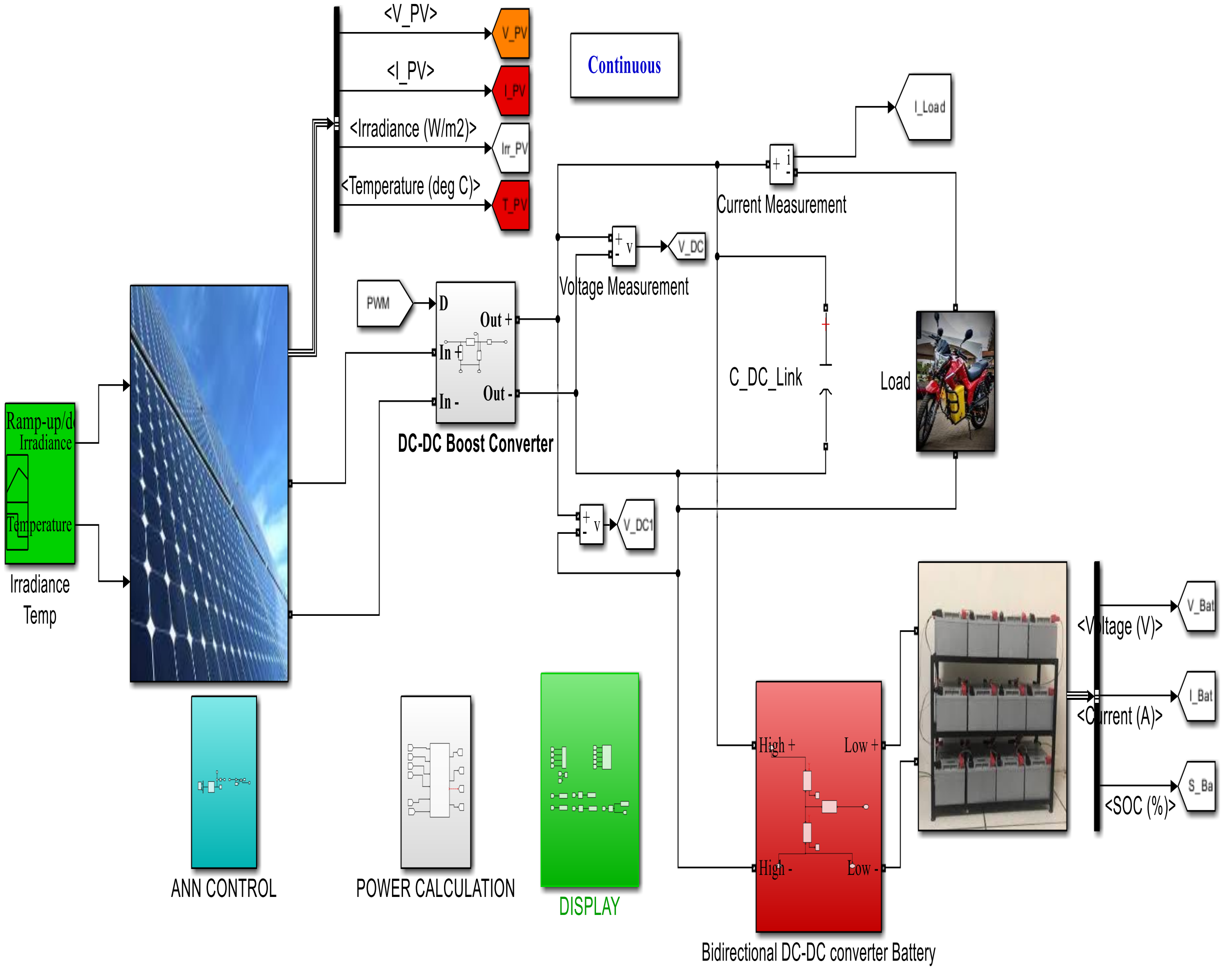


Figure 3-9: The Solar charging station model with ANN Controller.

CHAPTER 4 . RESULTS AND DISCUSSION

4.1 Calculated results.

with using the equations (1), (2), (3), (4), (5), (6), (7), (8), (9), and (10). The results obtained are shown in the **Table 4-1** below:

Table 4-1: The Calculated Parameters and obtained results.

Calculated Parameters	**Obtained results.**
Daily energy consumption:	30 kWh.
The minimum input power to the Load:	12 kW.
Daily PV energy output:	35.295kWh/day.
Required PV Capacity:	7.059 kW.
Number of PV panels:	20 Panels approximately 375W per panel where 10 are connected in parallel and 2 are connected in series.
Battery energy storage:	75kW.
Battery bank capacity:	1839Ah.
Number of battery string:	10 batteries.
Booster Input Power:	31.359kW approximately.
Inductance of booster inductor:	0.0075H 0r 7.5mH.
Inductor norminal output current:	625A.
Capacitance of the booster capacitor:	0.013F.
IGBT voltage rating V_{ce}:	150V.
IGBT current rating:	1250A for safe operation.
The type of IGBT recommended:	Infineon FZ1500R33HE3 or Mitsubishi CM 600HA.

4.2 ANN training Results.

4.2.1 Training process.

The ANN model was trained using supervised learning techniques with historical and real-time data. **Training Dataset:** Split from the collected data with 70% used for training, **Validation Dataset:** 15% of data for validation and 15% for testing, **Performance Metrics:** Mean Squared Error (MSE) and prediction accuracy were used to evaluate the model. The **Table 4-2** and Table **4-3** summarize the observations obtained during the ANN training process.

Table 4-2: The training start time and the obtained results for 10 sized layers.

Training start time: 15-Feb-2025 02:48:22

Layer size: 10

	Observations	MSE	R
Training	8	0.0255	0.9523
Validation	2	0.0795	1.000
Test	2	0.1692	1.0000

Training Progress:

Table 4-3: Training Progress results on Initial Valuer, Stopped Value and Target Value.

Unit	**Initial Value**	**Stopped Value**	**Target Value**
Epoch	0	6	1000
Elapsed time	-	00:00:02	-
Performance	2.25	6.29e-25	0
Gradient	6.63	1.45e-12	1e-07
Mu	0.001	1e-08	1e+10
Validation Checks	0	4	6

The Figure 4- below, represents key performance metrics the training of an Artificial Neural Network (ANN) using the Levenberg-Marquardt (LM) backpropagation algorithm. Each subplot is broken down and explained as below:

1st Subplot (Top): Gradient Vs. Epochs:

The y-axis(gradient) shows how the gradient of the performance function usually the mean square error (MSE) evolves over epochs. The x-axis (epochs) represents the number of training iterations. The gradient is decreasing, which indicates that the network is converging towards an optimal solution. The final gradient value at epoch 6 is 1.454e-12, which is very small suggesting that the training has almost reached a minimum error.

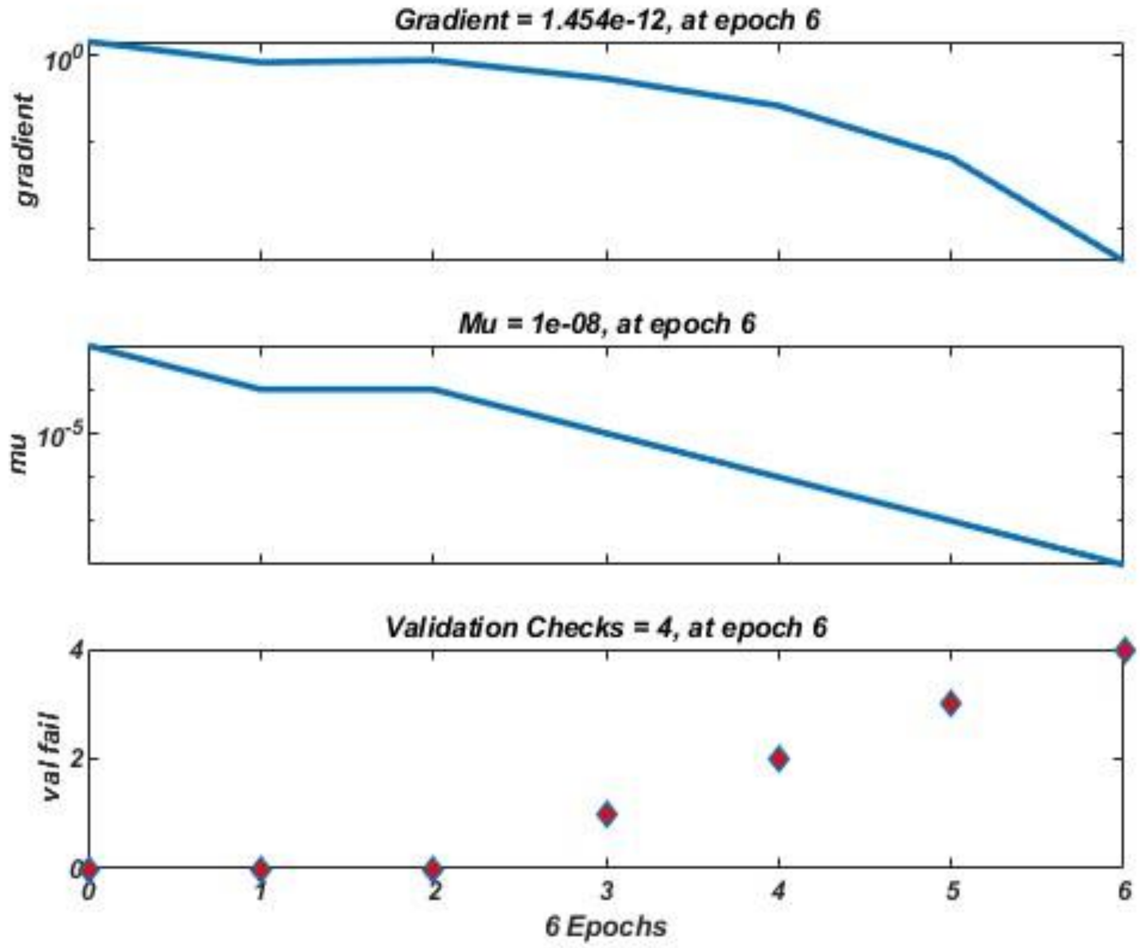


Figure 4-1: Validation state of ANN in training process.

2nd Subplot (Middle): Mu Vs. Epochs

The y-axis (Mu, the Marquardt parameter) represents the adaptive learning control parameter used in the Linear Marquardt LM algorithm. The x-axis (epochs) represents the number of training iterations. The decreasing trend in Mu indicates that the algorithm is refining the weights effectively and is stabilizing as training progresses. At epoch 6, Mu= 1e-8, meaning the network is no longer making large weight adjustments, which confirms convergence.

3rd Subplot (Bottom): Validation Checks Vs. Epochs.

The y-axis (val fail) represents the number of times the validation error has increased consecutively. The x-axis (epochs) represents the training iterations. The number of validations failures is increasing and reaches 4 at epoch 6. In ANN training, a certain number of validation failures trigger early stopping to prevent overfitting. Since it reached **4 validation checks**, the training likely stopped to avoid overfitting.

Overall interpretation

The ANN training converged successfully since the gradient became very small. The Mu value decreased, indicating stable optimization. The validation failures suggest the early stopping was applied, meaning further training might have led to overfitting. The model is likely well-trained, but you should verify generalization by evaluating its performance on a test set.

4.2.2 Performance Analysis.

The ANN-enhanced MPPT system was evaluated under variable solar irradiance to assess its: in tracking the maximum power point, Response time, Stability, and robustness.

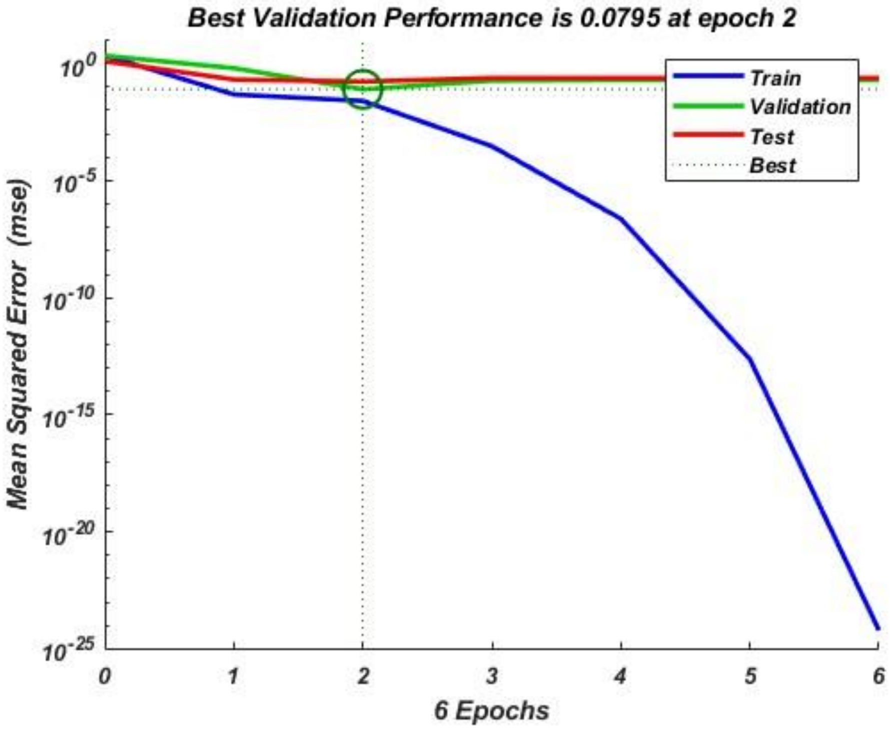


Figure 4-1: The best performance of ANN training.

Figure 4-1 represents the performance of an Artificial Neural Network (ANN) during training, validation, and testing phases, using the Mean Square error (MSE) as the performance metric, the figure is explained in details as follow.

Key observations:

Axes: the x-axis represents the number of epochs (iterations of training) and the y-axis (logarithmic scale) represents the Mean Square Error (MSE), which measures the error between predicted and actual values.

Curves: The blue line (Train): Represents the MSE during training. The error continues to decrease as the number of epochs increases. The Green Line (Validation) represents the validation MSE, initially, it decreases but after a certain point, it stops improving. The Red Line (Test): Represents the test error, which is typically similar to the validation error.

The best Validation Performance: the text at the top indicates that the best validation performance (lowest validation MSE) was 0.0795 at epoch 2. The black dotted line and the circle mark this epoch. After this epoch, the validation error does not improve significantly, which suggests that training beyond this point may lead to overfitting.

Overfitting Indication: The training error continues to decrease, but the validation and the test errors remains almost constant or increase slightly. This suggests that epoch 2, the model starts memorizing the training data instead of generalizing well.

Interpretation:

the model achieves its best generalization at epoch 2 with a validation MSE of 0.0795. training beyond this epoch leads to overfitting, where the training error decreases significantly, but the validation and test errors do not improve. To avoid overfitting, early stopping is applied at epoch2, selecting the best-performing model before overfitting occurs.

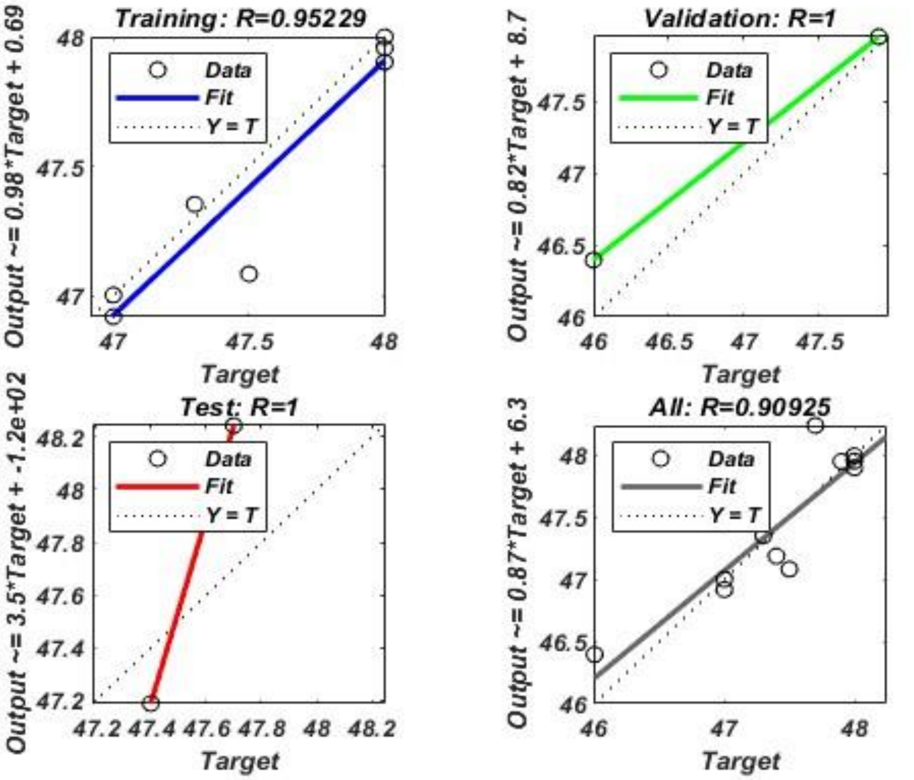


Figure 4-2: The coefficient of correlation of Training, Validation, Test, and overall data during ANN training.

The Figure 4-2 presents regression plots for the training, validation, and test phases of an Artificial Neural Network (ANN) model. Each subplot compares the predicted output (y-axis) to the target values (x-axis) for different datasets. The solid-colored lines represent the best fit between the predicted and target values, while the dotted line (Y=T) represents an ideal perfect fit. The correlation coefficient (R) indicates how well the model's predictions align with the actual targets, with R=1 being a perfect fit. In the training phase (top-left), R=0.95229, suggesting a strong correlation between predicted and actual values, though not perfect. The validation phase which is at the top-right shows an R-value of 1, indicating that the model fits the validation data perfectly. The test phase which is bottom-left also has an R-value of 1, implying excellent model generalization for unseen data. The overall performance which is at bottom-right has an R-value of 0.90925, suggesting a strong but slightly weaker correlation when all data is considered together. The slopes of the fit lines indicate the model's tendency to overestimate or underestimate predictions, with some deviations from the ideal Y= T line. While the test and validation sets show perfect correlation, the lower R-value for the overall dataset suggests room for improvement in the model's generalization across all data.

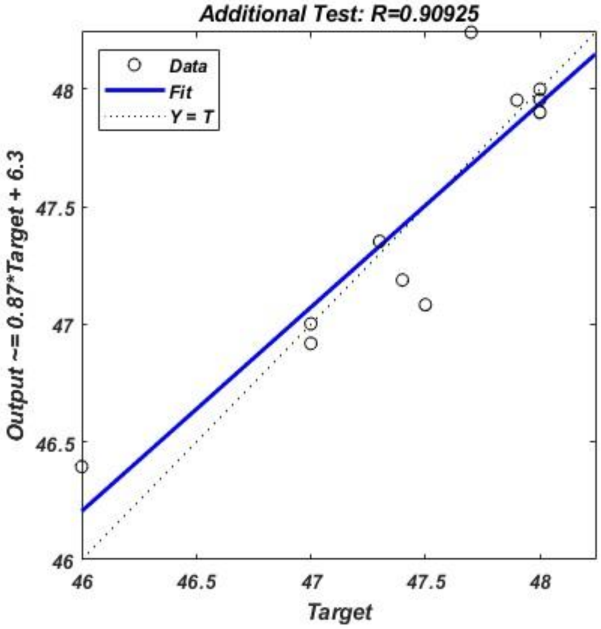


Figure 4-3: The Coefficient of correlation of the additional test in ANN training.

From the Figure 4-3 scatter plot shows the relationship between the **Target** values (x-axis) and **Output** value (y-axis). The **black circles** represent actual data points, indicating how well the predicted output matches the target. The **blue line** is a linear fit, representing the regression model that approximates the relationship between target and output. The equation of the fit, Output= 0.87*Target+6.3, suggests that the output is slightly lower than the target but with an offset of 6.3. The **dotted diagonal line** represents the ideal case (Y=T), where the output would perfectly match the target. The R-value (R=0.90925) indicates a strong positive correlation between target and output, suggesting a good model fit. Data points closely following the blue line indicate a well-performing model, while deviations show prediction errors. The slight scatter of points around the fit line suggests some level of error, likely due to model imperfections or noise. The y-intercept of 6.3 implies a systematic bias where outputs are consistently higher at lower target values. Overall, the figure suggests that the model is reliable but could benefits from fine- tuning to improve accuracy.

4.3 Simulation results with MPPT Controller.

With the MPPT controller method, final results were read on PV, Battery, and Output power scopes, and we analyzed the trends of the results obtained during simulation as **Table 4-4** shows.

Table 4-4: Displayed values after simulation.

Displayed Parameters	**Specifications**
PV maximum tracked solar irradiance	1000 W/m^2
Ambient temperature	25 ^oC
PV average output Voltage	44.32V
Average voltage of the DC-DC booster converter	44.31V
Displayed output power to the Load with MPPT controller	1.108e+04 W

The simulation with MPPT controller displayed maximum output power to the load of 1.108e+4 Watts (11080W=11.08kW), 44.31V and 44.32V as mean output voltage of DC converter and PV panel respectively. This maximum output power is not sufficient at maximum load of 30 000W (30 kW) which is connected to this system.

4.3.1 Trends of PV and Battery parameters, and Output power.

By regarding to the **Figure 4-4** below, the graph consists of four subplots displaying key parameters of a photovoltaic (PV) system's performance over time. **The first subplot in green color** represents the voltage of PV panel, showing oscillatory behavior before stabilizing, indicating the system's transient response before reaching steady-state conditions. **The second subplot in blue color** depicts the PV current, which varies in response to changes in irradiance and voltage, with a notable dip and recovery. **The third subplot orange color** illustrates the power output of the PV system, also experiencing initial oscillation before reaching stability, suggesting the influence of an MPPT (Maximum Power Point Tracking) algorithm optimizing power extraction. **The fourth subplot which is in purple color** represents irradiance levels in W/m^2, showing fluctuations that directly affect the PV system's power generation. The variations in irradiance correlate with changes in current and power, confirming the dependency of PV performance on sunlight intensity. The damping oscillations in power and voltage suggest an adaptive MPPT technique, likely based on perturb and observe or incremental conductance. The transient phase is characterized by rapid oscillations before the system stabilizes, ensuring optimal energy harvesting. The synchronization of changes in irradiance, current, and power demonstrates the PV system's dynamic response to environmental conditions. Overall, the graph highlights the effectiveness of the MPPT controller in stabilizing power output despite fluctuating irradiance.

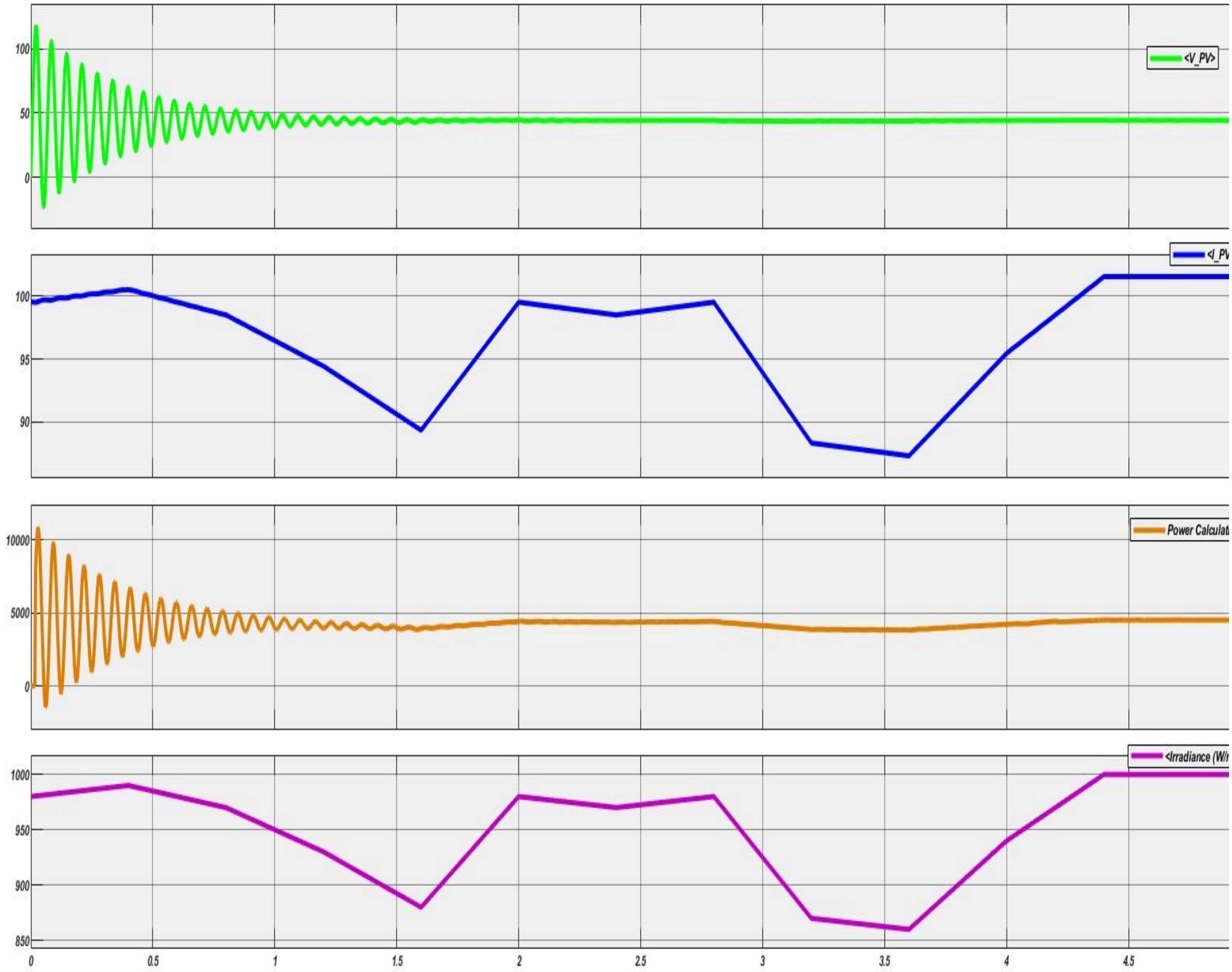


Figure 4-4: The PV Panel Voltage, Current, and Output power simulated results with MPPT Controller.

With regarding to this figure again, the PV output current vary as the solar irradiance vary and PV output power vary according to how output voltage of PV come to steady state. The PV output voltage become steady at 2nd seconds while the output PV power become steady even if it is somehow become distort a little bit due to some factors such as variation of sunlight intensity, partial shading, non-optimized control strategies of MPPT which can converge properly.

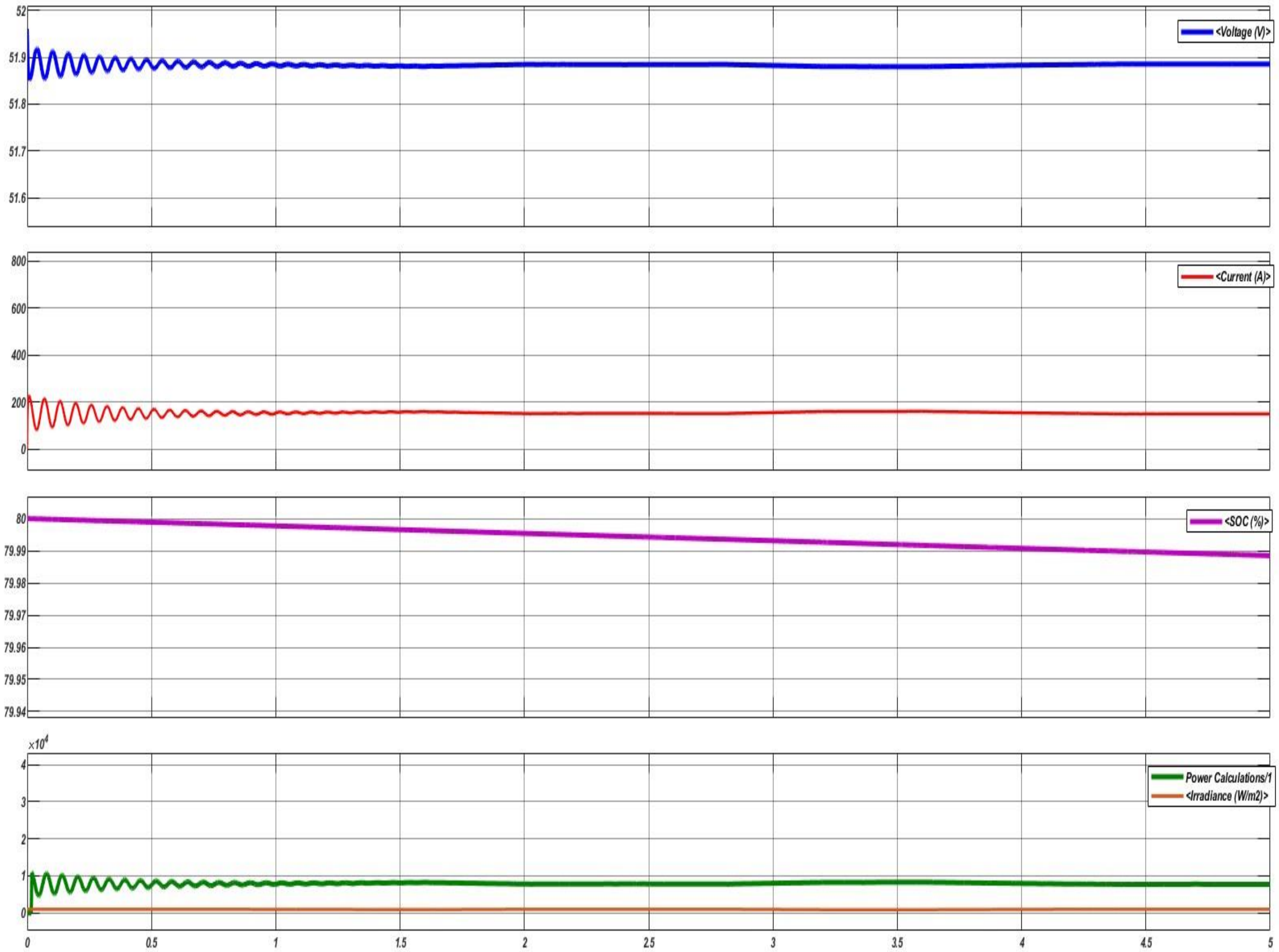


Figure 4-5: The variation of the voltage, current, power of the battery bank, and state of Charging (SOC).

Regarding this **Figure 4-5** above represents the dynamic behavior of battery response parameters on solar charging systems, illustrating variations in key battery electrical parameters over time. The first subplot in blue color represents the voltage (V), which exhibits initial oscillations before stabilizing around a steady-state value slightly above 51.8V. the second subplot in red color shows the current (A), which also undergoes transient oscillations before setting at a gradually declining value, indicating system stabilization. The third subplot in purple illustrates the state of charge (SOC) of the battery in percentage, showing a slow and steady decrease over time as energy is drawn from storage. The fourth subplot in green and orange colors compares power calculations with irradiance (W/m^2), where the power in green color exhibits minor oscillations and stabilizes, while the irradiance in orange color remains nearly constant at a low value. These results suggest that the system experiences initial transient fluctuations but reaches a steady-state operation. The gradual decline in SOC indicates that the battery is being discharged, possibly due to a load connected to the system. The voltage and current waveforms suggest a controller power management mechanism regulating energy flow. The power calculation and irradiance data indicate the impact of solar input on the charging dynamics. Overall, the system demonstrates stability after initial transients, reflecting efficient energy conversion and regulation. From this graph, at 1.5th seconds the battery voltage, current and power were at constant value of their steady state with a very little distortion as the battery state was discharged from 80% to79.98% for supplying the connected loads. This means the battery is supplying a small, relatively constant amount of power to a load. The load's requirements are such that the battery's output (current, voltage and power) is steady, and the change in SoC reflects the minimal energy being utilized by the load, this distortion was caused by connected loads.

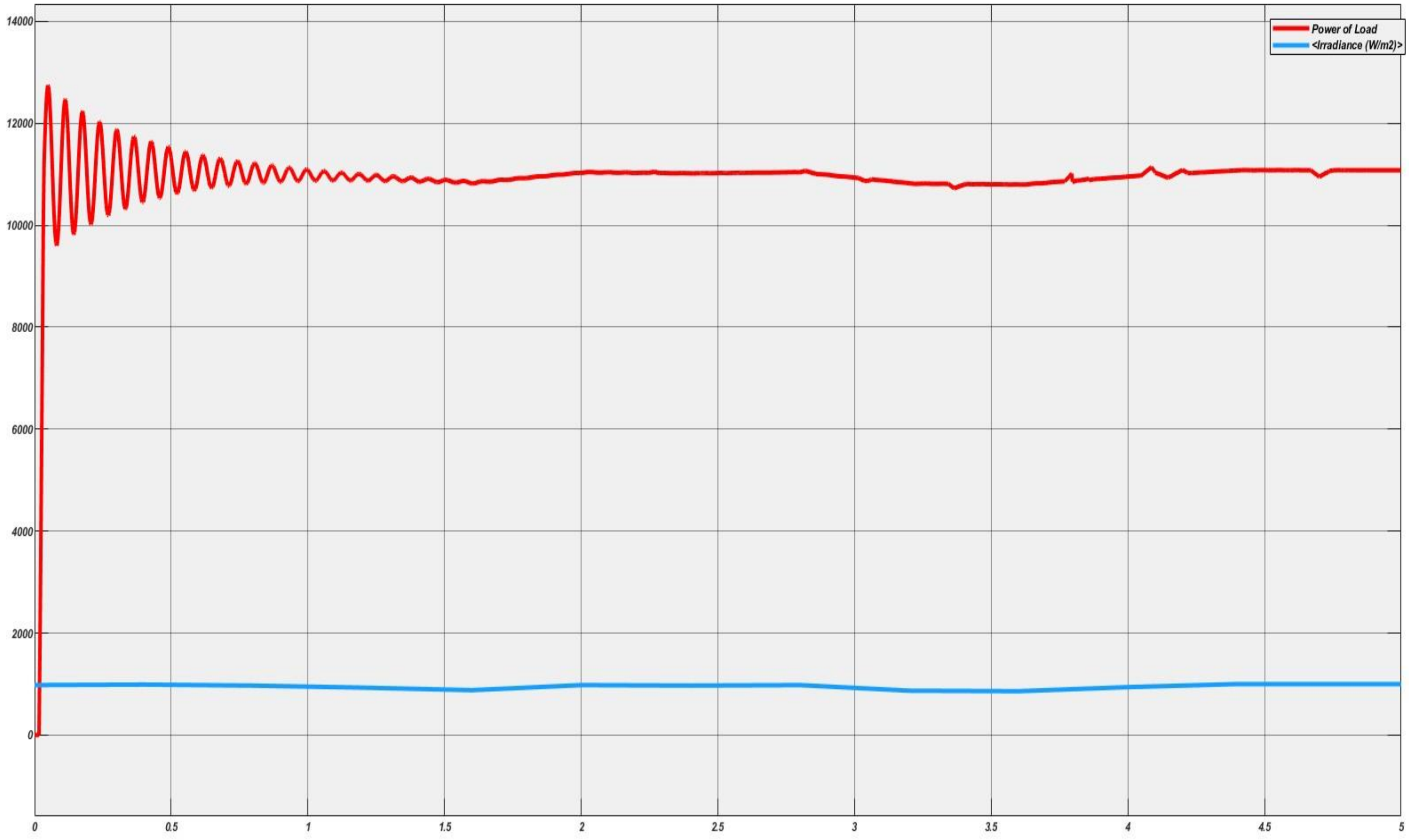


Figure 4-6: The variation of the output power to the connected Load.

This **Figure 4-6** illustrates also the dynamic response of load power and solar irradiance over time. The red line represents the power of the load, while the blue line represents solar irradiance in W/m^2. Initially, the load power exhibits high oscillations, indicating a transient response before gradually stabilizing. This behavior suggests a system adapting to change, possibly due to an MPPT algorithm optimizing power extraction from a solar PV system. Over time, the oscillations decrease, and the power of the load reaches a steady-state value. Meanwhile, the solar irradiance remains relatively stable, with minor variations, suggesting that external environmental conditions are not significantly fluctuating. The steady-state behavior of the power load suggests that the control mechanism if effectively regulating power delivery. The initial overshoot and oscillations indicate a non-instantaneous adaptation, like influenced by system inertia or control parameters. The graph highlights the importance of optimizing MPPT algorithms to minimize transient effects and improve power stability.

From this graph again, the total connected load is 13kW and 30kW, but the system is only able to provide 11.08kW and this can be analyzed as PV array is not enough and battery discharge limitation but it is due to lack of rapid tracking of maximum solar irradiance. About the fast response and stability, the system reaches steady 11.08kW in 2 seconds which means that power conversion system is efficiently to stabilize the power output and the minimal transient oscillation indicate good control dynamics.

4.4 Simulation results with ANN Controller

With the ANN controller method, results after simulation and the trend of the results after simulation were analyzed. As we can see from this **Table 4-5** containing the displayed results for PV, Battery, and input power to the load, integration of ANN shows good improvements on the solar charging station to harvest maximum solar irradiance. The trends of the output in this simulation are shown in this simulation are detailed on the following graphs.

Table 4-5: Displayed results for PV, Battery, and on load with ANN controller.

Displayed Parameters	**Specifications**
PV maximum tracked solar irradiance	1000 W/m^2
Ambient temperature	25 ºC
PV average output Voltage	87.17V
Average voltage of the DC-DC booster converter	83.75V
Displayed output power to the Load with ANN controller	3.958e+04 W or 39 580W

4.4.1 Trend of PV, Battery, and Output Power Simulated Results.

Figure 4-7 illustrates the output display of the photovoltaic (PV) system when integrated with an artificial neural network (ANN) within the solar charging station model. This figure showcases the system's ability to effectively adapt to varying solar irradiance conditions, demonstrating a notable enhancement in energy output stability and efficiency. The upward trend in output power corresponds to the ANN's capability to optimize the tracking of maximum power points, which is particularly important as solar irradiance fluctuates throughout the day. As the ANN processes real-time data, it adjusts the operational parameters of the PV system to maintain optimal performance, leading to higher energy extraction rates. Moreover, the data indicates that as irradiance increases, the ANN accurately regulates the output current and voltage to maximize power generation. This responsiveness mitigates potential losses associated with traditional maximum power point tracking methods, thereby enhancing overall system reliability. Conversely, during periods of consistent but lower irradiance, the output stabilizes, reflecting the ANN's skill in sustaining an efficient charging process even under less-than-ideal conditions. Consequently, the observable trends in the graph underscore the effectiveness of ANN integration in promoting higher performance levels and a more resilient solar charging infrastructure for electric vehicles. Ultimately, this not only validates the potential of ANN for optimizing renewable energy applications but also strengthens the foundation for embracing sustainable energy technologies.

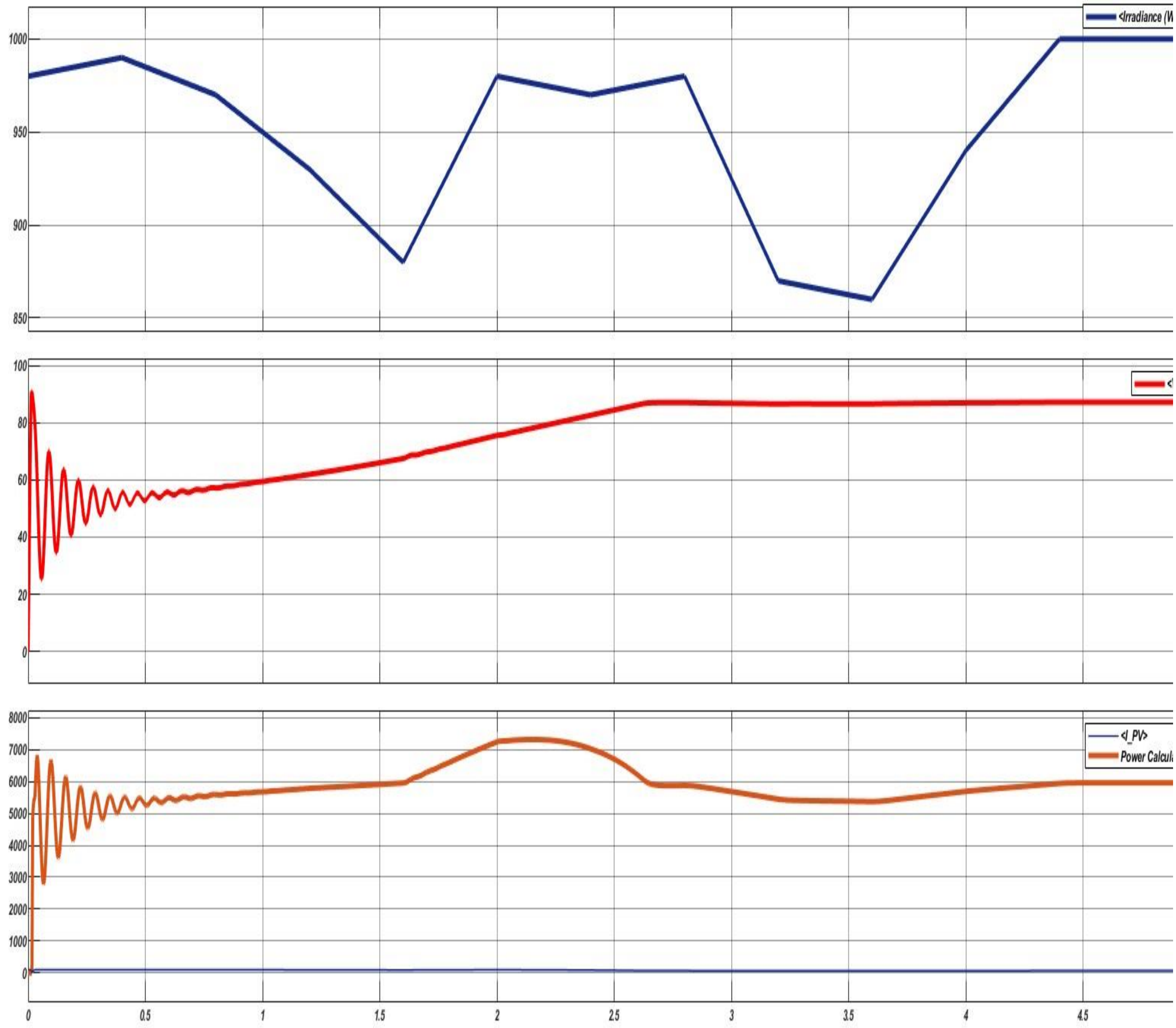


Figure 4-7: The output display of PV When ANN is integrated into the solar Charging station model.

From this graph, as irradiance changes, ANN tracks maximum solar irradiance so that the output current of PV is approaching to be 100Amperes, and PV output voltage of 87.17V which is steady 2.75th seconds and the PV power changed as solar irradiance changed.

4.4.2 The trend of battery response behaviors.

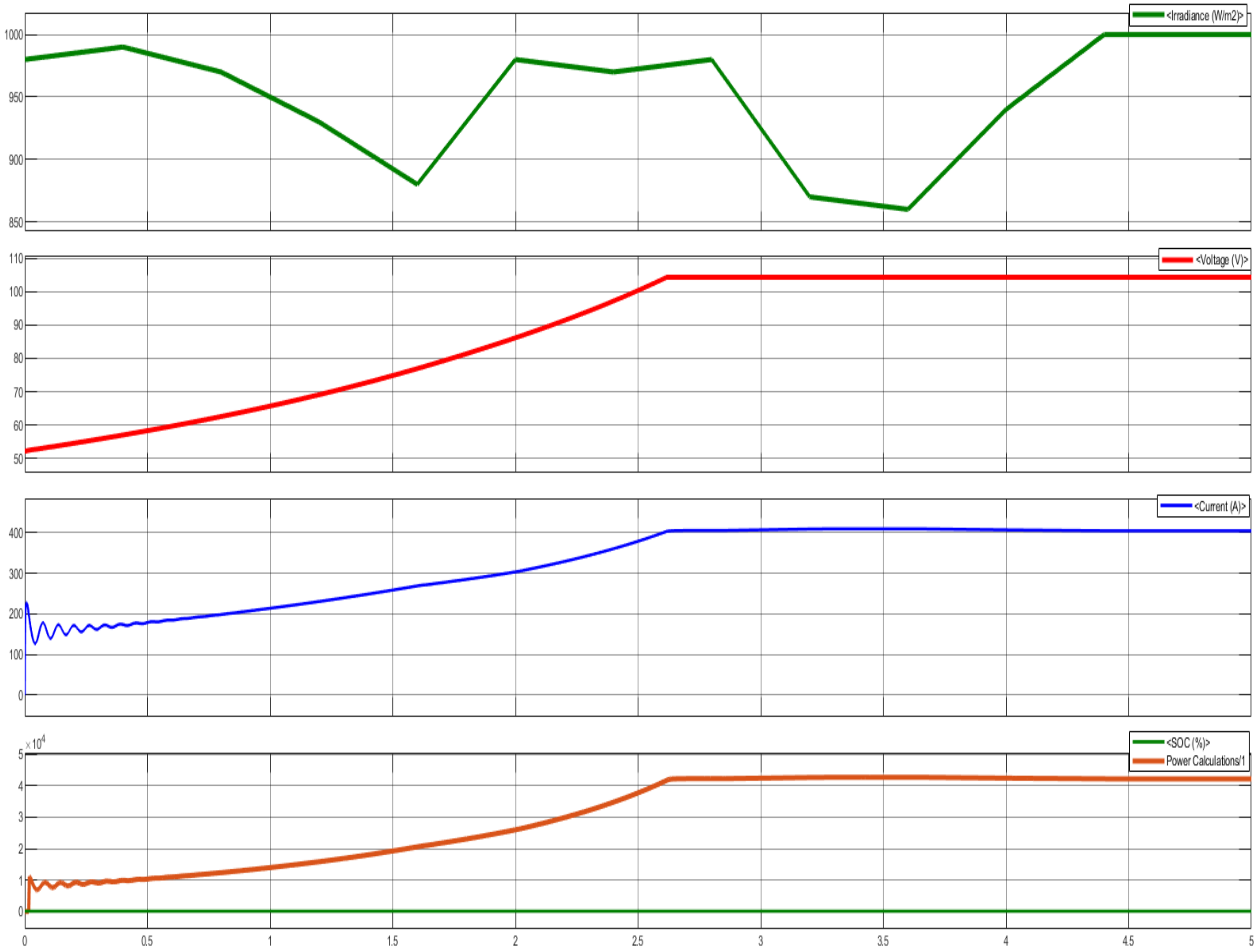


Figure 4-8: The trends in Battery behaviors with ANN simulation.

From this graph, battery SOC is steady from 0th seconds, and battery voltage, Current, and Power increased from 0th seconds up to 2.75 seconds and then become constant in the following seconds. This is because the battery was in the state of charging in the first 2.75 seconds. After, the battery becomes fully charged in 2.75th seconds the load is being powered without the supply of the battery. To this, we have 2 things to do; we can charge more motorcycles or increase the number of the battery storage to ensure the management of all energy harvested from this solar charging station.

4.4.3 The trend of the output power to the load.

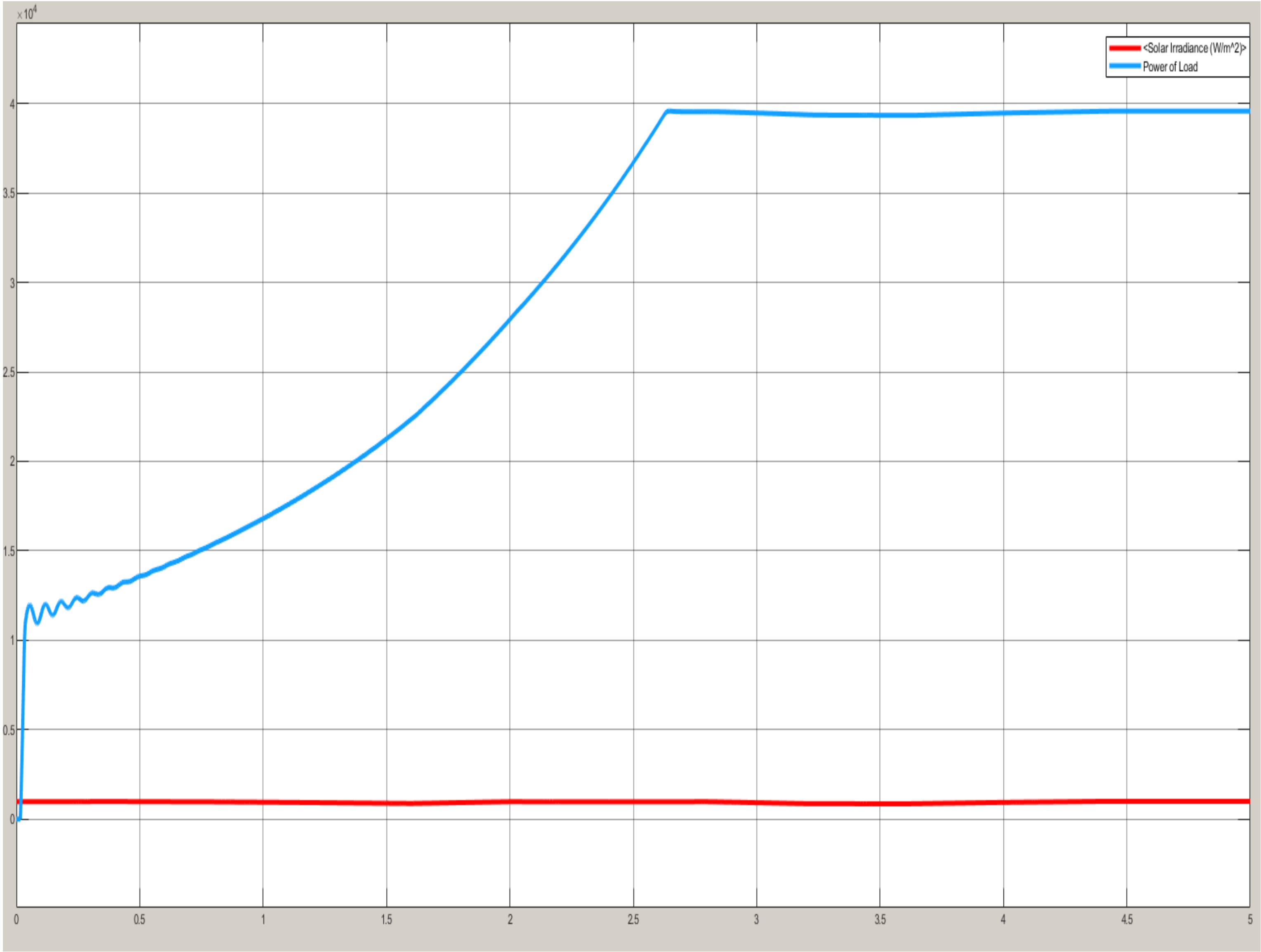


Figure 4-9: The Output power to the Load in simulated solar charging station model when ANN controller is used.

By regarding Figure 4-9 represents the relationship between irradiance and load power in a solar charging station model controlled by ANN. The red curve represents solar irradiance, which remains relatively stable with minor fluctuations. The blue curve, depicting load power, exhibits a rapid initial rise followed by a gradual increase until stabilization, indicating a successful ANN tracking technic. The observed power increase corresponds to improved energy harvesting as irradiance remains steady, optimizing load supply. This confirms the ANN controller's effectiveness in maximizing power extraction under varying conditions. This charging station generates more power 39.58kW than the connected load of 30kW, which is generally a positive sign. However, ensure that: the excess power can be managed properly by storing and charging more motorcycles. The ANN controller is properly sized to handle the power Fluctuations and the voltage level remains stable under different irradiance conditions.

4.5 Solar Charging Station (SCS) model Validation.

Then, we are going to validate this model with using these 3 types of panels and compare the obtained results with MPPT controller and with ANN, the three different PV panels with these properties which are in **Table 4-6** below:

Table 4-6: The three types of PV modules and their Parameter data used to validate a model.

PV module data.	**BYD Company Limited "BYD335P6K-36"**	**Canadian Solar Inc.CS3U-375 MS-AG.**	**Centro Solar America EM 72350SW.**
Maximum power	335.0295	375.314	350.0559
Cells per module (N_{cell})	72	72	72
Open circuit voltage (Voc)	47.28	47.6	47.64
Short circuit current Isc (A)	9.39	9.93	9.59
Voltage at maximum power V_{mp} (V)	37.35	39.8	38.51
Current at maximum power, Imp (A)	8.97	9.43	9.09
Temperature coefficient of Voc (% deg.C)	-0.3015	-0.293	-0.297
Temperature Coefficient of Isc (% deg.C)	0.040096	0.035005	0.049103
Light generated Current I_L(A)	9.4498	9.9881	9.6509
Diode saturation current Io (A)	3.3873*10^-11	2.473*10^-11	2.8976*10^-11
Diode Ideality Factor	0.96998	0.96345	0.97117
Shunt resistance Rsh (Ohms)	1137.3269	294.0017	367.1023
Series resistance Rs (Ohms)	0.51606	0.24088	0.407738

4.5.1 Model validation with BYD Company Limited “BYD335P6K-36” PV Panel.

The **Table 4-7** Shows the displayed results when we validate the SCS model by using the BY335P6K-36 PV panel of BYD Company Limited.

Table 4-7: Displayed results for validating SCS model using" BYD335P6K-36" PV Panel.

Parameters	**Displayed results with MPPT controller.**	**Displayed results with ANN controller.**
PV maximum tracked solar irradiance.	1000 W/m^2.	1000 W/m^2.
Ambient temperature.	25 ^{o}C.	25 ^{o}C.
PV average output Voltage.	44.04V.	85.4V.
Average voltage of the DC-DC booster converter.	44.03V.	82.96V.
Displayed output power to the Load	10.940kW.	38.84kW.

With BYD335P6K-36 PV Panel**,** doesn’t satisfy the connected loads of 30kW with using this with MPPT Controller and it doesn’t have a big difference with resulted obtained with PV Panel used to design the solar charging station model. Also, the **Table 4-7** above contain with displayed results on model validation with BYD335P6K-36 PV Panel in SCS model when ANN controller is integrated to give the output power of 38.84kW to the load and it is sufficient to the connected load of 30kW and the surplus power of 8.84kW will go to charge the battery banks.

4.5.2 Model Validation with Canadian Solar Inc.CS3U-375 MS-AG PV Panel.

Regarding to the **Table 4-8** below, validating the SCS MATLAB model using Canadian Solar Inc.CS3U-375 MS-AG PV Panel shows a good result when ANN is integrated because it gives an output power of 39.65kW which is 3.59times the output power obtained by using MPPT controller.

Table 4-8: The displayed results of SCS model validation with Canadian Solar Inc.CS3U-375 MS-AG PV Panel by using MPPT and ANN controller.

Parameters	**Displayed results with MPPT Controller**	**Displayed results with ANN controller**
PV maximum tracked solar irradiance	1000 W/m^2	1000 W/m^2
Ambient temperature	25 ^{o}C	25 ^{o}C
PV average output Voltage	44.26V	87.35V
Average voltage of the DC-DC booster converter	44.24V	83.83V
Displayed output power to the Load.	11.040 kW	39.65KW.

4.5.3 Model Validation with Centro Solar America EM 72350SW PV Panel.

With this panel, we validate the Simulink model using both the MPPT and ANN controllers also we obtain good results with the ANN controller and the output power to the load is **3.59** times that of the MPPT controller, and other displayed results are tabulated in **Table 4-8** below.

Table 4-8: Displayed results of SCS model validation with Centro Solar America EM 72358SW PV Panel by using MPPT and ANN controller.

Parameters	**Displayed results by using MPPT Controller**	**Displayed results by using ANN Controller**
PV maximum tracked solar irradiance	1000 W/m^2	1000 W/m^2
Ambient temperature	25 ^{o}C	25 ^{o}C
PV average output Voltage	44.11V	86.56V
Average voltage of the DC-DC booster converter	44.12V	83.47V
Displayed output power to the Load.	11.0kW	39. 32kW

4.6 Summarized results of this model validation.

In analyzing the performance of this model validation, the voltage performance under MPPT control, the mean PV output voltage remains around 44V for all panels. With ANN control, the voltage is nearly double 85V-87V which shows that ANN optimizes the voltage at a higher level for better energy harvesting. The power performance, MPPT controller output was 11kW for all panels, ANN controller output was 39kW approximately which is 3.5 times higher than MPPT, and the CS3U-375 MS-AG panel performs the best, reaching 39.65kW under ANN control. The performance Gain of ANN over MPPT; ANN control improves power extraction by 255-259.5% across all panels. The Canadian CS3U-375 MS-AG Panel achieves the highest improvement of +259.1%. ANN control significantly outperforms MPPT, delivering 3.5 times more power for the solar charging station. The CS3U375 MS-AG panel is the most efficient, achieving the highest power output of 39.65kW. As **Table 4-9** shows output power for all 3 PV panels used in validating Solar Charging Station model, then ANN should be the preferred control strategy for optimizing the performance of this solar charging station.

Table 4-9: Summarized results of this model validation.

PV Panel	**Output Voltage with MPPT Controller (V).**	**PV Mean Output Voltage with ANN Controller (V).**	**Output Power with MPPT controller (kW).**	**Output Power with ANN Controller (kW).**
BYD 335P6K-36	44.03	85.40	10.94	38.84
Inc. CS3U-375 MS-AG	44.26	87.35	11.04	39.65
EM 72350 SW	44.12	86.56	11.0	39.32

CHAPTER 5 . CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

This research has successfully designed and analyzed the performance of a solar charging station model for electric vehicles (EVs) using an Artificial Neural Network (ANN) control method. The study addressed the increasing demand for sustainable energy solutions in Rwanda, particularly in the transportation sector, by focusing on maximizing solar irradiance capture and optimizing charging operations. The Matlab/Simulink model developed in this research has demonstrated the potential of solar-powered EV charging stations to alleviate grid pressure, reduce reliance on fossil fuels, and encourage the widespread adoption of EVs in both urban and rural areas. The study's findings indicate that the ANN-based Maximum Power Point Tracking (MPPT) control method is significantly more effective in tracking the maximum power point compared to the traditional Perturb and Observe (P&O) method, especially under variable environmental conditions. This improvement enhances the overall efficiency of the solar charging station, ensuring optimal energy utilization. Additionally, the model demonstrated optimized charging performance, with the ANN controller contributing to a stable and reliable charging process, which is crucial for encouraging EV adoption.

Furthermore, the research highlighted the feasibility of solar charging stations in diverse settings, proving their functionality in both urban areas with grid connectivity and rural locations where grid infrastructure is limited. This finding is particularly significant in promoting EV adoption across different geographical contexts. Moreover, by leveraging Rwanda’s abundant solar energy resources, the proposed model offers a cost-effective and sustainable solution for EV charging. This approach reduces dependence on non-renewable energy sources and mitigates the environmental impact of transportation. The contributions of this research to the existing body of knowledge include the development of a comprehensive Matlab/Simulink model for a solar EV charging station with ANN-based MPPT control, the comparative analysis of the ANN controller against the traditional P&O method, and an in-depth examination of the impact of variable environmental conditions on the charging station’s performance. Additionally, this study demonstrates the potential of solar charging stations in supporting EV adoption in both urban and rural settings.

5.2 RECOMMENDATIONS.

Based on the findings of this study, several recommendations are proposed to enhance the implementation and effectiveness of solar EV charging stations. Firstly, future research should explore the integration of additional renewable energy sources, such as wind power, into the solar charging station model to improve sustainability and resilience. Investigating different ANN architectures and training algorithms could further optimize the controller's performance. Moreover, a real-world implementation of the proposed model would provide valuable insights for validating the simulation results and identifying practical challenges. Long-term research into the performance and degradation of battery storage systems in solar charging stations is also essential to ensure their efficiency and reliability over time. Secondly, policymakers and government agencies should consider incentivizing the development and deployment of solar EV charging stations, particularly in rural areas where electricity infrastructure is limited. This could be achieved through financial support, streamlined permitting processes, and public awareness campaigns to promote the benefits of solar-powered EV charging. Additionally, the development of standardized protocols for EV charging and grid integration is crucial to ensure compatibility and seamless operation within the broader energy system. Furthermore, community engagement plays a vital role in the successful implementation of solar charging stations. Involving local communities in the planning and operation of these stations can enhance their acceptance and long-term sustainability. Providing training and job opportunities related to the maintenance and operation of charging stations can also create employment opportunities and contribute to local economic development. Research into advanced materials, innovative charging techniques, and intelligent energy management systems can further optimize performance and ensure long-term sustainability. Lastly, further investigation into grid integration strategies is necessary to optimize the interaction between solar EV charging stations and the existing power grid. This includes addressing issues related to grid stability, demand management, and the potential for bidirectional power flow. Implementing smart grid technologies and demand-side management strategies can help maintain grid stability while accommodating increased EV charging loads. In summary, this research has demonstrated the feasibility and effectiveness of a solar EV charging station model utilizing ANN-based MPPT control. By addressing key challenges in solar energy capture, charging efficiency, and grid integration, the proposed model offers a promising solution for the sustainable expansion of EV infrastructure in Rwanda and beyond. Implementing the recommendations outlined above will further enhance the viability, sustainability, and widespread adoption of solar-powered EV charging stations.

REFERENCES

[1] E. Engineering, E. Engineering, E. Engineering, and E. Engineering, “Optimizing Electric Vehicle Charging Using a PV-Based Multi-Mode Converter with Enhanced ANN Control for Vehicle-to-Home Applications,” vol. 6, no. 10, pp. 4016–4023, 2024.

[2] M. Tejaswini and J. Shivdas, “Implementation of Charging Station for E-Vehicle using Solar Panel with IOT,” vol. 7, no. 8, pp. 261–265, 2020, [Online]. Available: www.jetir.org

[3] M. Dudi, M. Bhati, N. Sharma, N. Choudhary, V. Mahala, and J. Vijay, “Optimizing Solar Powered Charging Stations for Electric Vehicles: Integration Fast and Slow Charging with Renewable Energy Sources,” *Int. J. Electr. Electron. Comput.*, vol. 9, no. 2, pp. 10–15, 2024, doi: 10.22161/eec.92.3.

[4] S. S. Ambavane, S. R. Bhoir, S. S. Pimpare, and P. A. Kulkarni, “Designing of Solar Charging Stations for Electric Vehicle,” *Int. Res. J. Eng. Technol.*, pp. 1247–1251, 2021, [Online]. Available: www.irjet.net

[5] K. Methane and G. A. S. Power, “RWANDA : LEAST COST POWER DEVELOPMENT PLAN (LCPDP) 2024 – 2050,” no. December 2023, pp. 2024–2050, 2024.

[6] C. Ghenai, F. Faraz, and O. Rejeb, “Case Studies in Thermal Engineering Artificial neural network-based models for short term forecasting of solar PV power output and battery state of charge of solar electric vehicle charging station,” vol. 61, no. December 2023, 2024.

[7] A. B. Kebede and G. B. Worku, “Comprehensive review and performance evaluation of maximum power point tracking algorithms for photovoltaic system,” vol. 3, no. 4, 2020, doi: 10.14171/j.2096-5117.gei.2020.04.010.

[8] B. A. Kumar, B. Jyothi, A. R. Singh, M. Bajaj, R. S. Rathore, and M. B. Tuka, “Hybrid genetic algorithm-simulated annealing based electric vehicle charging station placement for optimizing distribution network resilience,” *Sci. Rep.*, vol. 14, no. 1, pp. 1–28, 2024, doi: 10.1038/s41598-024-58024-8.

[9] A. Niccolai, L. Bettini, and R. Zich, “Optimization of electric vehicles charging station deployment using evolutionary algorithms,” *Int. J. Intell. Syst.*, vol. 36, no. 9, pp. 5359–5383, 2021, doi: 10.1002/int.22515.

[10] S. Iqbal, N. F. Alshammari, M. Shouran, and J. Massoud, “Smart and Sustainable Wireless Electric Vehicle Charging Strategy with Renewable Energy and Internet of Things Integration,” *Sustain.* , vol. 16, no. 6, 2024, doi: 10.3390/su16062487.

[11] H. Zhao, J. Gao, and X. Cheng, “Electric Vehicle Solar Charging Station Siting Study Based on GIS and Multi-Criteria Decision-Making: A Case Study of China,” *Sustain.*, vol. 15, no. 14, 2023, doi: 10.3390/su151410967.

[12] K. Yang and P. Chen, “Optimization of Charging Schedule for Battery Electric Vehicles Using DC Fast Charging Stations,” *IFAC-PapersOnLine*, vol. 54, no. 20, pp. 418–423, 2021, doi: 10.1016/j.ifacol.2021.11.209.

[13] M. Li, Y. Wang, P. Peng, and Z. Chen, “Toward Efficient Smart Management: A Review of Modeling and Optimization Approaches in Electric Vehicle-Transportation Network-Grid Integration,” *Green Energy Intell. Transp.*, p. 100181, 2024, doi: 10.1016/j.geits.2024.100181.

[14] Z. Chen, A. Ghosh, and N. S. A. Lopez, “Optimisation of a standalone photovoltaic electric vehicle charging station using the loss of power supply probability,” *Heliyon*, vol. 9, no. 10, p. e20836, 2023, doi: 10.1016/j.heliyon.2023.e20836.

[15] S. Ps, K. Br, N. Thanushree, S. Tanushree, and H. K. K, “Smart Solar Powered Ev Charging Station,” *Int. Res. J. Mod. Eng. Technol. Sci.*, no. 07, pp. 255–260, 2023, doi: 10.56726/irjmets42888.

[16] P. Sharma and R. Chinnappa Naidu, “Optimization techniques for grid-connected PV with retired EV batteries in centralized charging station with challenges and future possibilities: A review,” *Ain Shams Eng. J.*, vol. 14, no. 7, 2023, doi: 10.1016/j.asej.2022.101985.

[17] A. Bhatia, “Design and Sizing of Solar Photovoltaic Systems Credit : 8 PDH,” no. 877.

[18] P. S. Shinde, B. S. Patil, and M. P. D. O.-10. 22214/ijraset. 2023. 5356. E. R. -, “Open access•Journal Article•DOI (1) Design and Implementation of Solar Powered Mobile Phone Fast Charging Station for Campus.”

[19] D. Ji, M. Lv, J. Yang, and W. Yi, “Optimizing the Locations and Sizes of Solar Assisted Electric Vehicle Charging Stations in an Urban Area,” *IEEE Access*, vol. 8, pp. 112772–112782, 2020, doi: 10.1109/ACCESS.2020.3003071.

[20] T. S. Geetha, V. Amudha, and C. Chellaswamy, “A Novel Dynamic Capacity Expansion Framework Includes Renewable Energy Sources for an Electric Vehicle Charging Station,” *Int. Trans. Electr. Energy Syst.*, vol. 2022, 2022, doi: 10.1155/2022/4813750.

[21] J. Sun, *Open Aircraft Performance Modeling Based on an Analysis of Aircraft Surveillance Data*. 2019. doi: 10.4233/uuid.

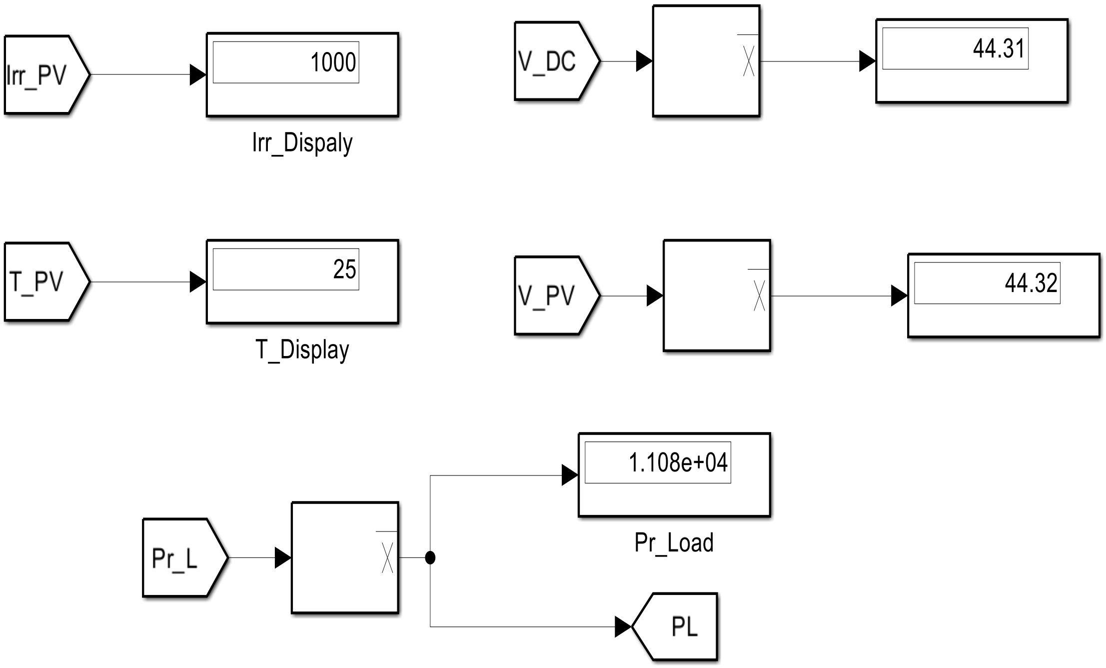
[22] J. Marc and R. Bernuz, “Sizing requirements of the photovoltaic charging station for small electrical vehicles,” vol. 13, no. September 2023, pp. 630–638, 2024.

[23] C. Stations, *PV-Powered Electric Vehicle Charging Stations*. 2021.

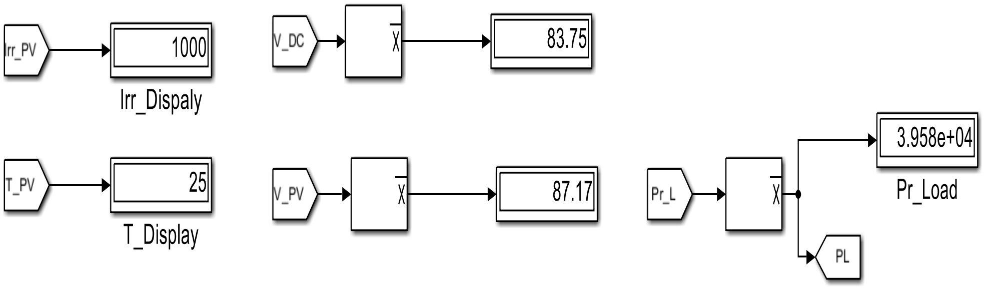
[24] B. Safari, “Trend Analysis of the Mean Annual Temperature in Rwanda during the Last Fifty-Two Years,” *J. Environ. Prot. (Irvine, Calif).*, vol. 03, no. 06, pp. 538–551, 2012, doi: 10.4236/jep.2012.36065.

APPENDIX

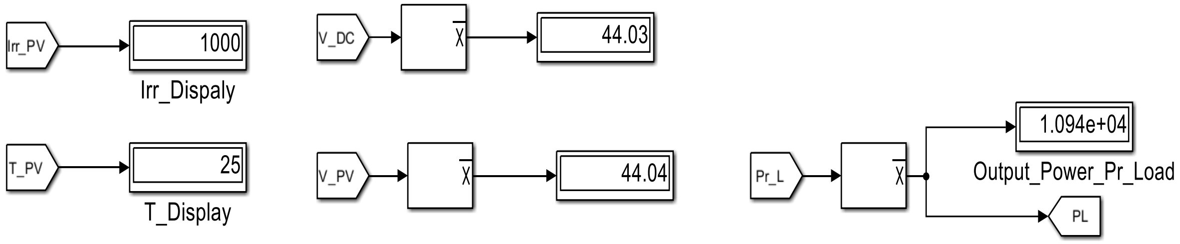
Displayed results on SCS model with MPPT controller



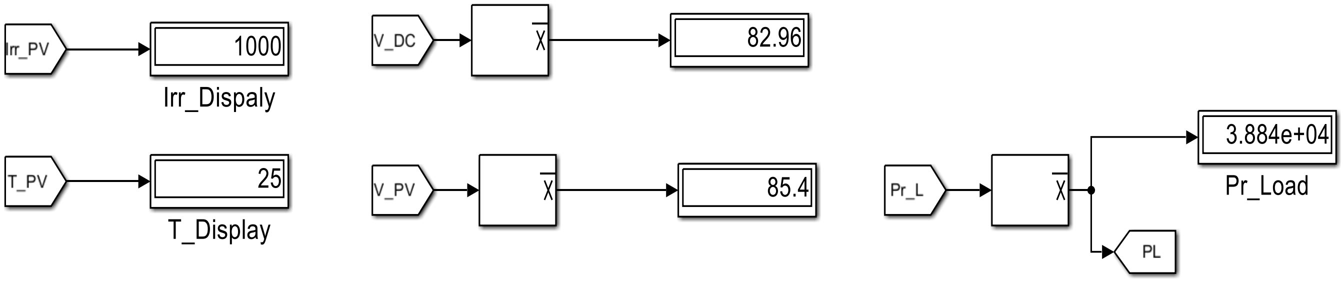
Displayed results on SCS model with ANN controller.



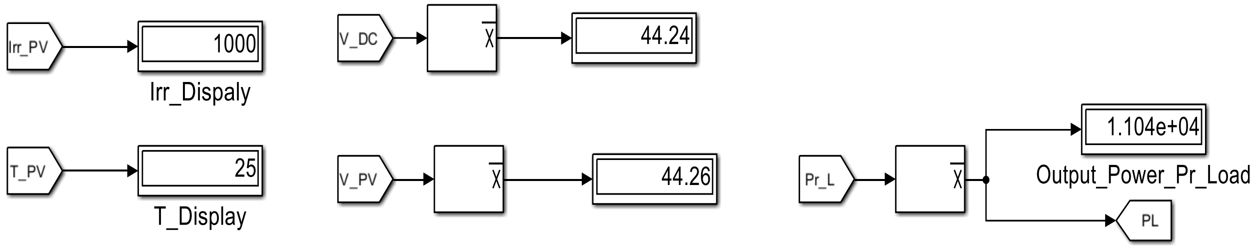
Displayed results by validating SCS model with using BY335P6K-36 PV panel of BYD Company Limited



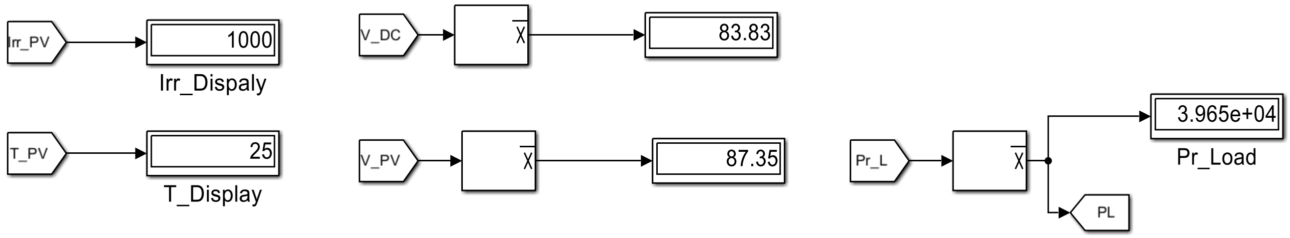
Displayed results of SCS model validation with BYD335P6K-36 PV Panel by using ANN controller.



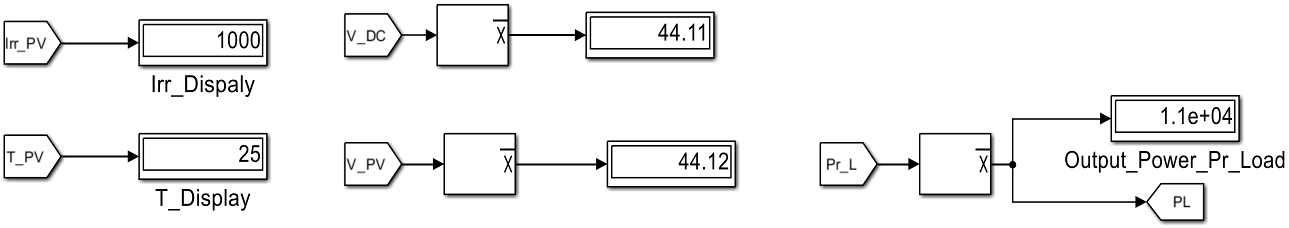
The displayed results of SCS model validation with Canadian Solar Inc.CS3U-375 MS-AG PV Panel by using MPPT controller.



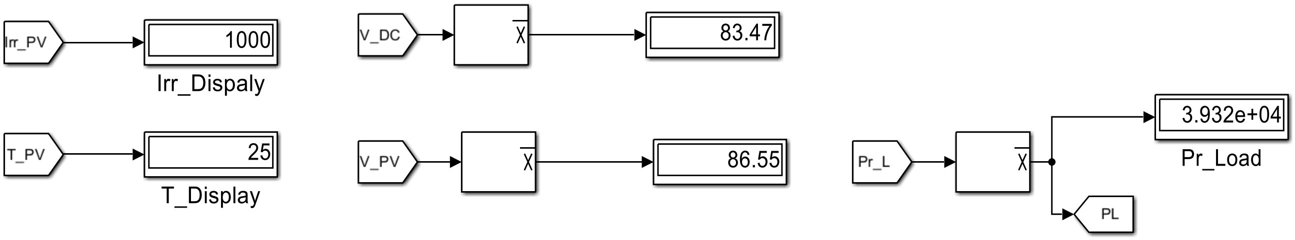
The displayed results of SCS model validation with Canadian Solar Inc.CS3U-375 MS-AG PV Panel by using ANN controller.



Model Validation results with Centro Solar America EM 72350SW PV Panel and MPPT controller.



Model Validation results with Centro Solar America EM 72350SW PV Panel and ANN controller.



QUESTIONNAIRE USED FOR THREE SAMPLED EV CHARGING STATION

COLLEGE OF SCIENCE AND TECHNOLOGY

Project Title:" **Design (Modelling) and Performance Analysis of Solar Charging Stations Using Artificial Neural Network (ANN) Control Method"**

INTERVIERS DATA CONSULTATIONS

	Names of EV Charging Stations.		
Types of corrected information	Station.1 …….	Station.2………..	station.3………
Location of Station			
Station type (Solar, Grid, Hybrid)			
Year of Establishment			
Total Installed Capacity (kW)			
Number of Charging Ports			
Charging Technology (Slow, or Fast)			
Battery Types Supported (Lithium-ion, Lead-acid, or other)			
Backup System (Battery/Generator) if any.			
Battery Capacity (kWh)			
Battery Efficiency (%)			
Charging Capacity per Session (kWh)			
Average Charging Time per motorcycle			
Average Daily Energy Consumption **(kWh)**			
Peak charging hours			
Number of Motorcycles Charged Daily			
Charging Tariff per kWh			
Power Outage Frequency			
Mitigation Measures, if any			