A Qualitative Analysis for the Effect of Different Orientation on Solar-Panel Outputs and its Generic Neural-Network Modeling

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CERTIFICATION OF RECOMMENDATION

This is certified that the thesis entitled **"A Qualitative Analysis for the Effect of Different Orientation on Solar-Panel Outputs and its Generic Neural-Network Modeling"** is a bonafide work carried out by **Mr. Biplab Mani Das** under supervision and guidance for partial fulfilment of the requirements for the post Graduate Degree of Master of Technology in Energy Science and Technology, during the academic session 2024.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains literature survey and original research work by the undersigned candidate, as part of his Master of Technology in Energy Science and Technology studies during academic session 2023-2024.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

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Dedicated to Maa, Baba

and

Respected Teachers.

Table of Contents

List of Figures

CHAPTER- 1

INTRODUCTION

1.1. Introduction of Solar-Panel Outputs and Neural-Network Modeling

Solar energy is a critical renewable resource, but maximizing its potential requires optimizing panel efficiency. One key factor is orientation – the direction the panel faces relative to the sun. This work qualitatively analyzes how orientation impacts energy production. Traditional methods for optimizing orientation can be complex. In the course of the work, we hope to identify which of the above parameters (time or direction) is more fundamental in influencing Current-Voltage (I-V) output of the solar panels. As Building-Integrated Photovoltaic (BIPV) systems represent a unique synergy between sustainability and design, this work thus assesses its possible impact on energy efficiency and the overall environmental sustainability of buildings. To address this, we introduce neural networks, powerful computational models inspired by the brain. Modeling the relationship between orientation and energy output using neural networks will be explored.

1.2. Overview of Building-Integrated Photovoltaics (BIPV) System

Solar power producing devices or systems known as Building-Integrated Photovoltaics (BIPV) are smoothly incorporated into building architecture. These systems have two purposes: they produce electricity from solar energy and serve as construction materials (roofs, walls and windows). Here are some essential BIPV points.

1.2.1. Important Elements and Kinds

- **Solar Panels:** Conventional photovoltaic systems may be included into the design of buildings.
- **Solar Roofing Tiles/Shingles:** These materials generate electricity while serving as roofing components.
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1.2.2. Challenges in Application

- **Greater Initial Costs:** Installing BIPV systems might be more costly than installing conventional solar panels.
- **Technical Complexity:** To guarantee effectiveness and attractiveness, integration calls for meticulous engineering and design.
- **Regulatory Obstacles:** Adoption and installation of BIPV systems may be impacted by building rules and regulations.
- **Effectiveness Trade-offs:** Compared to traditional PV panels, some BIPV materials may be less efficient.

1.2.3. Decreased Environmental Impact

One of the biggest obstacles in the battle against climate change is the built environment. A key technique to overcome this issue is building-integrated photovoltaics (BIPV), which smoothly integrates solar energy generation into the structure itself. BIPV systems use solar energy, which is a clean, renewable energy source. This naturally lessens the need for fossil fuels to generate energy, which significantly lowers greenhouse gas emissions from the construction industry.

1.2.4. Aesthetics that Enhances Performance

BIPV integrates with the building envelope in a way that conventional rooftop solar panels do not. High-performing solar energy generation is made possible by this creative method without compromising the goals of architectural design.

1.2.5. Enhanced Efficiency and Life-Cycle Cost Savings

BIPV systems can be used as solar energy sources and construction materials (cladding, roofing). This gets rid of the requirement for extra materials and might save building expenses. Additionally, the clean energy produced results in long-term operating savings on power costs.

1.2.6. Active Participation in a Sustainable Built Environment

Buildings that use BIPV technology become active participants in the renewable energy grid, replacing their previous role as passive energy consumers. This lessens the built environment's total environmental impact and promotes a more sustainable building sector.

1.2.7. Investigating BIPV Performance Optimization: Impact of Time, Direction, and Tilt Angle

The increasing global concern over climate change and the pressing need for sustainable energy solutions have driven the integration of renewable energy technologies into various aspects of modern life. As one of the key contributors to greenhouse gas emissions, the building sector has become a focal point for exploring innovative solutions to reduce its environmental impact and sustainable energy generation. Building-Integrated Photovoltaic (BIPV) systems have emerged as a ground-breaking approach, combining solar energy generation with architectural design, to transform buildings into active contributors to the renewable energy landscape. The principle of BIPV revolves around embedding solar photovoltaic elements directly into the building's structure and facade, rather than relying solely on traditional rooftop solar panels. This integration allows buildings to harness solar energy while preserving their essential functions as habitable spaces, setting Building-Integrated Photovoltaic (BIPV) systems apart from conventional solar installations. By seamlessly blending renewable energy technology with architectural elements, Building-Integrated Photovoltaic (BIPV) systems offer a unique opportunity to merge aesthetics and functionality, paving the way for more sustainable and visually appealing buildings. The current work delves into the underlying principles of Building-Integrated Photovoltaic (BIPV) systems, unravelling their distinctions from conventional solar installations. The project hopes to investigate the fundamental effect of time of the day and the solar panel direction North (N) South (S) East (E) West (W) for various panel inclinations (theta) w.r.t. surface level on panel output qualitatively. This comprehensive analysis aims to shed light on how Building-Integrated Photovoltaic (BIPV) systems can be improved for more efficient energy generation. Moreover, the work hopes implement to neural network-based modelling to speculate the possible Current-Voltage (I-V) output for any time-stamp (i.e., collection-time of data) and theta, based on the observed experimental data set values.

1.2.8. Significance of BIPV Research: Optimizing Efficiency and Shaping Sustainable Architecture

In the course of the work, we hope to identify which of the above parameters (time or direction) is more fundamental in influencing IV output of the solar panels. As Building-Integrated Photovoltaic (BIPV) systems represent a unique synergy between sustainability and design, this work thus assesses its possible impact on energy efficiency and the overall environmental sustainability of buildings. Understanding the influence of the above installation parameters is crucial for the widespread adoption and success of BIPV as a sustainable energy solution. As the field of renewable energy evolves rapidly, the work hopes to contribute to the emerging trends and breakthroughs that promise to revolutionize Building-Integrated Photovoltaic (BIPV) Systems technology, shaping the trajectory of sustainable architecture. Through an in-depth ideation of Building-Integrated Photovoltaic (BIPV) principles, architectural integration, benefits, challenges, real-world applications, and future possibilities, a growing body of knowledge on sustainable building practices can be achieved. By embracing Building-Integrated Photovoltaic (BIPV) technology, the architectural industry can play a pivotal role in fostering a more sustainable future, where buildings actively participate in combating climate change and ensuring a cleaner and greener planet for generations to come. The current work hope to qualitatively and in some degree quantitatively help in ideation of new aspects of BIPV technology.

Innovation in renewable energy is required due to climate change. Though they present a promising option, Building-Integrated Photovoltaics (BIPV) performance optimisation need a better comprehension of important variables. In order to address this issue, this study looks at how time and panel orientation affect solar panel I-V production over a 30-day period at different inclinations. The study tries to determine the primary parameter (time or direction) determining output symmetry through the analysis of I-V graphs. BIPV panel placement techniques can be informed by this knowledge. In order to forecast I-V output, the study also investigates a fundamental neural network model in MATLAB. The goal of this model is to lay the foundation for more intricate models by mapping variables such as time and tilt angle to voltage and current. The study's ultimate goal is to analyse the data and maybe identify input-output links.

1.3. Hypothesis, Aims and Objectives

The primary aims and objectives of this work is to develop a qualitative understanding of the influence of parameters like time and direction on the current-voltage output generation of solar panels w.r.t. various panel inclinations. In this regard an exhaustive literature review is initially carried out based on available works done in the BIPV sector both regarding installation as well as regarding simulation and software-based modeling. Following the literature review, the idea is to study the nature of the output voltage and current graphs over a period of 30 days, for seven different panel inclinations, and recognize which of the two parameters time or panel-direction is more fundamental in effecting the nature of the graphs (w.r.t. symmetry). This qualitative ideation may help us in making decisions that how placements of solar-panels w.r.t. various inclinations should be prioritized based on the criteria of more significance of time of output collection as a parameter or direction of output collection. The next phase of the work is carrying out simple input/output modeling of the collected data based on a neural network in MATLAB software. The idea is to map input set of data values like time-stamp and panel-inclination angle (theta) to output values of open-circuit voltage and short-circuit current and then train the network model based on those data, so that a fresh set custom input values can be mapped into a predictive set of corresponding targets (output) values. The purpose is to solely use all inbuilt training and activation functions, weights and biases to generate the model and see how such mapping fits without implementing any custom-built functions. This simple modelling, can help in building foundational understanding for developing more complex and more accurate input/output neural network models for such data-mapping and even later deriving an analytical equation relating such input (say time and theta) to output (current, voltage) values of solar panels. The ultimate objective would be to analyze and conclude the observations made and computations done and eventually publish the same in peer-reviewed journals.

1.4. Conclusion

Building industry activity is required in response to climate change. By integrating renewable energy directly into buildings, Building-Integrated Photovoltaic’s (BIPV) provide a ground-breaking option. This work paves the way for optimized designs by examining the effects of time, direction, and tilt angle on BIPV output. Optimizing BIPV efficiency and promoting sustainable construction practices require an understanding of these elements. The significance of this initiative is that it has the ability to completely transform sustainable architecture. Buildings might become active participants in a cleaner future if BIPV is widely adopted.

This work is an important step towards a more sustainable built environment, since it explores neural network applications and BIPV optimization. BIPV technology has the potential to make our buildings positive change agents with more research and development.

In this study we observed:

- The output voltage and current graphs over a period of 30 days.
- Mapped the input set of data values like time-stamp and panel-inclination angle (theta) against output values of open-circuit voltage and short-circuit current and study which of the parameters like time or panel direction is more fundamental in influencing the symmetry of the plotted graphs.
- Plotted the same data in a simple input/output modeling based on a neural network in MATLAB software and study the predictive output of such network based custom input data.

CHAPTER- 2

REVIEW OF EARLIER WORK

2.1. Introduction

This literature review aims to create a thorough grasp of the present state of knowledge by synthesizing the available research on BIPV and highlighting important trends and knowledge gaps. This study seeks to offer a cogent narrative that illustrates the development of thinking in this field by critically examining the significant contributions and methodological methods.

This system combines battery storage, backup natural gas for residences, solar panels, and an incredibly efficient heater/generator. By utilizing less energy during peak hours, storing extra, and optimizing solar power, it seeks to reduce lifetime costs. They put it to the test in a computer model and discovered that peak hour demand reduction and solar panel maximization result in the most savings.

2.2. Literature Survey

C. Wang et al. developed a regulatory approach using artificial neural networks (ANNs) to manage the operation of a hybrid Building-Integrated Photovoltaic/Thermal (BIPV/T) facade. This approach effectively addressed overcooling and overheating issues, reducing air conditioning demand by 165.0 kWh in Xining and 255.9 kWh in Lhasa. The ANN model predicted indoor temperature with an error rate of less than 1%, leading to over 40% energy savings in the plateau regions studied. [1] F. Ghani et al. investigated the impact of coolant flow distribution on the thermal efficiency of solar thermal collectors in BIPV/T systems. They used a numerical method to measure the potential negative impact of flow dispersion on solar output and found that decreasing fin width does not always improve PV production despite potential gains in fin efficiency. The study suggested that using a single riser could enhance PV output and reduce system complexity and costs. An artificial neural network was proposed to approximate the photovoltaic yield of an array under different flow conditions. [2] Alnaqi, Abdulwahab A. et al. assessed the efficiency of combining particle swarm optimization (PSO) with an optimized artificial neural network (ANN) to estimate the energetic performance of BIPV/T systems. The performance evaluation criterion indicated that the PSO-ANN model performed slightly better than the traditional ANN during both training and testing stages. [3] M. Barthwal et al. modeled a BIPV/T system for the Indian Himalayan Region, particularly in Srinagar, to provide electricity and thermal energy for space heating. Using an application-centric approach, they trained an ANN to predict annual thermal and exergy outputs. The neural network model demonstrated good performance against the test dataset, optimizing annual thermal and exergy gains. [4] L. Serrano-Luján et al. explored the complex physical and material properties of photovoltaic modules and their influence on thermal behavior, which traditional modeling techniques often fail to comprehensively define. They developed an AI-based method to forecast the temperature of poly-crystalline silicon photovoltaic modules based on local weather and indoor comfort parameters. [5] M. Perera et al. explored the challenge of forecasting solar power in a given region, crucial for ensuring a consistent electricity supply. Due to the vast amount of solar generation and weather data from various locations, accurate forecasting can be difficult. This study introduced two innovative deep-learning-based regional forecasting techniques that effectively combine solar generation and weather data with local meteorological information. These techniques employ hierarchical temporal convolutional neural networks (HTCNNs), specifically architectures HTCNN A1 and A2. Evaluated using a large dataset from 101 locations across Western Australia, the proposed methods achieved a forecast skill score of 40.2% while requiring fewer trained networks. [6] F. Almonacid et al. addressed the increasing prevalence of grid-connected photovoltaic systems in developed nations, emphasizing the role of global cooperation in advancing these technologies. They developed a technique using artificial neural networks (ANNs) to electrically characterize PV modules and produce V-I curves for silicon-crystalline modules. This method is intended to determine the power output of specific installations, such as the "Univer generator," using identical modules. [7] M. J. Deka et al. aimed to develop a photovoltaic thermal system capable of mitigating temperature drops and generating both thermal and electrical energy. The system integrates absorber tubes and phase change materials (PCM) based on biochar. An ANN model utilizing Multilayer Perceptrons accurately predicted the system's performance, showing an impressive R-value of 0.9982 and a mean square error (MSE) of 1.1328 during training. [8] T. Yang et al. also focused on creating a photovoltaic thermal system that addresses temperature drops and produces thermal and electrical energy. This system incorporates absorber tubes and PCM based on biochar. Similar to Deka et al., their study used a neural network model with Multilayer Perceptrons to predict system performance, achieving an outstanding R-value of 0.9982 and a commendable MSE of 1.1328 during training. [9] D. C. Nguyen et al. presented a deep learning approach to optimize the tandem structure design of 2-terminal perovskite/silicon tandem solar cells. They trained and validated an ANN using Atlas-simulated results for tandem cells with varying perovskite layer bandgaps and thicknesses under real-world conditions. The ANN model demonstrated a high correlation coefficient of 0.99979 and a mean square error of 1.26, indicating its accuracy in predicting the annual energy output of these tandem solar cells. [10] R. Javadijam et al. conducted a study aimed at enhancing the performance of a BIPV/T thermoelectric system. The research focused on optimizing the system's efficiency using both artificial intelligence and traditional techniques. Attention was given to improving electrical energy production, heat recovery, and the system's payback period. The optimized system achieved a payback period of 5.16 years and demonstrated a 6.93% improvement over the standard BIPV/T system. Additionally, the study investigated the influence of factors such as air inlet temperature, wind speed, and irradiance on the efficiency of both electrical and thermal energy production. [11] In another study, R. Kabilan et al. presented a machine learning-based prediction methodology for estimating the power output of integrated photovoltaic systems in buildings. Their methodology included an accuracy assessment, weather clustering, algorithm development, and data quality evaluation. By utilizing linear regression coefficients, the model improved the accuracy of PV power generation forecasts, achieving precise predictions with a root mean square error of 4.42%. [12] S. Kaliappan et al. employed artificial neural networks (ANN) to predict the performance of Building Integrated Semitransparent Photovoltaic (BISTPV) systems. They used three types of neural network models: Elman, feed-forward, and generalized regression neural networks. Their findings indicated consistent performance across these models, suggesting that forecast accuracy could be enhanced by applying strategies such as EN, FFN, and GRN. [13] A.J. Aristizábal et al. developed an artificial neural network model to calculate the power produced by integrated photovoltaic systems in buildings. Their model incorporated variables such as zenith and azimuth solar angles, solar radiation, and ambient temperature. Validation using real data from a 6 kW BIPV system at Universidad de Bogotá Jorge Tadeo Lozano demonstrated the model's reliability under various conditions. The model was implemented in MatlbabTM software for practical application. [14] D. Paul et al. addressed the challenge of efficiently extracting solar radiation data for solar photovoltaic energy systems. They proposed constructing hourly insolation annual frequency distributions using MATLAB to overcome this challenge. Additionally, they explored the potential of using a composite frequency distribution for Building Integrated Photovoltaic (BIPV) systems, aiming to provide an effective tool for BIPV system designers. [15] D. Lee et al. conducted a study aimed at improving short-term hourly predictions of photovoltaic power output using machine learning and feature engineering techniques. They found that a recurrent neural network outperformed five other models when forecasting photovoltaic power output over 64 test days. By applying dropout observation to the normative sky index through feature engineering, they enhanced the hourly prediction performance. They observed a 20% improvement in prediction accuracy for overcast days compared to the original weather dataset without dropout observation. This method effectively enhances short-term predictions of photovoltaic power output in buildings, even when using basic weather forecasting services. [16] In another study, J. Polo et al. utilized laser imaging detection and ranging (LIDAR) data to create high-resolution elevation digital models for building-integrated and building-attached photovoltaic systems (BIPV and BAPV). They employed an artificial neural network (ANN) to model power generation of different BIPV arrays using meteorological and solar irradiance conditions and shading patterns. The ANN model exhibited high accuracy, demonstrating its potential for creating a digital twin for BIPV systems. This complements conventional monitoring strategies and aids in diagnosing performance anomalies. [17] W. Gao et al. conducted a study comparing three computational intelligence approaches—artificial neural network (ANN), genetic programming (GP), and adaptive neuro-fuzzy inference system (ANFIS)—to predict the energetic performance of a building-integrated photovoltaic thermal (BIPVT) system. The study evaluated the performance of these models using the performance evaluation criterion (PEC). While all models performed well, the ANN marginally outperformed GP and ANFIS. However, due to its simplicity and robustness, the GP model was deemed more appropriate. [18] C. Ghenai et al. developed forecasting models to predict power output and assess the performance of bifacial solar PV systems on flat roof buildings with controlled surface albedo. They combined cutting-edge cool roof and bifacial solar PV technologies to balance supply and demand and boost power output. Using machine learning and energy forecasting, they employed an artificial neural network. The results showed an increase in annual bifacial solar PV power production by 7.75% and 14.96%, respectively. These forecast models have implications for demand-side management, power production, building operations, and advanced energy purchases. [19] In a related study, C. Qiu et al. investigated a cutting-edge building-integrated photovoltaic (BIPV) window with exceptional thermal performance and renewable energy use known as vacuum PV glazing. Despite limited research on energy usage and daylighting performance, they created a RADIANCE model to simulate behavior during the day. They used an artificial neural network (ANN) model to predict interior illumination and lighting consumption. Compared to Energy Plus's daylighting calculation methods, the ANN model provided more accurate predictions, resulting in lower computational costs and more dependable results. [20] Woo-Gyun Shin et al. conducted a study focusing on the growing use of building-integrated photovoltaic (BIPV) systems for producing renewable energy. They addressed the challenge of shading loss, which makes it difficult to predict power generation for colored BIPV modules. To improve power prediction accuracy by accounting for shading loss, they proposed a new model utilizing neural network machine learning. Their model demonstrated a significant improvement in R2 values over the simulation model, indicating high-accuracy power estimations, particularly for colored modules. This advancement may aid in diagnosing BIPV system performance. [21] A. Fedorova et al. developed a testing method for measuring water intrusion in BIPV systems. Their research aimed to classify and compare BIPV systems based on their water resistance, assisting professionals in selecting and designing systems for areas prone to wind-driven rain. They designed a specialized water collection system for BIPV, allowing accurate measurement of water penetration under varying wind-driven rain levels. Testing BIPV systems in different weather conditions revealed their performance, crucial for widespread adoption and long-term effectiveness. [22] A thorough state-of-the-art review of recent advancements in BIPV implementation studies was conducted by A. Taser et al. In addition to summarizing the existing body of knowledge in this area, they analyzed variables and drew specific conclusions and generalizations. This approach provides a better understanding of the factors influencing BIPV system performance by identifying gaps and deficiencies in the existing literature. Through a comprehensive interpretation and graphical representation of the results, the research offers a more lucid understanding of the influence of different factors on BIPV systems, inspiring further research in this field. [23] Md. R. Elkadeem et al. developed a system that combines solar panels, a combined heat and power generator, battery storage, and a natural gas boiler. The goal is to minimize the overall cost of running this system over its lifetime while considering charging stations for electric vehicles and programs that encourage reduced electricity use during peak hours. Their research, tested in a computer model using a real apartment building as an example, found that maximizing solar panels on the roof and reducing electricity use during peak times resulted in the best performance. [24] V. Stoichkov et al. reported on the outdoor performance of Organic Photovoltaics (OPVs) configured for Building Integrated Photovoltaic (BIPV) arrays in a Northern European climate. They focused on how diurnal weather patterns and module orientation affect OPV-based BIPV systems' energy yield. By gathering electrical characteristics under standard and part-load conditions from laboratory-scale OPV module experimental data, they evaluated the performance of BIPV arrays based on OPVs. Their research evaluated different energy-saving technologies for buildings in various climates, presenting different scenarios for a 4.22kWp OPV system in a small commercial building. [25] Y. Elaouzy et al. conducted a study simulating the performance of various systems including solar panels (PV), solar panels with heat collection (PVT), ground source heat pumps (GSHP), and rainwater harvesting (GR). Their findings revealed that solar panels, both PV and PVT, are the most cost-effective and environmentally friendly options across all climates, particularly in hot and dry climates. While GSHP and rainwater harvesting systems can reduce energy use and environmental impact significantly, their high costs make them uneconomical in any climate. The study also assessed the potential impact of a carbon tax on these results, ultimately suggesting that solar panels are a viable choice for reducing energy costs and emissions in buildings. [26] F. Wang et al. conducted a study demonstrating a system designed to enhance the efficiency of PVT panels by over 22% and reduce building heating needs by 1.65%. They recommended installing the PVT panels at a 45-degree angle, using dark roofs with high absorptivity, and integrating as many energy piles as possible into the foundation. This innovative system harnesses both solar and geothermal energy, offering a sustainable and energy-saving solution for buildings. [27] T. Yang et al. conducted a study introducing a new solar panel design for buildings (BIPV/T) featuring two air inlets, resulting in a 5% improvement in heat capture, which can be increased to 7.6% by using special translucent panels. This cost-effective and straightforward design holds promise for further advancements in efficient solar energy utilization. [28] A. Azami et al. investigated the impact of form configuration and orientation on energy generation, highlighting a preference for roof-based scenarios with lower BIPV utilization, indicated by an optimal BIPV-based FF value of 0.71. Their study also revealed a strong correlation (correlation value > 0.92) between the BIPV coverage index and the total envelope for ideal forms and orientations. [29] F. Nicoletti et al. proposed an assessment model as a valuable tool for evaluating the BIPV potential of different building designs, which can be adapted to various forms in different locations. They presented equations for calculating the electrical power generated by solar photovoltaic blinds (SPB), applicable to different slat inclinations, orientations, and geometries, enabling the evaluation of slat mutual shading and view factors. Their research provides valuable insights into the functionality and optimization of solar photovoltaic blinds. [30] Z. Liu et al. proposed an approach aimed at streamlining the assessment procedure and enhancing understanding of the variables influencing Solar Photovoltaic Blinds' (SPBs) capacity to generate electricity. The study's results have implications for improving building energy efficiency through the effective design and application of SPBs. Addressing engineering and sociological challenges associated with changes in both supply and demand, temporally and spatially, the paper outlines obstacles and conventional data usage practices in Smart Building-Integrated Photovoltaic (SBIPV) systems. The proposed concept of data-driven SBIPV comprises four main components: Data Sensing, Data Analysis, Data-driven Prediction, and Data-driven Optimization. Data sensing transcends simple measurements by establishing a link between the supply and demand sides. Data analysis elucidates how electricity supply fluctuates under varying environmental conditions and how demand-side response evolves. Energy management relies on data-driven prediction of load and electricity supply, while data-driven optimization addresses engineering and sociological aspects through system optimization and demand-side trading. [31] A.K. Shukla et al. provided a comprehensive review of the development of solar photovoltaic (PV) technology for building integration and design, emphasizing the classification of solar PV cells and Building-Integrated Photovoltaic (BIPV) products. The review underscores the significant opportunity presented by the era of distributed power generation, particularly for building-integrated photovoltaic systems. BIPV emerges as a robust and adaptable tool to meet the future demand for zero-energy buildings, offering advantages such as on-site power generation and the visual appeal of thin-film module form factors. Despite lingering policy issues, the benefits of BIPV are increasingly recognized. [32] Z. Wang et al. introduced a novel heat pipe building-integrated photovoltaic/thermal system (HP-BIPV/T) for Chinese residential buildings, demonstrating its effectiveness in producing electricity and hot water. Experimental results indicated daily average thermal, electrical, and total efficiencies of 61.1%, 7.8%, and 68.9%, respectively, under simulated solar radiation and water flow rate conditions. Although the suggested system is comparatively more expensive and less efficient than traditional BIPV/T systems, its potential for cost savings through mass production and waste material recycling makes it a promising solution. [33] F.E. Boafo et al. developed a novel building material by combining solar panels with ultra-thin insulation material to improve insulation, potentially reducing heating costs and meeting energy codes for buildings. Tests demonstrated its effectiveness in winter conditions, with acceptable electricity generation efficiency (12.3%) under those circumstances. [34] S.S.S. Baljit et al. covered two building integration technologies, namely Building-integrated photovoltaic (BIPV) and building-integrated photovoltaic-thermal (BIPV/T), aimed at increasing electrical output and cooling PV panels. The paper examines various heat transfer working fluids and installation methods for BIPV and BIPV/T systems on walls and roofs, incorporating economic factors and case studies to provide relevant information for engineers and researchers in the building and construction sectors. [35] A. Ghosh et al. conducted research exploring the integration of solar panels directly into buildings (BI) or attaching them to existing structures, known as Building Applied Photovoltaics (BAPV). They discussed various materials and locations for these panels, along with challenges such as overheating and potential solutions. Additionally, the paper explored promising future applications for solar panels in buildings, including integration with electric vehicles, highlighting the potential of solar energy in building design and functionality. [36] Z. Liu et al. investigated the feasibility and applicability of building-integrated photovoltaic (BIPV) systems in areas with high solar irradiance. The study emphasized the potential for BIPV systems to decrease building energy consumption and promote sustainable development. Various performance-influencing variables such as PV module temperature, solar radiation intensity, orientation, tilt angle, module types, and inverters were examined, and the energy efficiency, environmental benefits, and economic performance of BIPV systems were systematically evaluated. The study also discussed optimal coordination models to encourage the development of BIPV systems and suggested future research directions in areas with high solar radiation. [37] S. Saadon et al. investigated a novel building facade design that incorporates partially transparent solar panels (PV) to generate electricity. The facade featured a ventilated air cavity to aid in cooling the panels during summer and recovering heat in winter. Through computer modeling, the researchers assessed the facade's performance in various French climates, finding that while the facade might slightly increase cooling needs, its impact on heating requirements is minimal. [38] G. Barone et al. introduced a new window technology called Concentrating Photovoltaic/Thermal Glazing (CoPVTG), which utilizes lenses to focus sunlight in the summer for electricity generation and allows sunlight to pass through in the winter for heating. The system includes a built-in air-cooling mechanism to capture excess heat for other purposes. Tests demonstrated that CoPVTG can significantly increase electricity generation compared to standard windows while also reducing heating and cooling costs. The technology offers potential for creating energy-efficient and cost-effective buildings. [39] M.M. Uddin et al. focused on Bangladesh's climate and investigated three configurations of semi-transparent CdTe combined

BIPV window systems in an office building. Using data from outdoor experiments, they developed and verified a numerical simulation model based on Energy Plus. The annual energy simulation results showed that CdTe combined BIPV windows can save between 30% and 61% of electricity consumption compared to conventional window systems under all climate conditions. Additionally, the study demonstrated that east-facing BIPV windows are more effective at reducing net electricity consumption, while south-facing windows are more efficient at power generation. [40] C. Sirin et al. investigated the utilization of building façades for generating renewable energy using Building-Integrated Photovoltaic/Thermal (BIPV/T) systems. They discussed how BIPV/T systems can contribute to reducing building-related greenhouse gas emissions and energy consumption. [41] A.M. Ekoe et al. emphasized the benefits, working principles, and methods for enhancing the performance of BIPV/T systems. Their study provided a general overview of BIPV/T technology and highlighted its potential to improve building energy efficiency. They examined the use of solar panels (BIPV) on rooftops to fulfill a building's energy needs, demonstrating that BIPV systems can significantly reduce energy consumption and costs while promoting reliance on renewable energy sources. This technology holds promise for creating a more sustainable and environmentally friendly energy future in Cameroon. [42] R.P.N.P. Weerasinghe et al. examined building-integrated photovoltaic technology (BIPV) as a renewable energy source with building material functionality, addressing questions regarding BIPV's economic viability and its impact on investment choices. [43] J. Ko et al. reviewed 45 BIPV projects in non-domestic buildings across 12 western countries between 2009 and 2018. They assessed the true economic worth of BIPV projects by estimating levelized cost energy, net present value, and payback periods. Their analysis demonstrated that BIPV projects can be financially feasible when both direct and indirect benefits are considered. Various building application types, features, and module technologies showed profitable results, suggesting that policymakers and decision-makers could encourage the adoption of BIPV by better understanding these findings. [44] L. Gullbrekken et al. optimized phase change material properties through MATLAB simulations, resulting in an annual increase in energy generation of 1.09% compared to traditional photovoltaic systems. By enhancing thermoelectric generator performance and thermal resistance, the proposed system could produce 4.47% more energy. Their research focused on the use of photovoltaics (PV) in buildings in Nordic climates, addressing challenges posed by low solar radiation and temperatures below zero. [45] S. Khanam et al. provided a summary of the challenges and recent experiences with roof-integrated PV systems, particularly focusing on the Nordic region. Addressing critical challenges such as practical guidelines for roofing installation and ventilation will be essential for the adoption of PV systems in these areas. Additionally, they assessed and compared the performance of various photovoltaic module types (monocrystalline, polycrystalline, and thin-film) in four climatic zones of India, estimating parameters like radiation intensity, ambient temperature, and design factors using analytical expressions based on energy balance equations. [46] C.S. Rajoria et al. concluded that peak temperatures of photovoltaic modules have a greater impact on electrical efficiency than solar radiation intensity. Despite a hotter climate, Bangalore produces more electrical energy annually than Jodhpur due to its more temperate climate. The study identified amorphous silicon modules as the best performers in terms of electrical energy output. Additionally, they provided a review of flat-plate building-integrated photovoltaic/thermal (BIPV/T) systems, covering recent advancements, experimental findings, and the parametric effects on building performance. Different BIPV/T technologies such as air-based, water-based, or hybrid systems were discussed, along with their performance metrics. Notably, nano-PCM-

PVT systems demonstrated the highest thermal efficiency of 72%, suggesting promising applications for phase change materials and nanoparticles in BIPV/T systems. [47] S. Yang et al. conducted a simulation study on the sensitivity analysis of design parameters for Building-Integrated Photovoltaic/Thermal Double-Skin Façade (BIPV/T-DSF) systems, aiming to assess their influence on energy consumption and indoor thermal comfort across various configurations and climates. Key findings highlighted the significant impact of external window solar heat gain coefficient and cavity depth of the BIPV/T-DSF on building performance. The study emphasized the importance of considering these design factors to maximize BIPV/T-DSF system performance for energy-efficient and comfortable buildings. Additionally, they proposed the use of colored BIPV modules to address aesthetic concerns while still promoting clean energy generation and reducing carbon emissions. [48] A.H. Hamzah et al. tested the concept of colored BIPV modules using 3D model simulations on buildings in Malaysia, finding promising results. [49] F.M. Amoruso et al. conducted life cycle assessments (LCA) and life cycle costing (LCC) for apartments, mixed-use commercial/industrial buildings, and low-rise multi-unit residential buildings equipped with BIPV systems. They measured electricity production using simulation tools and computed minimum and average carbon life cycle assessments over a 50-year period. [50] S. Kim et al. calculated greenhouse gas (GHG) emission savings associated with replacing conventional energy supplies in buildings with BIPV systems. Their results indicated significant reductions in GHG emissions, with positive cumulative net present values (NPV) for both 25 and 50-year life cycle costing scenarios. [51]

2.3. Gap of Knowledge

The study focuses on the effects of data collection time and panel face direction on panel outputs, aiming to identify the most fundamental parameters in dictating panel outputs like voltage and current. It also explores the use of neural networks for predictive output of solar panels, despite the need for a large dataset and complex machine learning models. To the best of our knowledge comparatively lesser amount of work has been done on these particular aspects. The next chapter provides a comprehensive explanation of the methods and computation. The details of the discussion are provided in the sections 2.3.1. and 2.3.2.

2.3.1. A Qualitative Study

To the best of our knowledge, relatively lesser amount of work has been done regarding qualitative examination of the effects of time of data-collection and direction of panel-face on panel outputs and vis-a-vis the detection of which of the parameters i.e., time-stamp or direction is more fundamental in dictating the nature of the panel outputs like voltage and current. Such analysis based on real-world data might offer more profound insights on BIPV system optimization.

2.3.2. Predictive Output of Solar-Panels based on Neural Networks

To provide reliable predictions of panel outputs based on such generic input parameters like time-stamp of data-collection and panel-inclination angle, a neural network modeling of the input/output data can be carried out and trained and then studied for custom inputs. This may need a sizable dataset. However, in order to create a baseline, it is best to investigate simpler machine learning models initially and such work on generic mapping has been less done to the best of our knowledge.

2.4. Probable Solution

A Qualitative analysis of such solar panel outputs based on plotted voltage/current graph symmetry w.r.t. time or panel direction and determination of the more fundamental nature of these parameters on graph output. Secondly, using MATLAB-based neural network modeling one can generate a predictive output modeling of output voltage/current against input time-stamp and panel inclination. This consequently allows further custom mapping of user-defined input values to predictive output values. The details of the discussion are provided in the sections 2.4.1. and 2.4.2.

2.4.1. Improvement on Qualitative Analysis

Real-world data like voltage and current outputs of solar panels over range of days can be used to plot the graphs with variables of time and panel-direction, with various panel-inclinations, and then by observing the symmetry of the graphs an inference can be drawn that which of the parameters i.e., time-stamp or panel direction is more fundamental. This would lead to a qualitative analysis of the panel-outputs w.r.t. to generic input values of time-stamp, panel-directions, while taking into account various panel-inclinations.

2.4.2. MATLAB based Neural Network Modelling

A simple MATLAB based feedforward neural network mapping of input data like time-stamp and panel inclination w.r.t. target data like output voltage and current can help us to train such models for custom mapping of user-defined fresh input values of time and panel-inclination to predictive output values. Such models can be easily build using inbuilt deep-learning toolbox of MATLAB and gives us the scope to initiate foundational works of such complex model-generation of BIPV systems.

2.5. Scope of the Present Work

The purpose of this thesis is to investigate the complex interplay between two important variables—time and panel direction—and how they affect the current-voltage output production of solar panels at different angles of inclination. Through a thorough examination of voltage and current graphs collected over a 30-day period with seven different panel orientations, the research aims to identify the main factor influencing the symmetry of these graphs. This qualitative study has the potential to offer insightful information about how decisions about the orientation of solar panels should be prioritized, either by highlighting the importance of output collection time or by concentrating on output collection direction.

The next stage of the study aims to take input/output modeling to a basic yet profound level by utilizing neural networks and the MATLAB software environment. The main goal is to provide a strong mapping mechanism that maps a set of input data values (time-stamp and panel inclination angle, or theta) to matching output values that indicate short- and open-circuit current and voltage, respectively. The research seeks to enable the smooth prediction of output values for a new set of custom input values by carefully training the network model on the gathered dataset. This will help to clarify the intrinsic link between the input parameters and the output values that are produced.

We used MATLAB's Neural Network Toolbox, which is a feature of the Deep Learning Toolbox. This tool is an effective means of developing, optimising, and deploying neural networks, allowing for the modelling and prediction of intricate systems. In Chapter 4, This research looks at, how direction and time affect solar panel output over a 30-day period. It uses 4200 observations over 30 days, or 140 observations per day, to analyse voltage and current graphs on a sliding solar panel. In Chapter 5, Across all time-stamps and inclination, the analysis revealed symmetry in the voltage and current values for the opposing directions (East-West and North-South). When changing time-stamps for fixed directions, however, no such symmetry was observed, suggesting that direction is not as important as time of day in determining panel output. A generic ideation of neural network modelling was carried out in Chapter 4 as well, which dent with the basic tenets of feed forward neural network in detail. The acquired knowledge was implemented in Chapter 5, to train the input time spends and panel inclination against output open circuit voltage and short circuit current and later a custom set of fresh input values were used to generate predictive voltage and current values. The predictive values were further analysed to evaluate the accuracy of this simple deep learning model. All result were eventually summarised in Chapter 6 and concluded.

2.6. Conclusion

In view of the above works done, the current project hopes to carry out a qualitative understanding of the nature and effect of natural parameters like time and direction on the voltage, current output of the solar-panels w.r.t. various panel-inclinations. The objective is to study that which of the parameters is more fundamental in influencing the nature of the voltage, current graphs over duration of days. Also, a MATLAB based simple neural network modeling of the collected input/output data is hoped to be implemented, to generate predictive input/output mapping of the solar panels, based on custom input values. A much-detailed description of the Methods and Computation are given in the next chapter.

CHAPTER- 3

General Description of MATLAB Software Applied in This Work

3.1. Introduction

The main software tool used in the current work for doing computational analysis, data processing, and algorithm creation is MATLAB. Because of its robust numerical computation, visualisation features, and large function library, MATLAB is a flexible programming environment that is extensively utilised in both academia and industry. Its use in this work enables significant discoveries and propels research forward by facilitating the discovery, analysis, and interpretation of complicated data sets.

3.2. Overview of Matlab Software

A strong tool for creating, honing, and implementing neural networks is MATLAB. Its Neural Network Toolbox, which is now a part of Deep Learning Toolbox, offers an extensive set of features and applications for neural network modelling of complicated systems. Neural networks may be used to model and forecast connections, detect patterns, and improve comprehension of the underlying physical events in the context of Current-Voltage (I-V) data.

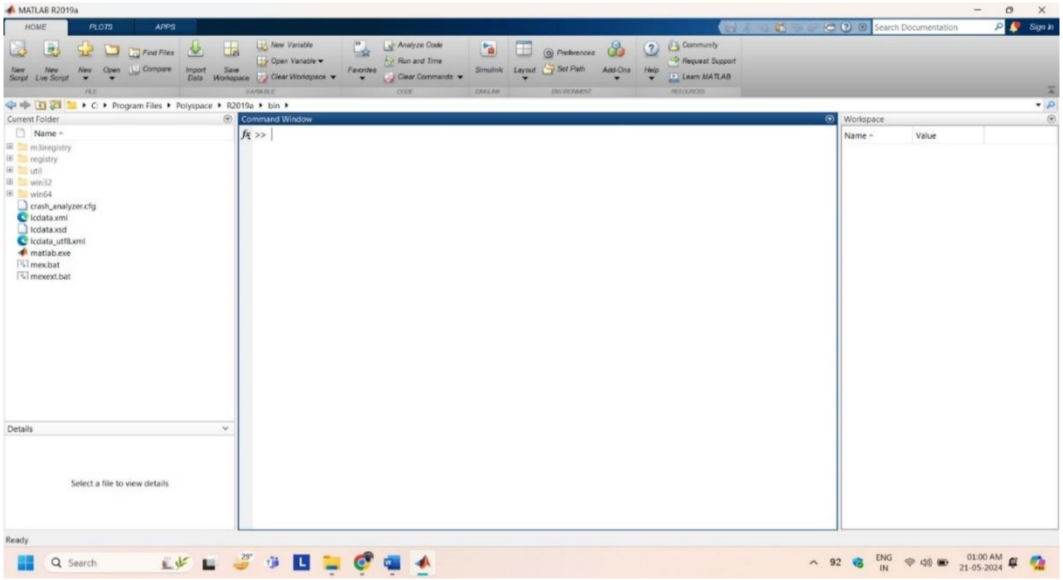


Figure 3.1. MATLAB R2019a Software

3.3. Benefits and Drawbacks of Matlab Software

Benefits:

- Friendly to Users.
- Wide-ranging Toolbox Collection.
- Information Visualisation Ability.
- Good Community Reaction.

Drawbacks:

- Expensive Software.
- Interpreted Language.
- Not Suitable for Real-Time Uses.

3.4. Deep Learning Toolbox

Blocks from the Deep Learning Toolbox of MATLAB is used for creating, putting into practice, and modeling deep neural networks. A framework for creating and utilizing a variety of networks, including transformers and convolutional neural networks or CNNs, is provided by the toolkit. Network attributes may be verified, projections can be visualized and interpreted, and networks can be compressed via quantification, presentation, or trimming. One can import pretrained models, export networks to Simulink, and construct, edit, and evaluate networks dynamically with the Deep Network Designer application. One can collaborate with various deep learning frameworks using the toolbox. A MATLAB based simple neural network can help ingenerating predictive output values for custom input values, based on erstwhile training of such network with training of input vectors to its' respective target output vectors. In our work, we have implemented in particular simple feedforward neural network for such input/output mapping of collected solar panel output values w.r.t. input time-stamp and panel inclination. As such feedforward neural networks are made up of several levels. The network input is connected to the first layer. Every layer that comes after has a link to the layer before it. The output of the network is produced by the last layer. One can use feedforward networks for any type of mapping from input to output. Any limited input-output mapping issue can be fitted by a feedforward network comprising of one hidden layer and sufficient neurons in the hidden layers. In our current work we have taken help of such inbuilt, simple feedforward neural network present in MATLAB and have carried out input/output mapping transformation using all the inbuilt functions set by default. The detail discussion of the computation is given in the following chapters.

3.5. Conclusion

The present work makes extensive use of MATLAB, which offers a versatile software environment for data visualisation, method building, and computational analysis. It is an essential tool for scholars looking to push the boundaries of knowledge and creativity in their domains because of its vast feature set, user-friendly design, and comprehensive documentation. In particular the Deep Learning Toolbox in MATLAB has rigorous role in data clustering data mapping and predictive output generation modeling. In that regard Deep Learning toolbox of MATLAB in particular have been very useful for computation analysis in our following chapters. Thus researchers may solve difficult issues more quickly, improve science and technology, and quicken the rate of discovery by utilising MATLAB's capabilities.

CHAPTER- 4

METHODS AND COMPUTATION

4.1. Introduction

In this work, we set out to investigate the complex relationships between direction and time as they relate to solar panel output characteristics. We seek to clarify whether the spatial orientation or the temporal aspect is more important in determining the voltage and current profiles of solar panels by conducting a thorough analysis.

We achieve this by carefully monitoring voltage and current outputs under various conditions for thirty days, all while conducting a rigorous series of experiments. We carefully monitor and document the panel's response to various environmental stimuli using a sliding solar panel setup that is able to be adjusted to different inclination angles and directional facings.

Moreover, we further investigate predictive modelling by utilising neural networks built in MATLAB to extrapolate future outputs of voltage and current from observed data. Even though we have started modelling using simple training approaches, we recognise that there is a great deal of room for improvement and augmentation using unique training algorithms and more input parameters.

Our work sits at the nexus of advanced modelling approaches and conventional experimentation in a world where neural networks are redefining computational paradigms. We advance the conversation on the use of renewable energy sources and open the door to more sustainable and efficient solar technology by elucidating the basic dynamics of solar panel performance.

4.2. Measuring the Effect of Time and Orientation on the Output of Solar Panels

In this current work, a simple qualitative ideation of the effect of time and direction on solar-panel output has been studied with respect to various panel-inclination angles. The idea was to carry out a generic study of voltage, current output graphs of a solar-panel over a period of 30 days and identify which of the above parameters i.e., the time of observation (say 1, 2 or 3 pm etc.) or direction of panel-face during observation (North, South, East or West) had a more fundamental effect on the nature of the voltage and current graphs. For this reason, a sliding solar panel on a fixed wooden base was used for experimentation, which could be inclined and fixed at various custom angels (θ) using a protractor (Figure: 4.1.1 – 4.1.4). Every day 140 observations were taken w.r.t. 5 different time-stamps (12 O'clock, 1 pm, 2pm, 3pm, 4pm), for 4 different directions of panel-face (North, South, East, West) and 7 different panel-inclination angels (0°,15°,30°,45°,60°,75°,90°) respectively. A total 4200 observations were taken over a period of 30 days and each observation was w.r.t. open-circuit voltage (VOC) and short-circuit current (ISC) of the panel. In absence of source-measuring unit at our disposal, this was the best possible quantitative output measurement of the panel (VOC and ISC) we could implement. The idea was to plot every voltage and current graphs w.r.t. days (1-30), by keeping time fixed, for seven numbers of θs, for the 4 directions. A different plot of every voltage and current graphs w.r.t. days (1-30) was also conducted, but by keeping directions fixed, for seven number of θs and for the 5 different time-stamps. A visual study of both sets of graphs were carried out to determine that in which set of graphs, would the observed voltage-current graphs have showed general symmetry over the data collection duration, i.e., for fixed time and varying direction for various theta values or for fixed direction and varying time for various theta values. The idea was to qualitatively determine that which of the fundamental parameters like Time of Observation or Direction of Observation had a more fundamental influence on the nature of the output voltage/current of the system. The results so found were promising as would be discussed in detail in the latter sections. Data values as such were collected between 19th February - 2nd April, 2024.

Figure 4.1.1.

Figure 4.1.2.

Figure 4.1.3.

Figure 4.1.4

Figure 4.1. Representative Images of Movable Solar Panels at four different inclination 0°, 45°, 60° and 90°.

4.3. Neural Network Architecture and General Modelling

A further MATLAB based simple neural network modeling of the observed data values were carried out to create a general predictive voltage, current output suggestion of such solar panels for individual time and theta values. The training of the data and consequent modeling was not exhaustive and used the basic inbuilt training functions and feed-forward neural-network commands of the software to suggest such predictive outputs. Lot of scopes lie in developing custom training algorithms or functions to train such observed data values as well as include other training data-set parameters like solar-insolation values and direction-specific theta-values of the panels concerned into such models. Contemporary computing is being reshaped by neural networks, which combine artificial intelligence with brain-inspired architecture. These networks imitate the complex functions of the human brain by using complicated networks of interwoven artificial neurons, which has allowed for amazing advancements in machine learning. Neural networks come in various flavors, each designed for a particular task: feedforward, recurrent, convolutional, and so on. Neural networks are motivated by the way the human brain perceives information and function fundamentally like it does. Its quick response times and capacity for rapid computations enable it to handle a variety of real-time jobs. A vast number of interlinked processing units or "Nodes", make up an artificial neural network. A connection link is used for attaching these nodes to other nodes. Weights are present in the connection link, and these weights include input signal information. In turn, every input and iteration update these weights. The final neural network weights and architecture, after all the data occurrences from the training data set have been input, are referred to as the Trained Neural Network. It is referred to this procedure as Neural Network Training. The specified tasks of the issued statements are resolved by these trained neural networks.

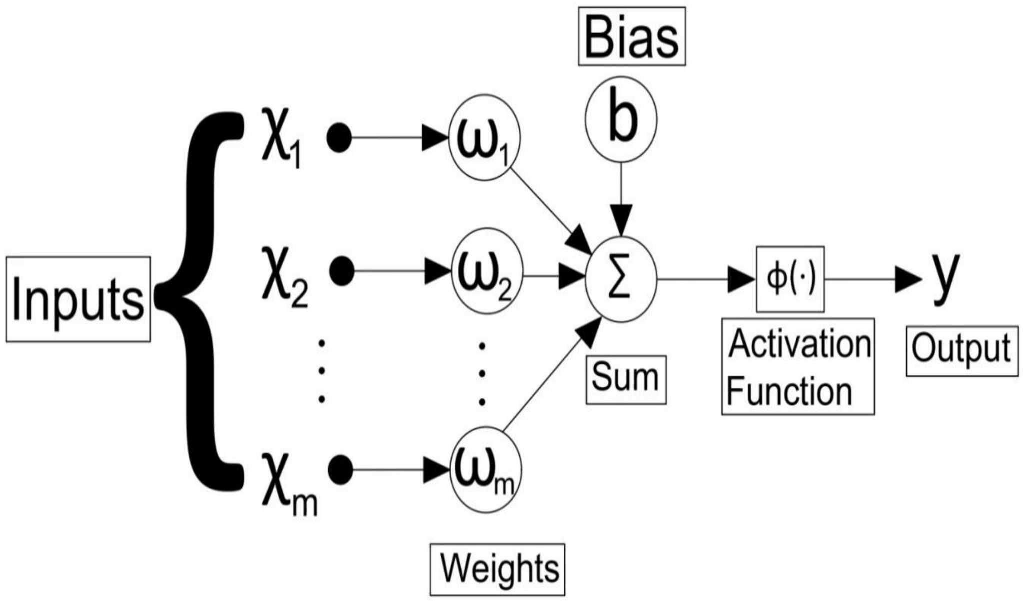


Figure 4.2. A Single Neuron is displayed with Xi number of Inputs, each having a Weight ωi, a Bias term, and an applied Activation Function.

An artificial neural network with circular connections between its nodes is called a feed forward neural network. A feed-forward neural network is the exact opposite of a recurrent neural network because it has some cycled paths. The fundamental kind of neural network is the feed-forward model since it only processes information in a single direction. Learning a function that converts a given X to a predetermined Y and using it to ascertain the correct Y for a new X is what is known as supervised learning and helps in adjustment of weights in neural networks.

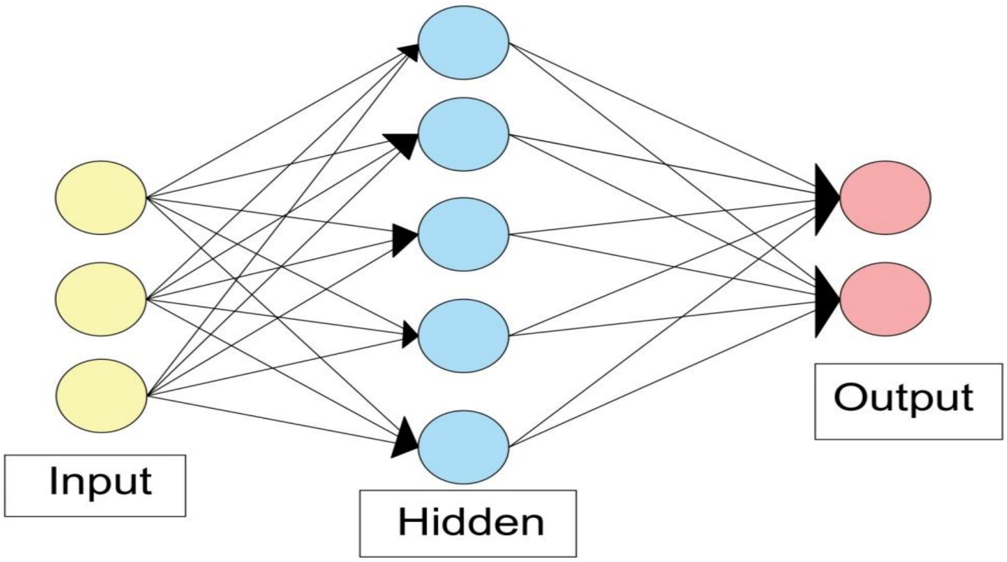


Figure 4.3. Architecture of an Artificial Neural Network.

4.4. Using Custom Neural Network Training to Generate Predictive Output of Solar Panel

In our current work, certain sets of the obtained data values of Voltage and Current was transformed as the output with corresponding sets of input values of data-observation times and solar panel inclination of theta values. Then using a simple feedforward neural network of 25 hidden layers, that we transformed a fresh set of input time and theta values into predictive output voltage and current values. The transformation used a standard inbuilt training function inside the deep-learning tool box of MATLAB and all other weights, biases and activation functions were selected as by-default value. The transformation showed good predictive values for all the output voltage values, while for the current values outputs were often far from offset values and even negative at times. It suggested that though the model is promising in generating such predictive outputs, it is ultimate formulation of custom training functions, and selection of weights, biases and activation function that will help in rectifying such models and lead to determination of correct predictive transformed outputs.

4.5. Conclusion

We have learned a great deal about the intricate interactions between time, direction, and panel inclination angles from our research into the dynamics of solar panel performance. Over the course of a 30-day period, we have identified distinct patterns in the voltage and current outputs of solar panels through methodical experimentation and qualitative analysis. The importance of direction and time as essential factors influencing solar panel performance is underscored by our findings. Furthermore, our investigation into neural network-based predictive modelling has produced encouraging outcomes for panel output forecasting based on input parameters like time and panel inclination values. All these are analyzed in detail in the next chapter. In conclusion, Study emphasises how crucial thorough analysis and modelling methods are to comprehending and maximising the performance of solar panels. It will be essential to conduct more research in this area as we move closer to a future where renewable energy sources will be used more and more to advance solar technology's efficiency and sustainability.

CHAPTER- 5

RESULT AND DISSCUSSIONS

5.1. Introduction

Solar energy has emerged as a vital source of renewable power. Optimizing the efficiency of solar panels is crucial for maximizing energy generation. This study investigates the relationship between voltage, current output, and several key factors influencing a solar panel's performance.

5.2. Exploring the Effect of Data Gathering Timing on Solar Panel Output Properties

Voltage and Current values so obtained over 30 days were plotted against days w.r.t. to 5 different time-stamps (12 O'clock, 1 pm, 2 pm, 3 pm and 4 pm) for the 4 different directions (North, South, East and West) in each of the graphs. All these graphs were obtained individually for 7 different panel inclination angles, theta, (0°,15°,30°,45°,60°,75°,90°) respectively. Consequently, for each theta there are 5 Voltage and 5 Current graphs, for 5 different time stamps. Each graph containing values obtained for the 4 different directions. The observed graphs (Voltage and Current) all showed qualitatively a general symmetry w.r.t. each other values over the 4 directions, for every graph-plots and also the values obtained for the exactly opposite directions (North and South) and (East and West), for all time-stamps and all theta values reflected greater symmetry in shapes. A rough plot of every voltage and current graphs w.r.t. days (not shown here) was also conducted by keeping directions fixed, for seven numbers of θs and by varying the 5 different time-stamps. No such symmetry in the voltage and current graphs were obtained like before, for the 5 varying time-stamps in each graph, suggesting that the nature of voltage-current graphs is more of a function time-stamp at which the values are collected and less influenced by direction. This suggested that Time at which data is collected is much more a fundamental parameter in dictating the nature of the panel voltage-current output instead of the direction at which the panel is faced. The shapes of the graphs are more symmetric for the exactly opposite directions for every time stamp. This suggests that while time-stamp is more a fundamental parameter, for every time-stamp exactly opposite directions also play a role in influencing the symmetric-nature of the graphs. Figures (5.1.1. - 5.7.10.), shows the Voltage-Current graphs for each time-stamp over different 7 theta values, taken over 30 days.

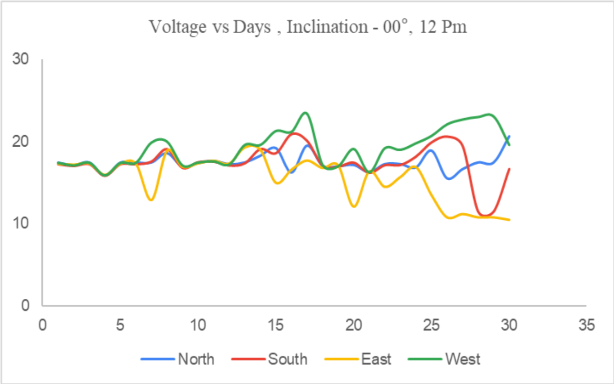


Figure: 5.1.1. Voltage vs Days, Inclination - 00°, 12 PM

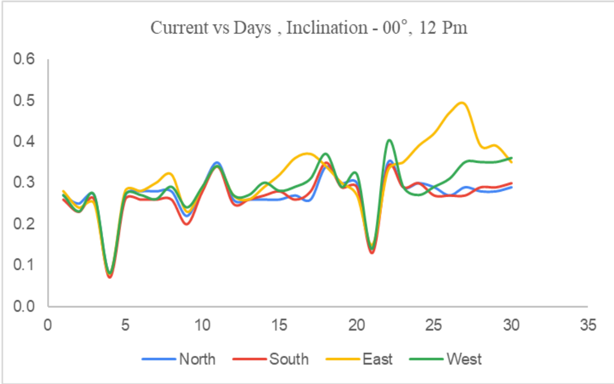


Figure: 5.1.2. Current vs Days, Inclination - 00°, 12 PM

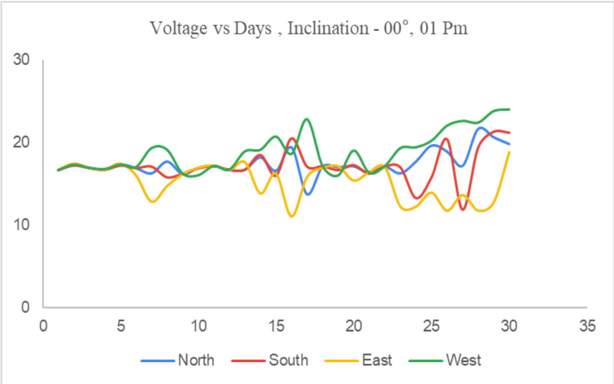


Figure: 5.1.3. Voltage vs Days, Inclination - 00°, 01 PM

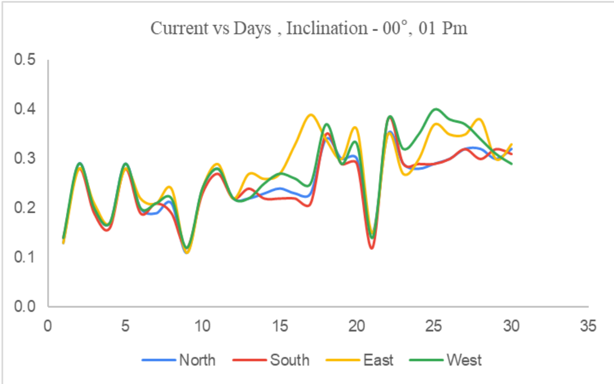


Figure: 5.1.4. Current vs Days, Inclination - 00°, 01 PM

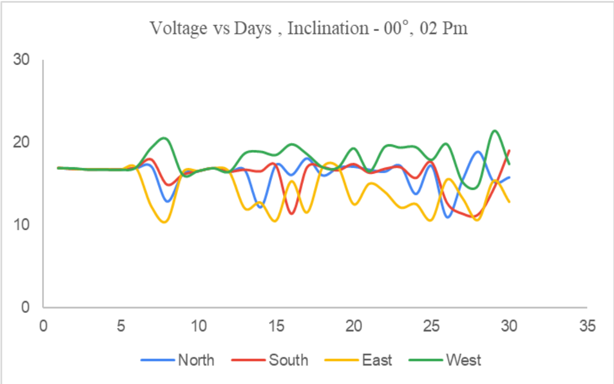


Figure: 5.1.5. Voltage vs Days, Inclination - 00°, 02 PM

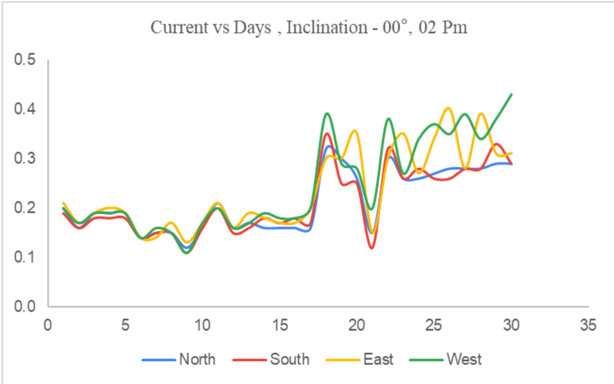


Figure: 5.1.6. Current vs Days, Inclination - 00°, 02 PM

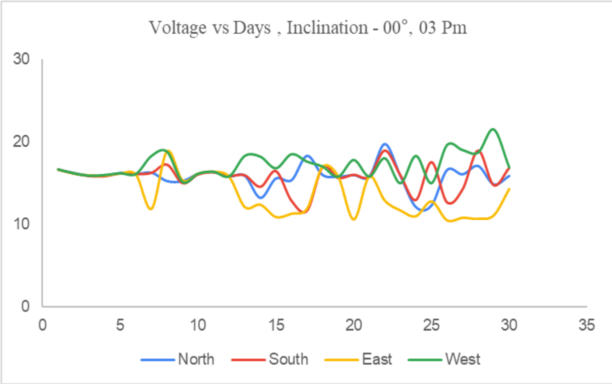


Figure: 5.1.7. Voltage vs Days, Inclination - 00°, 03 PM

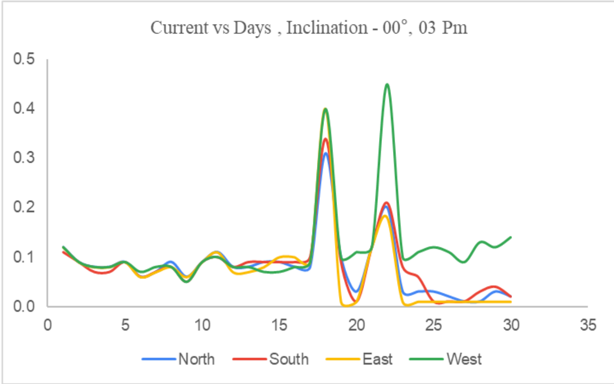


Figure: 5.1.8. Current vs Days, Inclination - 00°, 03 PM

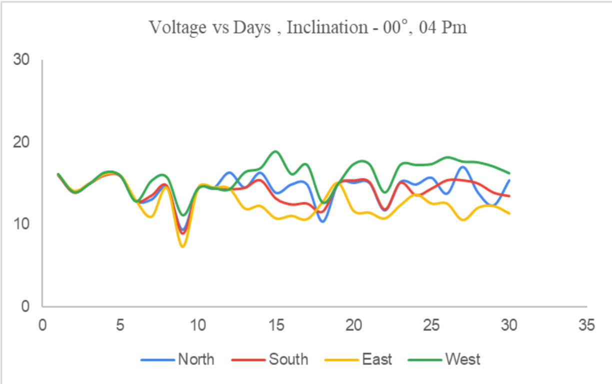


Figure: 5.1.9. Voltage vs Days, Inclination - 00°, 04 PM

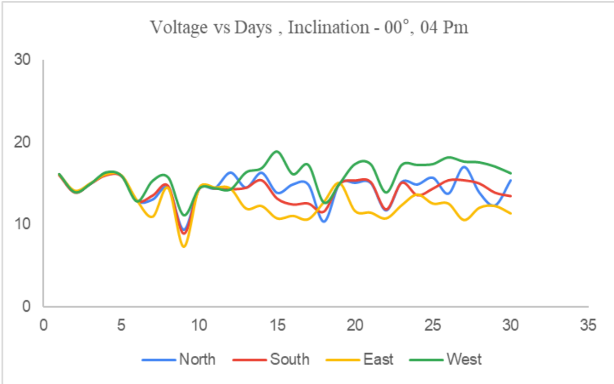
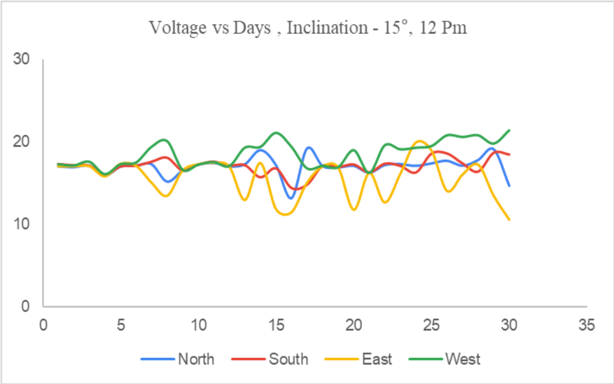


Figure: 5.1.10. Current vs Days, Inclination - 00°, 04 PM



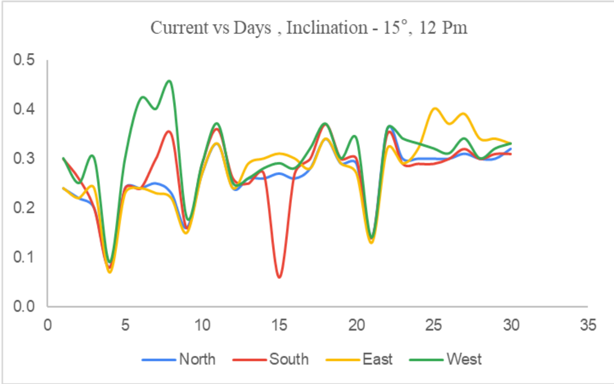
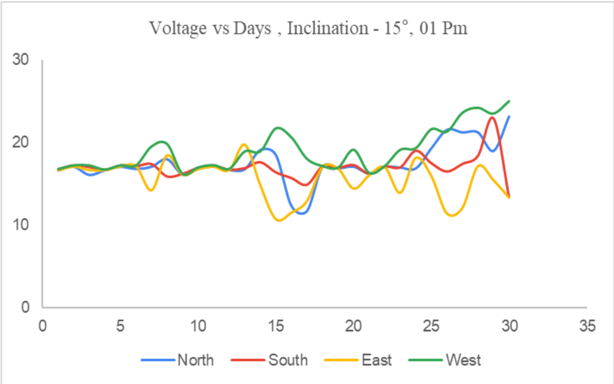


Figure: 5.2.1. Voltage vs Days, Inclination - 15°, 12 PM

Figure: 5.2.2. Current vs Days, Inclination - 15°, 12 PM



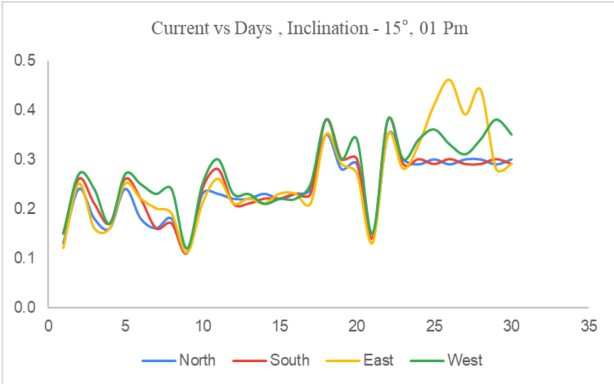
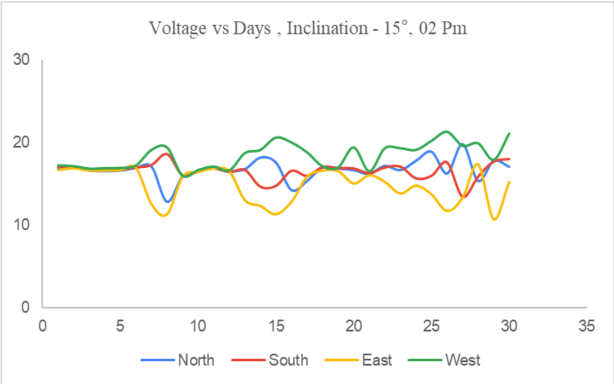


Figure: 5.2.3. Voltage vs Days, Inclination - 15°, 01 PM

Figure: 5.2.4. Current vs Days, Inclination - 15°, 01 PM



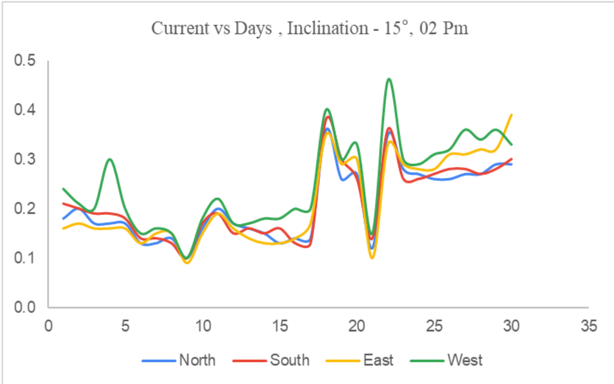


Figure: 5.2.5. Voltage vs Days, Inclination - 15°, 02 PM

Figure: 5.2.6. Current vs Days, Inclination - 15°, 02 PM

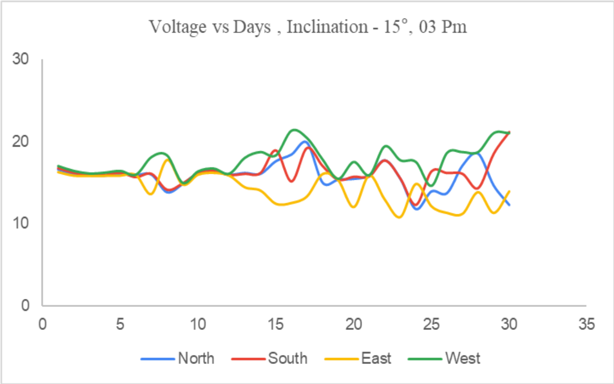


Figure: 5.2.7. Voltage vs Days, Inclination - 15°, 03 PM

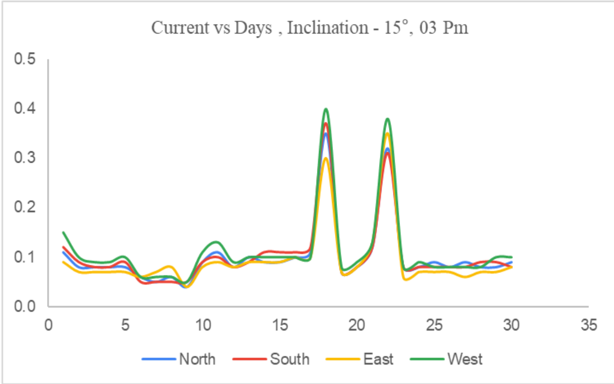


Figure: 5.2.8. Current vs Days, Inclination - 15°, 03 PM

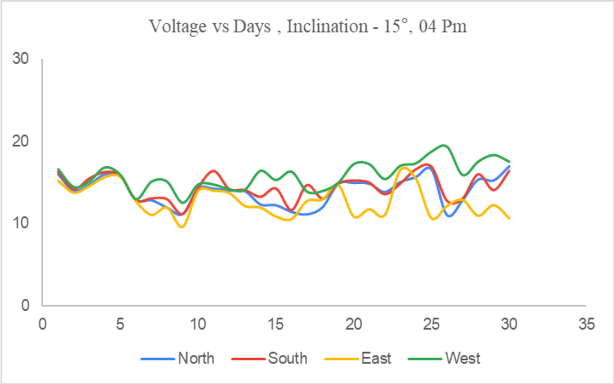


Figure: 5.2.9. Voltage vs Days, Inclination - 15°, 04 PM

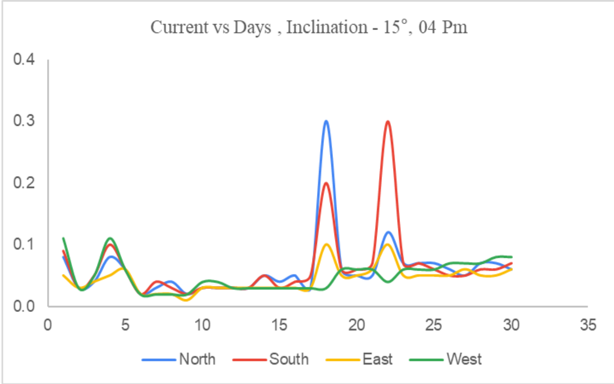


Figure: 5.2.10. Current vs Days, Inclination - 15°, 04 PM

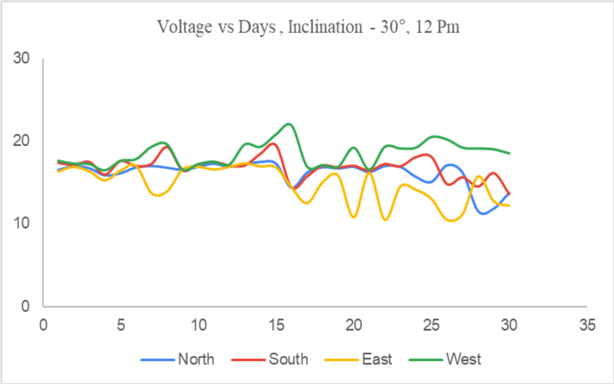


Figure: 5.3.1. Voltage vs Days, Inclination - 30°, 12 PM

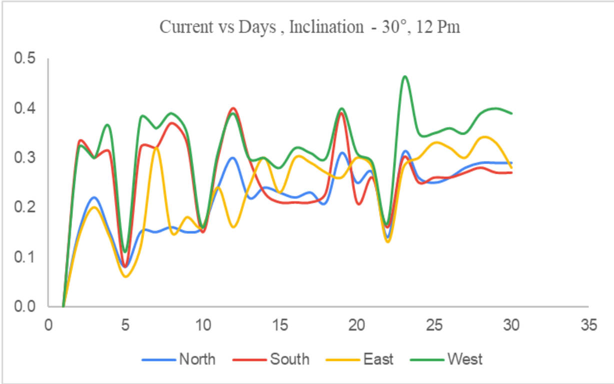


Figure: 5.3.2. Current vs Days, Inclination - 30°, 12 PM

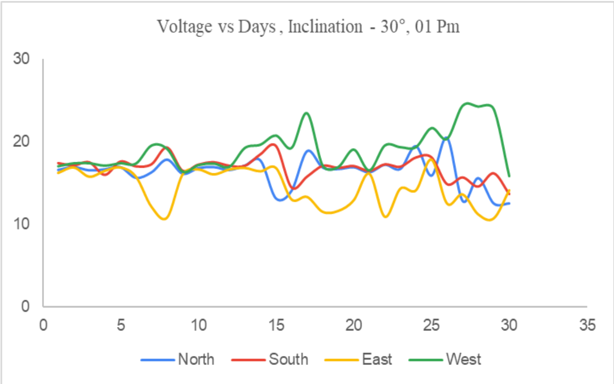


Figure: 5.3.3. Voltage vs Days, Inclination - 30°, 01 PM

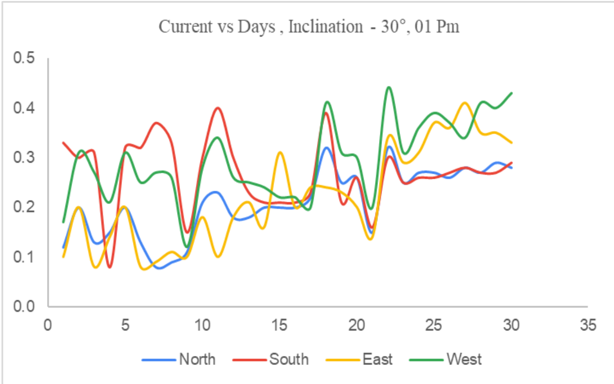


Figure: 5.3.4. Current vs Days, Inclination - 30°, 01 PM

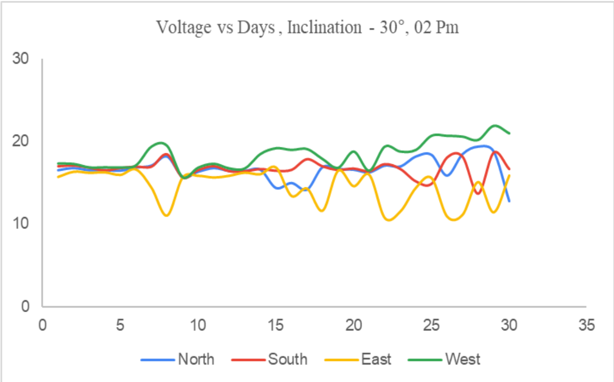


Figure: 5.3.5. Voltage vs Days, Inclination - 30°, 02 PM

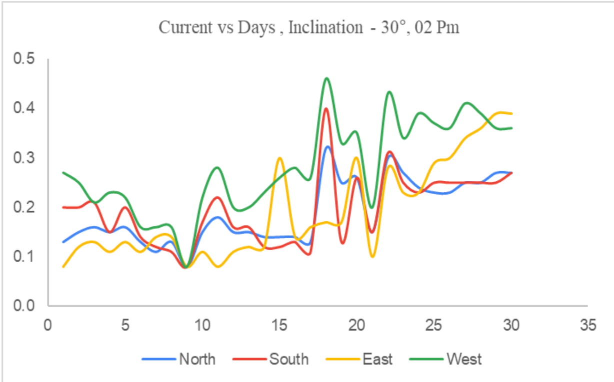


Figure: 5.3.6. Current vs Days, Inclination - 30°, 02 PM

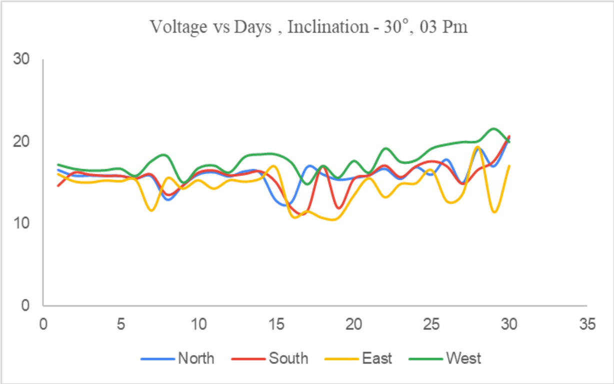


Figure: 5.3.7. Voltage vs Days, Inclination - 30°, 03 PM

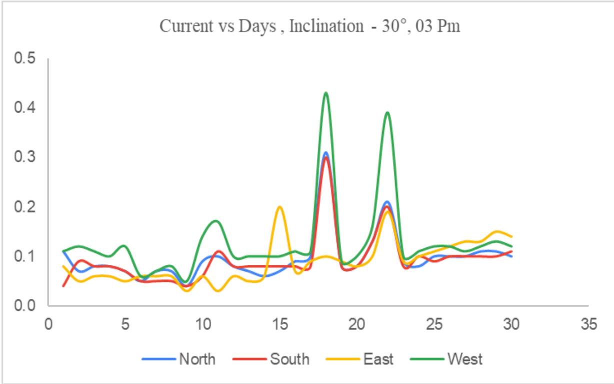


Figure: 5.3.8. Current vs Days, Inclination - 30°, 03 PM

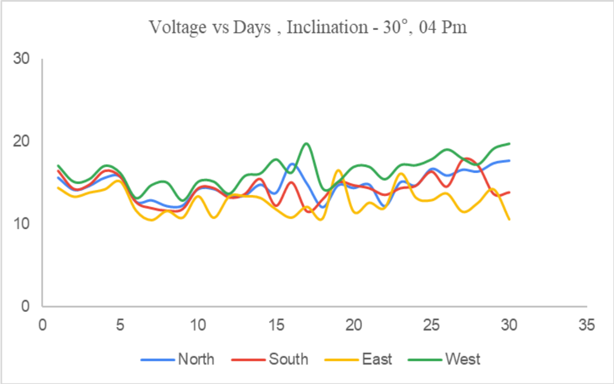


Figure: 5.3.9. Voltage vs Days, Inclination - 30°, 04 PM

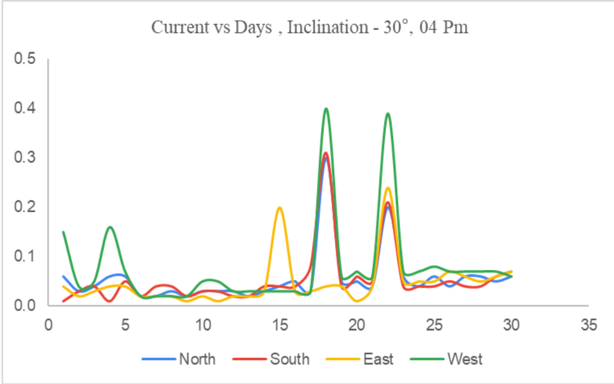
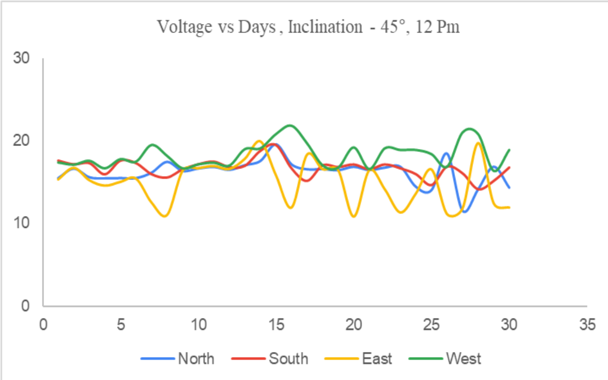


Figure: 5.3.10. Current vs Days, Inclination - 30°, 04 PM



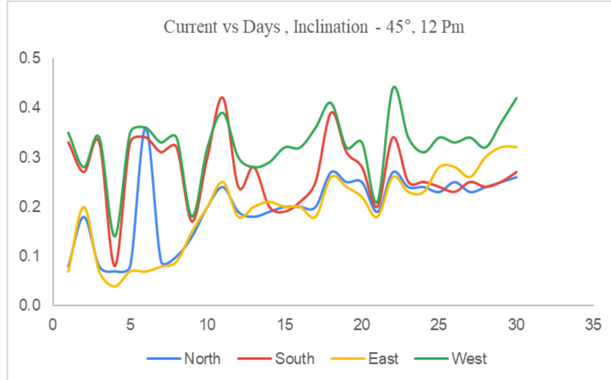
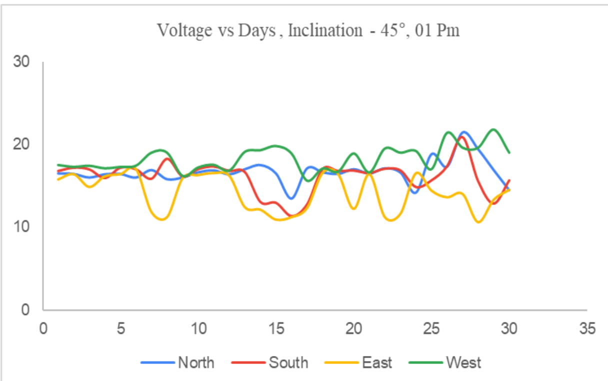


Figure: 5.4.1. Voltage vs Days, Inclination - 45°, 12 PM

Figure: 5.4.2. Current vs Days, Inclination - 45°, 12 PM



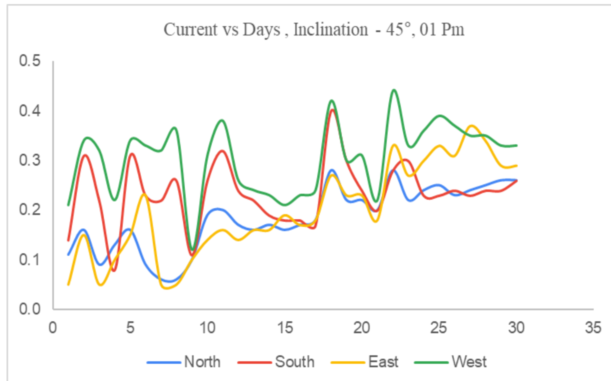
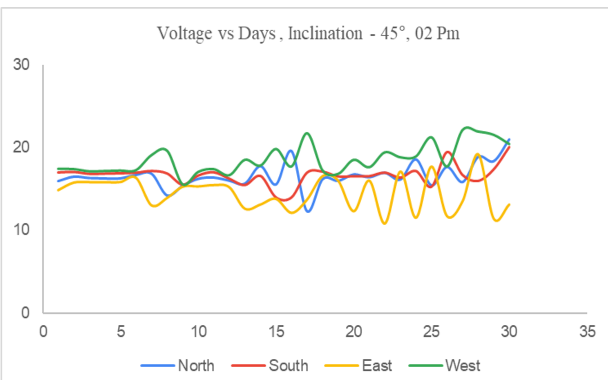


Figure: 5.4.3. Voltage vs Days, Inclination - 45°, 01 PM

Figure: 5.4.4. Current vs Days, Inclination - 45°, 01 PM



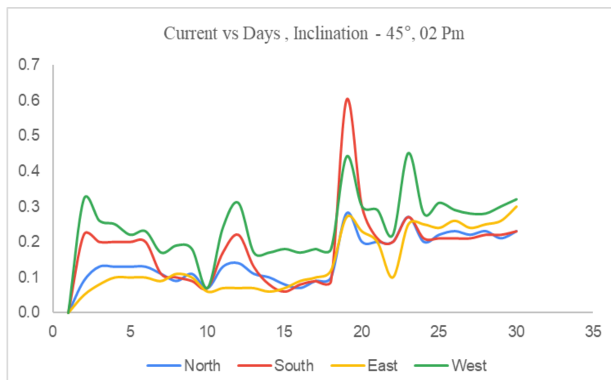


Figure: 5.4.5. Voltage vs Days, Inclination - 45°, 02 PM

Figure: 5.4.6. Current vs Days, Inclination - 45°, 02 PM

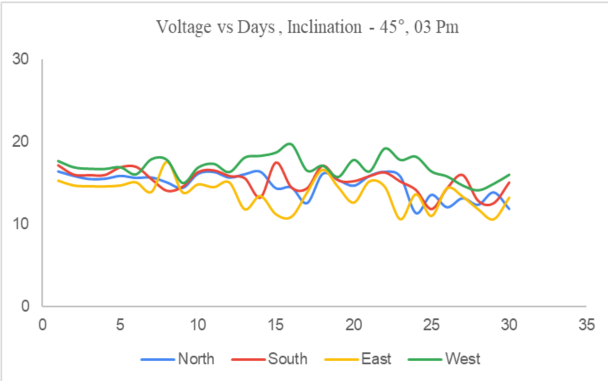


Figure: 5.4.7. Voltage vs Days, Inclination - 45°, 03 PM

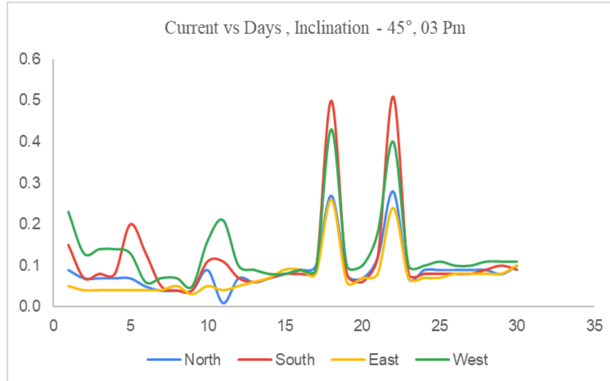


Figure: 5.4.8. Current vs Days, Inclination - 45°, 03 PM

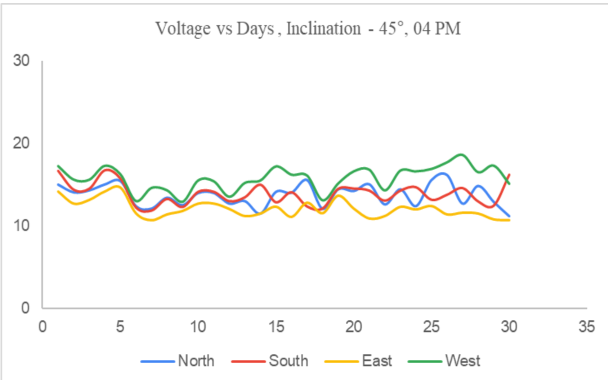


Figure: 5.4.9. Voltage vs Days, Inclination - 45°, 04 PM

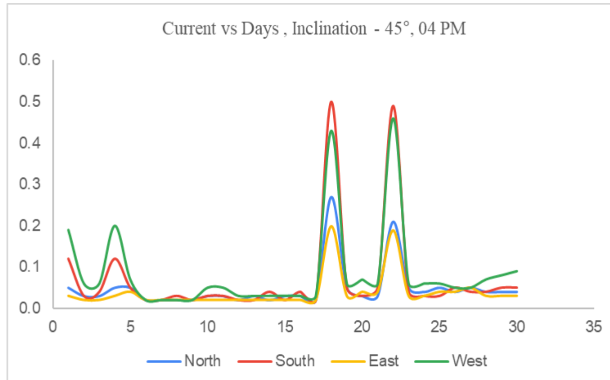
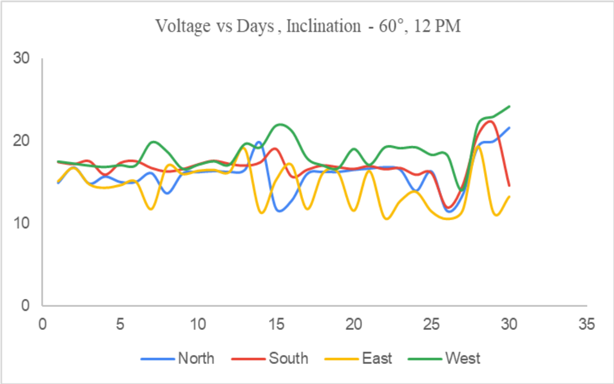


Figure: 5.4.10. Current vs Days, Inclination - 45°, 04 PM



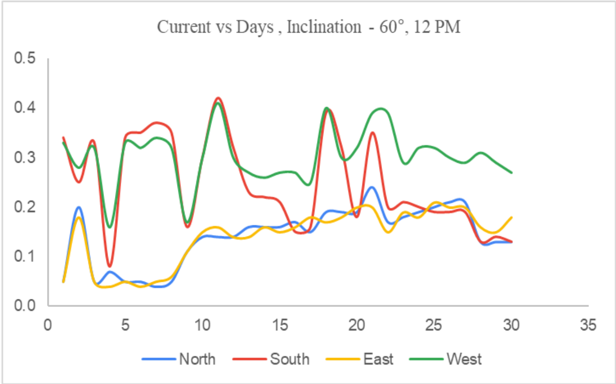
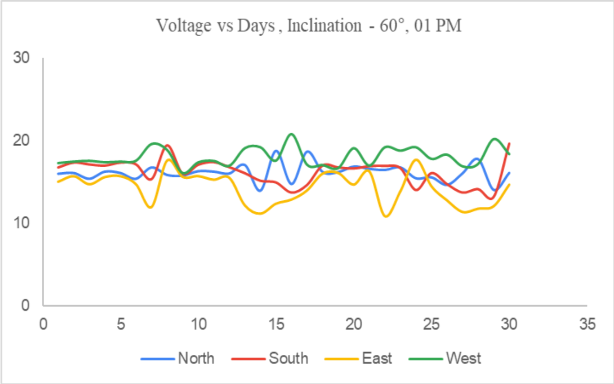


Figure: 5.5.1. Voltage vs Days, Inclination - 60°, 12 PM

Figure: 5.5.2. Current vs Days, Inclination - 60°, 12 PM



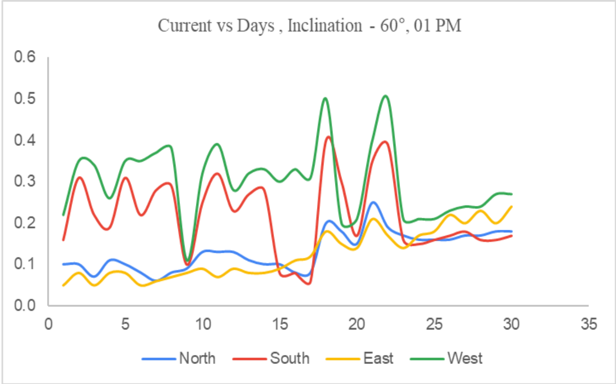
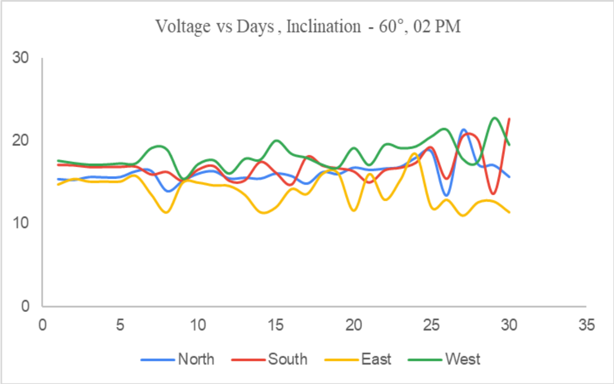


Figure: 5.5.3. Voltage vs Days, Inclination - 60°, 01 PM

Figure: 5.5.4. Current vs Days, Inclination - 60°, 01 PM



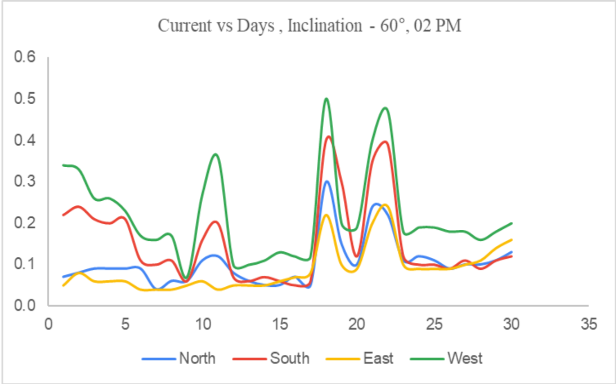


Figure: 5.5.5. Voltage vs Days, Inclination - 60°, 02 PM

Figure: 5.5.6. Current vs Days, Inclination - 60°, 02 PM

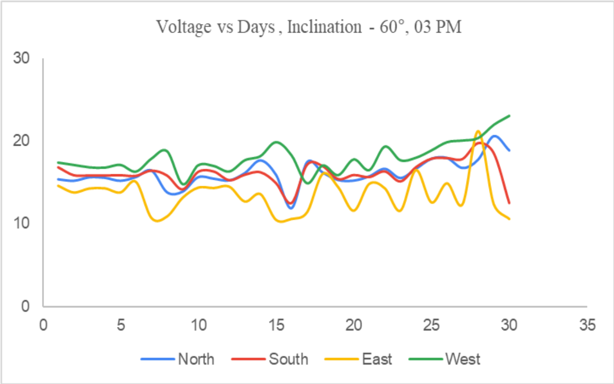


Figure: 5.5.7. Voltage vs Days, Inclination - 60°, 03 PM

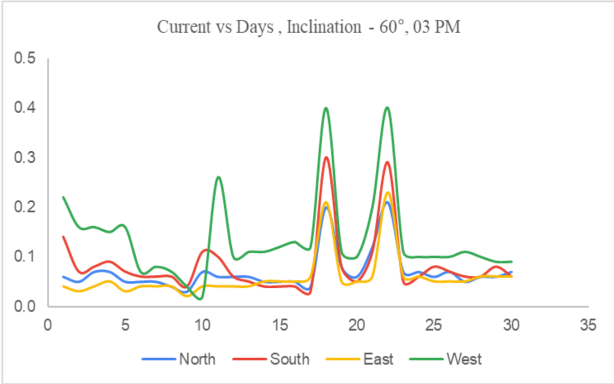


Figure: 5.5.8. Current vs Days, Inclination - 60°, 03 PM

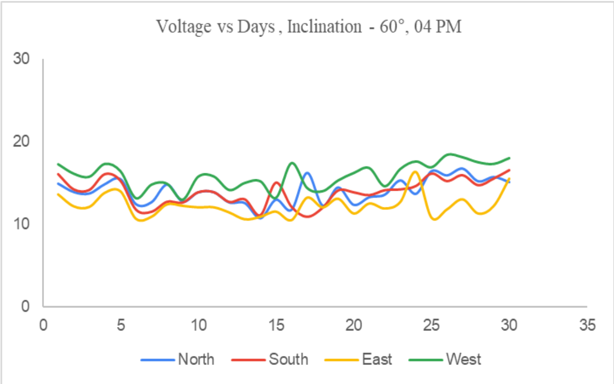


Figure: 5.5.9. Voltage vs Days, Inclination - 60°, 04 PM

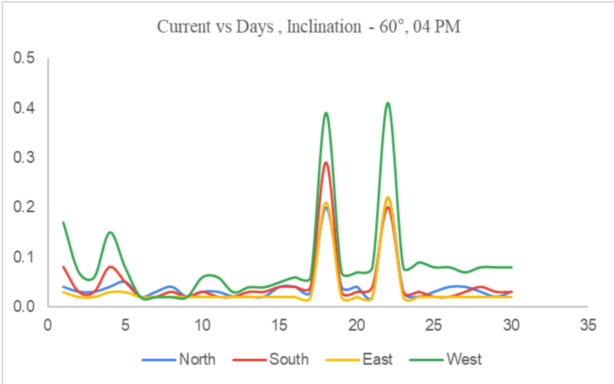
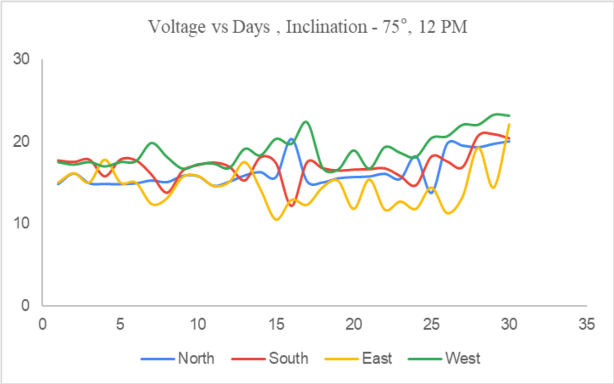


Figure: 5.5.10. Current vs Days, Inclination - 60°, 04 PM



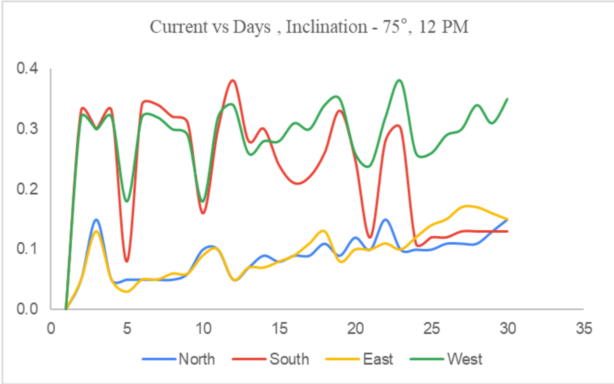
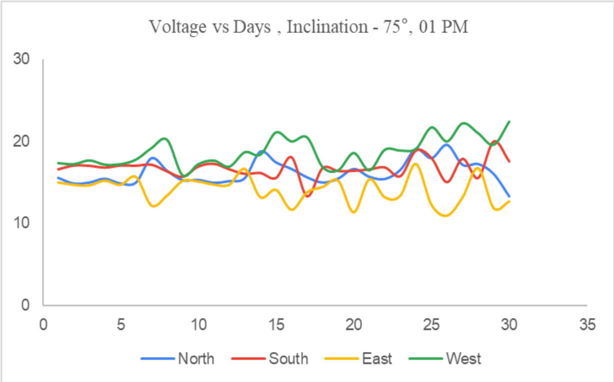


Figure: 5.6.1. Voltage vs Days, Inclination - 75°, 12 PM

Figure: 5.6.2. Current vs Days, Inclination - 75°, 12 PM



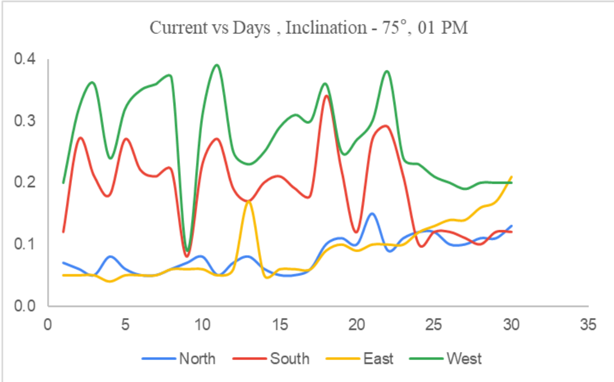
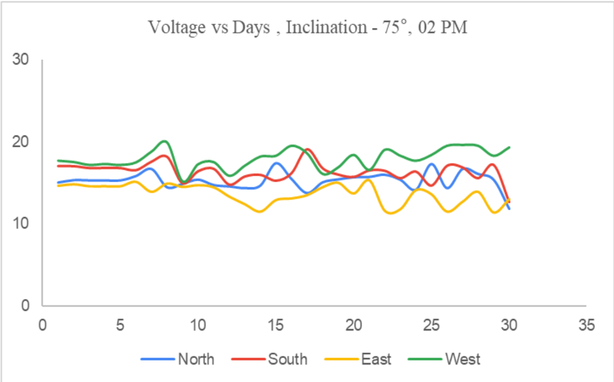


Figure: 5.6.3. Voltage vs Days, Inclination - 75°, 01 PM

Figure: 5.6.4. Current vs Days, Inclination - 75°, 01 PM



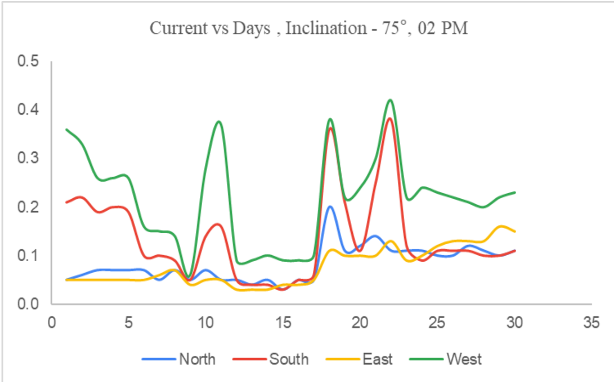


Figure: 5.6.5. Voltage vs Days, Inclination - 75°, 02 PM

Figure: 5.6.6. Current vs Days, Inclination - 75°, 02 PM

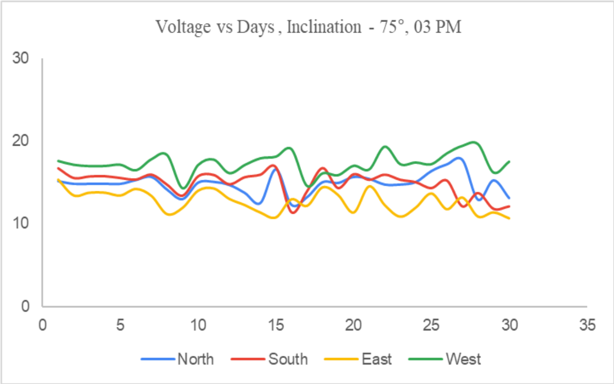


Figure: 5.6.7. Voltage vs Days, Inclination - 75°, 03 PM

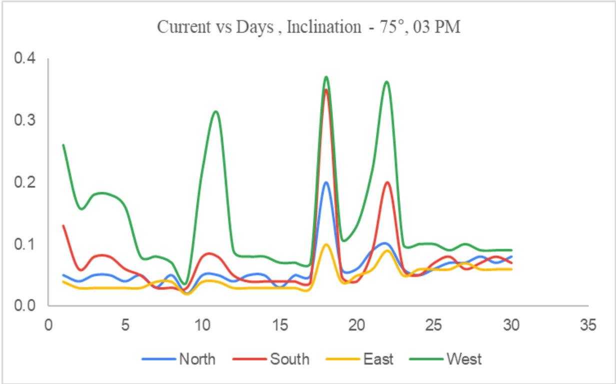


Figure: 5.6.8. Current vs Days, Inclination - 75°, 03 PM

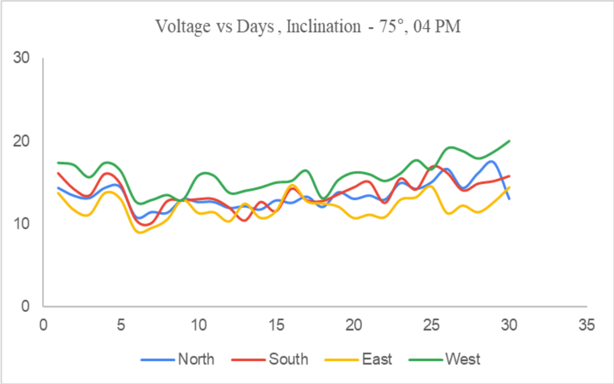


Figure: 5.6.9. Voltage vs Days, Inclination - 75°, 04 PM

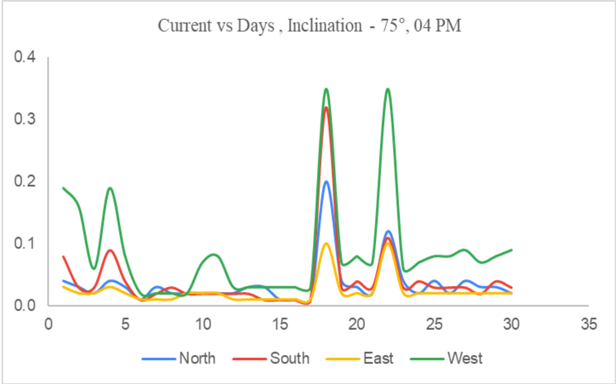


Figure: 5.6.10. Current vs Days, Inclination - 75°, 04 PM

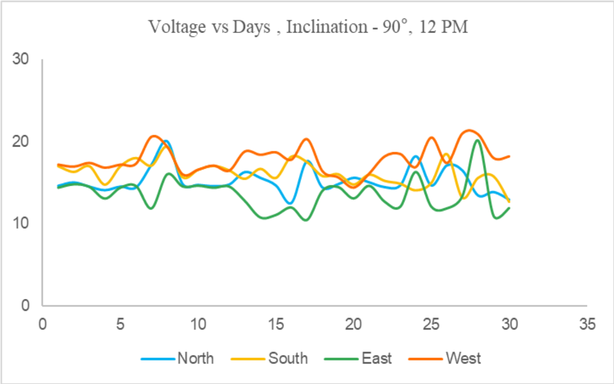


Figure: 5.7.1. Voltage vs Days, Inclination - 90°, 12 Pm

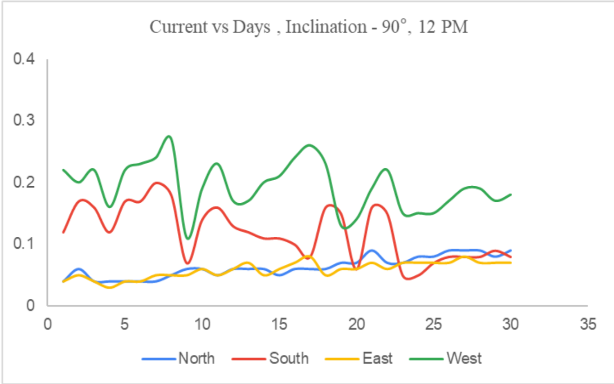


Figure: 5.7.2. Current vs Days, Inclination - 90°, 12 PM

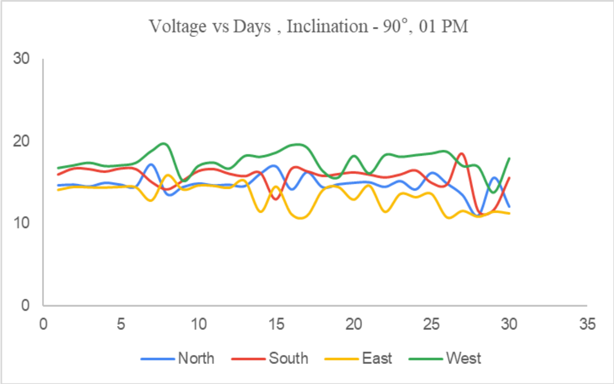


Figure: 5.7.3. Voltage vs Days, Inclination - 90°, 01 PM

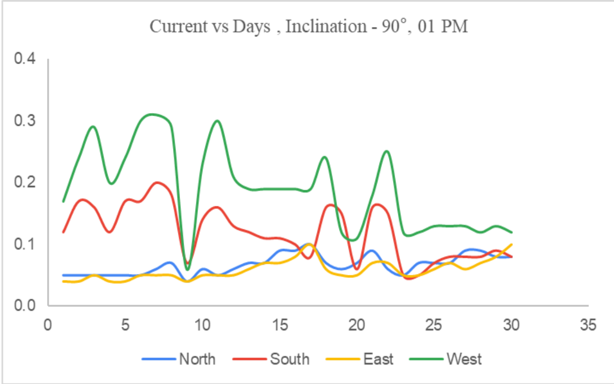


Figure: 5.7.4. Current vs Days, Inclination - 90°, 01 PM

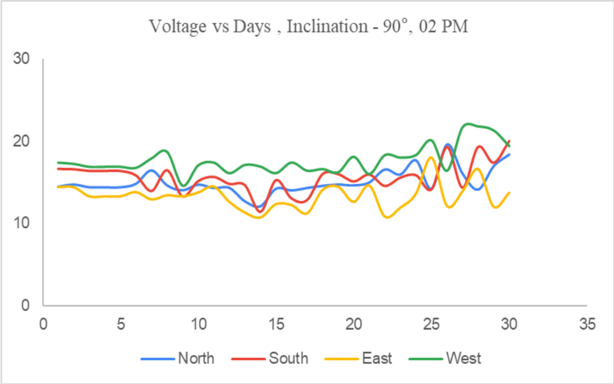


Figure: 5.7.5. Voltage vs Days, Inclination - 90°, 02 PM

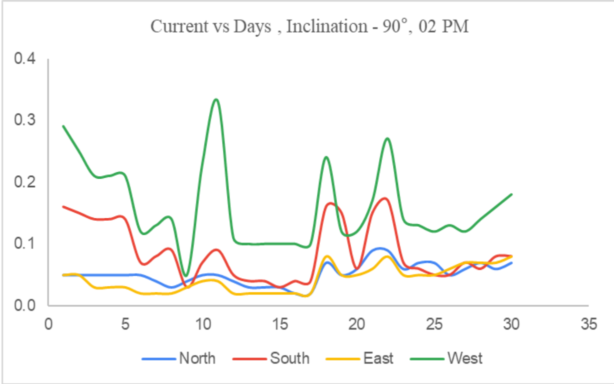


Figure: 5.7.6. Current vs Days, Inclination - 90°, 02 PM

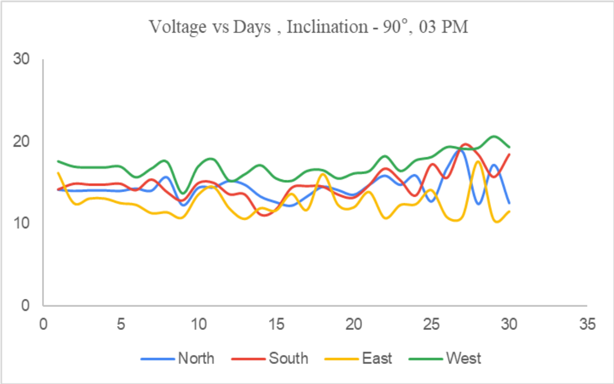


Figure: 5.7.7. Voltage vs Days, Inclination - 90°, 03 PM

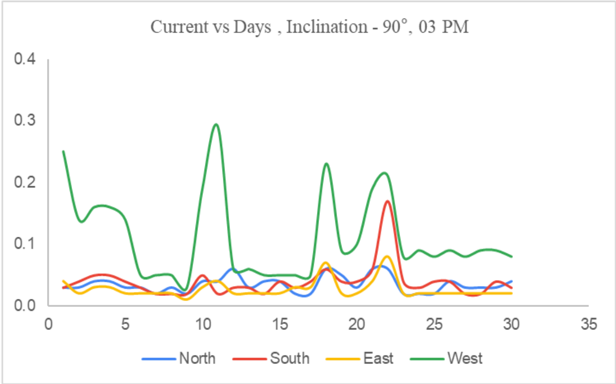


Figure: 5.7.8. Current vs Days, Inclination - 90°, 03 PM

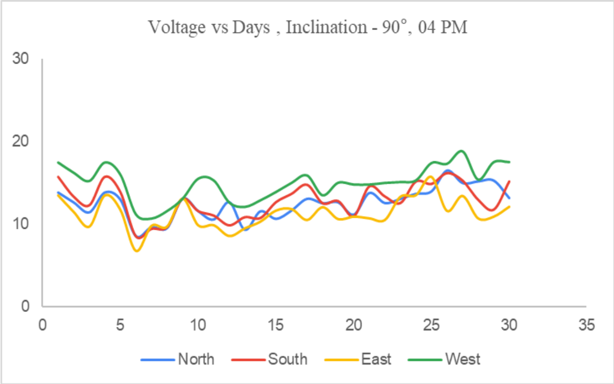


Figure: 5.7.9. Voltage vs Days, Inclination - 90°, 04 PM

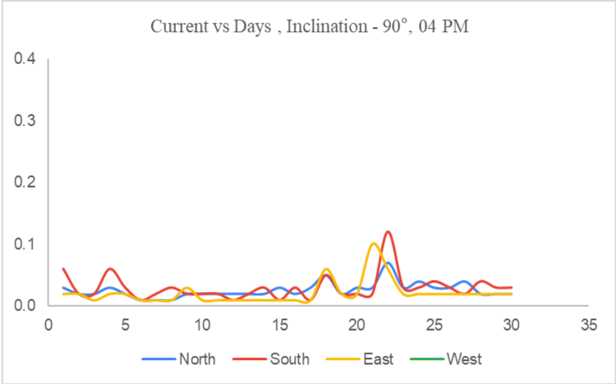


Figure: 5.7.10. Current vs Days, Inclination - 90°, 04 PM

5.3. Feed Forward Neural Network and Predictive Output Modelling

A subset of input values was selected from the collected data values to feed as input to feedforward neural-network in MATLAB, to train the network, w.r.t. to a target set of output values for the corresponding input values. The input values so selected were time and theta, while the target output values were the corresponding voltage and current. A total 120 observations or vectors of input values were thus selected with each containing 2 features or elements (time and theta) for a total number of 120 output observations with 2 features or elements each (voltage and current). The Model was created and trained using standard command prompts and used the inbuilt, by-default weight and bias values and the training-function algorithm. First the input training vectors were declared as a 120 x 2 matrix (theta and time) and was put inside the variable array 'X' as: -

X =

12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75
12	90	12	90	13	75	13	75

14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45	15	45
14	60	14	60	15	45		
14	60	14	60	15	45		
14	60	15	45	15	45		
14	60	15	45	15	45		

Output target vectors were also declared as a 120 x 2 matrix (theta and time) and was put inside the variable array 'T' as: -

T =

14.6000	0.0400	15.0200	0.0900	14.9900	0.0500
15.0100	0.0600	14.4400	0.0700	15.1900	0.0700
14.5000	0.0400	14.6500	0.0700	15.5600	0.0800
14.0700	0.0400	18.1800	0.0800	18.7900	0.0600
14.5000	0.0400	14.6500	0.0800	17.4700	0.0500
14.4000	0.0400	17.0700	0.0900	16.6700	0.0500
17.1700	0.0400	16.4600	0.0900	15.6600	0.0600
20.0000	0.0500	13.4300	0.0900	15.0200	0.1000
14.8100	0.0600	13.8400	0.0800	15.5000	0.1100
14.7100	0.0600	12.9300	0.0900	16.6700	0.1000
14.5600	0.0500	15.5900	0.0700	15.7200	0.1500
14.7600	0.0600	14.9000	0.0600	15.4500	0.0900
16.2600	0.0600	15.0200	0.0500	16.5700	0.1100
15.5600	0.0600	15.4800	0.0800	19.0900	0.1200
14.6500	0.0500	14.9000	0.0600	17.9800	0.1200
12.5300	0.0600	15.0200	0.0500	19.6000	0.1000
17.5800	0.0600	17.9800	0.0500	17.1700	0.1000
14.3900	0.0600	16.4600	0.0600	17.2700	0.1100
14.7900	0.0700	15.3100	0.0700	16.0600	0.1100
15.5600	0.0700	15.3500	0.0800	13.3300	0.1300

15.3900	0.0700	17.9800	0.1200	12.3200	0.1000
15.2900	0.0800	18.6900	0.1100	16.2000	0.2800
15.6400	0.0900	13.4300	0.0900	16.0000	0.2000
15.6000	0.0900	21.3100	0.1000	16.7700	0.2000
15.6500	0.0900	17.1700	0.1000	16.4400	0.2000
16.3500	0.0900	17.0700	0.1100	16.9700	0.2700
16.3600	0.0400	15.6600	0.1300	16.1600	0.2000
13.9400	0.0600	15.9700	0.0900	18.5900	0.2200
15.1600	0.0600	16.5000	0.1300	15.4500	0.2300
16.0400	0.1100	16.3400	0.1300	17.6800	0.2200
16.3400	0.1200	16.2900	0.1300	15.8600	0.2300
15.4600	0.0800	16.3000	0.1300	18.8900	0.2100
15.5600	0.0600	16.7100	0.1100	18.3800	0.2300
15.4500	0.0500	16.8700	0.0900	21.0100	0.2400
16.0600	0.0500	14.2400	0.1100		
15.7600	0.0700	15.3800	0.0700		
14.8500	0.0500	16.2400	0.1300		
16.2400	0.3000	16.3900	0.1400		
16.0000	0.1500	16.0200	0.1100		
16.7700	0.1000	15.6600	0.1000		
16.5000	0.2400	17.7800	0.0800		
16.6700	0.2200	15.5600	0.0700		
16.8700	0.1100	19.6000	0.0900		

Now the feedforward neural network 'net' was created using the following command with 30 hidden layers: -

net = feedforwardnet(30);

The network was then trained with the following command: -

net = train(net,X,T);

where the input training vectors of 'X' are trained w.r.t. output training targets of 'T', for the network 'net' with 30 hidden layers. All other values of weights, biases, iterations and training functions were kept at inbuilt, by-default values. Figure 5.8. shows the simulation model of the training network so obtained.

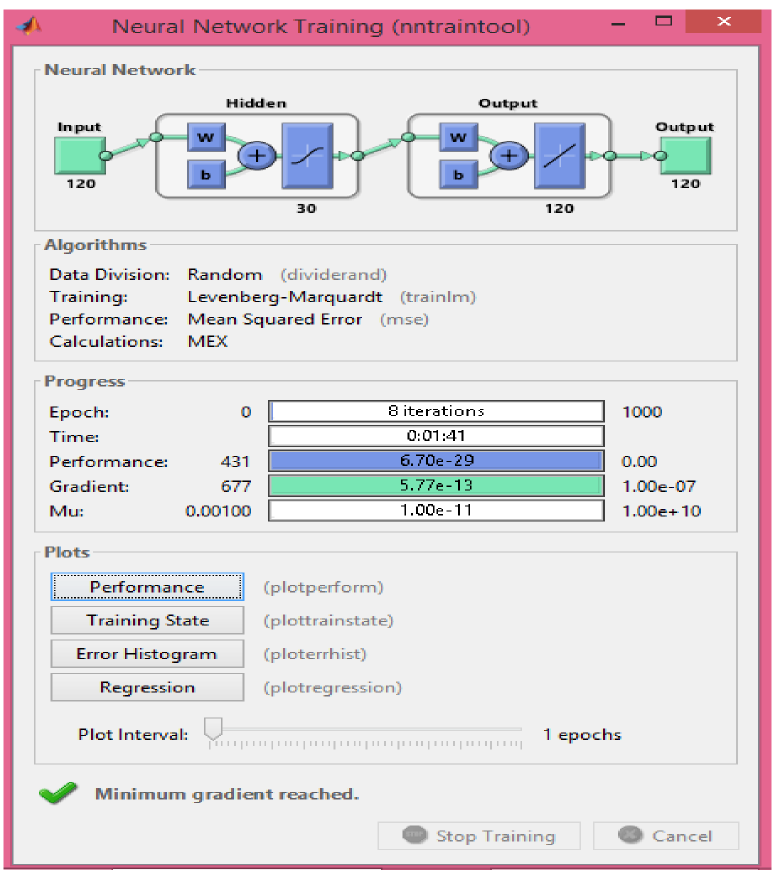


Figure 5.8. Simulation Model of the Training Network

The output ‘Y’ was now mapped for a fresh set of input vectors ‘I’ defined as a similar 120 x 2 matrix of user-defined custom data values (time and theta) namely: -

I =

12.0000	89.5161	12.0000	79.8387	13.0000	70.1613	14.0000	60.4839
12.0000	89.0323	12.0000	79.3548	13.0000	69.6774	14.0000	60.0000
12.0000	88.5484	12.0000	78.8710	13.0000	69.1935	14.0000	59.5161
12.0000	88.0645	12.0000	78.3871	13.0000	68.7097	14.0000	59.0323
12.0000	87.5806	12.0000	77.9032	13.0000	68.2258	14.0000	58.5484
12.0000	87.0968	12.0000	77.4194	13.0000	67.7419	14.0000	58.0645
12.0000	86.6129	12.0000	76.9355	13.0000	67.2581	14.0000	57.5806
12.0000	86.1290	12.0000	76.4516	13.0000	66.7742	14.0000	57.0968
12.0000	85.6452	12.0000	75.9677	13.0000	66.2903	14.0000	56.6129
12.0000	85.1613	12.0000	75.4839	13.0000	65.8065	14.0000	56.1290
12.0000	84.6774	13.0000	75.0000	13.0000	65.3226	14.0000	55.6452
12.0000	84.1935	13.0000	74.5161	13.0000	64.8387	14.0000	55.1613
12.0000	83.7097	13.0000	74.0323	13.0000	64.3548	14.0000	54.6774
12.0000	83.2258	13.0000	73.5484	13.0000	63.8710	14.0000	54.1935
12.0000	82.7419	13.0000	73.0645	13.0000	63.3871	14.0000	53.7097
12.0000	82.2581	13.0000	72.5806	13.0000	62.9032	14.0000	53.2258
12.0000	81.7742	13.0000	72.0968	13.0000	62.4194	14.0000	52.7419
12.0000	81.2903	13.0000	71.6129	13.0000	61.9355	14.0000	52.2581
12.0000	80.8065	13.0000	71.1290	13.0000	61.4516	14.0000	51.7742
12.0000	80.3226	13.0000	70.6452	13.0000	60.9677	14.0000	51.2903

14.0000	50.8065	15.0000	45.9677	15.0000	41.1290	15.0000	36.2903
14.0000	50.3226	15.0000	45.4839	15.0000	40.6452	15.0000	35.8065
14.0000	49.8387	15.0000	45.0000	15.0000	40.1613	15.0000	35.3226
14.0000	49.3548	15.0000	44.5161	15.0000	39.6774	15.0000	34.8387
14.0000	48.8710	15.0000	44.0323	15.0000	39.1935	15.0000	34.3548
14.0000	48.3871	15.0000	43.5484	15.0000	38.7097	15.0000	33.8710
14.0000	47.9032	15.0000	43.0645	15.0000	38.2258	15.0000	33.3871
14.0000	47.4194	15.0000	42.5806	15.0000	37.7419	15.0000	32.9032
14.0000	46.9355	15.0000	42.0968	15.0000	37.2581	15.0000	32.4194
14.0000	46.4516	15.0000	41.6129	15.0000	36.7742	15.0000	31.9355

Output ‘Y’ (voltage and current) for input vectors ‘I’ is given by the command prompt: -

Y = net(I);

Y =

14.6000	-2.4751	14.8100	-1.4799	17.5800	8.5370	14.6500	4.9881
15.0100	-5.2935	14.7100	12.0036	14.3900	-5.1487	17.0700	-11.3216
14.5000	9.5708	14.5600	11.2985	14.7900	9.2129	16.4600	4.6323
14.0700	-1.5309	14.7600	1.5653	15.5600	5.7887	13.4300	4.5412
14.5000	4.6310	16.2600	4.5540	15.0200	-3.8538	13.8400	1.7903
14.4000	-6.5638	15.5600	3.2878	14.4400	14.0136	12.9300	-0.2071
17.1700	-0.9891	14.6500	1.3540	14.6500	0.9387	15.5900	1.6727
20.0000	2.9234	12.5300	9.3488	18.1800	8.5555	4.9000	-3.5675

15.0200	8.4140	19.6000	15.7296	16.0000	11.1718	16.0200	9.5931
15.4800	13.7118	17.1700	-7.2318	16.7700	1.0730	15.6600	2.8544
14.9000	-4.4377	17.2700	1.6543	16.5000	10.7761	17.7800	-10.1466
15.0200	3.9851	16.0600	9.2692	16.6700	-0.0417	15.5600	2.2147
17.9800	-5.3566	13.3300	-2.7432	16.8700	8.9485	19.6000	2.4231
16.4600	8.1235	15.3900	2.1820	17.9800	8.8922	12.3200	8.2561
15.3100	-2.7860	15.2900	2.7382	18.6900	-3.0364	16.2000	5.9233
15.3500	-0.5700	15.6400	8.7127	13.4300	7.0651	16.0000	-8.8784
14.9900	4.9181	15.6000	-8.5976	21.3100	-9.1809	16.7700	-5.9413
15.1900	0.8220	15.6500	-2.3129	17.1700	-4.8404	16.4400	-2.3525
15.5600	-1.7301	16.3500	-2.1688	17.0700	-16.0426	16.9700	-5.0052
18.7900	2.8813	16.3600	8.9564	15.6600	11.1493	16.1600	0.0348
17.4700	7.9515	13.9400	6.7770	15.9700	-1.1886	18.5900	11.5618
16.6700	5.3072	15.1600	0.5044	16.5000	-0.6956	15.4500	-0.7923
15.6600	-1.9049	16.0400	-1.1078	16.3400	6.8980	17.6800	-1.5461
15.0200	9.8148	16.3400	-2.3947	16.2900	-11.9675	15.8600	-13.8399
15.5000	-10.7042	15.4600	-6.2994	16.3000	0.1967	18.8900	-0.6906
16.6700	2.6299	15.5600	3.0269	16.7100	-1.2622	18.3800	-12.5809
15.7200	1.9755	15.4500	-0.8145	16.8700	-4.5254	21.0100	-10.1786
15.4500	2.8916	16.0600	15.5432	14.2400	-2.0473		
16.5700	8.6560	15.7600	8.9905	15.3800	-10.4317		
19.0900	-11.9791	14.8500	0.7910	16.2400	2.6026		
17.9800	-7.3083	16.2400	-10.3046	16.3900	4.3698		

It was found that the transformed output values for the new set of input values showed good relevance w.r.t. voltage output. The current values, however, so obtained, showed no possible parity at all with actual collected values and could clearly be rejected. The voltage values, however, was very well speculated within possible ranges of actual voltage output and could thus be remarked, that the simple model gives quiet relevant predictive voltage outputs for custom choice of theta and time. The predictive voltage output of the system for 30 days (but for various thetas) was plotted (Figure 5.9.) and revealed a qualitative symmetry in the graph structure compared to those obtained by actual data values.

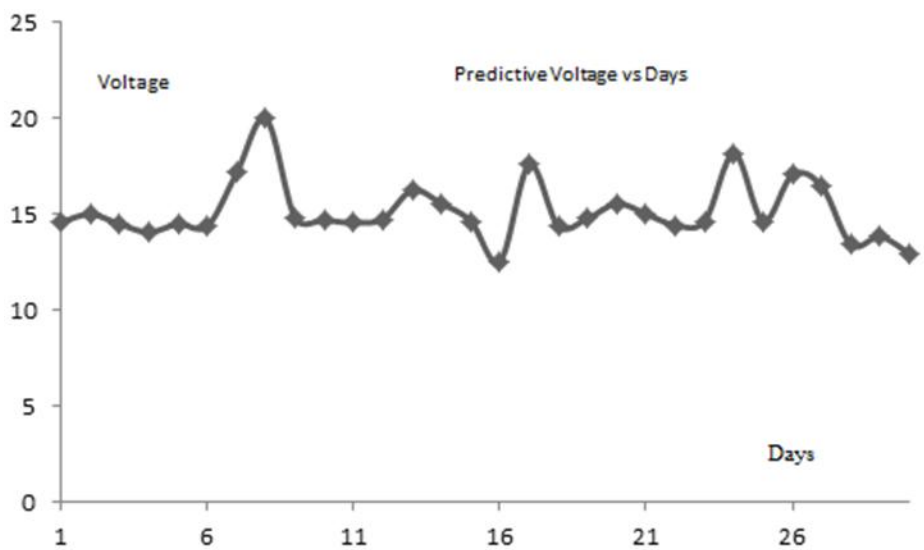


Figure 5.9. Predictive Voltage vs Days

5.4. Conclusion

The model used an inbuilt training function and other by-default weight, biases and activation functions, a lot of scopes lie in the prospect of developing custom training functions and selection of proper weights, biases and activation function, to also give a good predictive output current values for custom input theta and time. The purpose of the current work was to see if such neural-network modeling can be implemented to generate predictive output of solar-panels, and in this regard the present project is successful.

CHAPTER- 6

CONCLUSION AND FUTURE SCOPE OF WORK

6.1. Conclusion

The current project work revealed in a qualitative sense that the voltage-current output of a solar panel is fundamentally more of a function of the time of the day when the data is collected and that nature of the graphs are dictated by this time-stamp of data-collection. Next, the nature of the graphs for exactly opposite directions bear more symmetry with each other for all the panel-inclinations and can thus be concluded that the next more fundamental parameter for influencing output graph nature is the exactly opposite-directions in tally of which the data are collected. The simple neural network modeling of the voltage current output data w.r.t. input time and panel inclination suggested that a predictive neural-network output model can at least be easily generated for custom input of time and theta and can be used to transform into predictive voltage and current outputs albeit with certain degree of modification of the inbuilt training-functions, weights, biases and activation functions. The work has at least shown that the predictive voltage values so-obtained are very much in tally with actual data collected and the current output can also be tuned necessarily with modifications in the algorithm of the neural network. Such possibilities are explained further in detail in the future scope of work section.

6.2. Future Scope of Work

- In future a possible application of source-measuring unit can be implemented to collect voltage-current outputs of the solar panel against various loads and various inclination, keeping other parameters same as before. This will help us to obtain the various IV curves for every theta value at different time-stamps and directions and would lead to a much more comprehensive study.
- Data-collection duration can also be extended over a whole season or an entire year as well as those in different locations.
- Fixing a solarimeter against the surface of the solar-panel at perpendicular would help us to obtain the combined direct and diffused solar irradiance at various observations and could be used as another parameter in the next stage of predictive modeling of the panel outputs w.r.t. different inputs.
- Parameters like fine latitude-longitude values as well as altitude can also be used as inputs in those predictive models.
- The predictive model itself will be overhauled in the next stage with exhaustive formulation of suitable training functions for the proper input/output mappings for all the parameters and could also lead to ideation of a new analytical equation which relates the input time, theta and probably solar isolation to output voltage, current and power values.
- This neural network modeling itself can actually help in creating a dynamic working formula or at least a static one which controls the positioning and movement of solar-panels at different time of the day and at different seasons to generate the best output

power at any point of collection and could actually help in improving efficiency of building-integrated solar photo-voltaic systems and also those for the large solar parks.

CHAPTER- 7

REFFERENCES

7. REFFERENCES

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