A Predictive Model for Performance Analysis of Solar PV Systems in Kajiado County, Kenya

Benjamin Elmard Ogweno[1, 2], David Wafula Wekesa[1, 2], Fenwicks Shombe Musonye[3]

[1]Department of Physics, Multimedia University of Kenya, P.O. BOX 15653 – 00503, Nairobi, Kenya
Corresponding author: Benjamin Elmard Ogweno
Emails: belmard[at]mmu.ac.ke

[2]Renewable Energy Research Consortium, Multimedia University of Kenya, P.O. BOX 15653 – 00503, Nairobi, Kenya
Emails:dwekesahit[at]gmail.com

[3]Energy and Petroleum Regulatory Authority, P.O. BOX 42681 – 00100, Nairobi, Kenya
Emails: *fenshombe[at]gmail.com*

Abstract: ***Solar photovoltaics is one of the emerging technologies widely recognized as a potential solution to energy poverty due to its high reliability, long life, and automatic operation with minimal maintenance requirements. despite its low conversion efficiency and high capital costs. However, solar energy is non-dispatchable, hence not used as a peak load energy source, due to its sporadic nature. Solar PV system design and operation is also affected by intermittency. System design should consider site specific ambient conditions that may affect the output. Such conditions are not often modeled and designers always use standard test conditions. There is need to develop such models that can be used to guide system designers. This study focuses on the development and validation of a predictive numerical system for solar PV systems in Kajiado County. Real-time data on solar irradiance, temperature, and system performance were collected to model and simulate the performance of solar PV systems. The study employed an exploratory and predictive research design, utilizing analytical and numerical techniques to develop and refine the predictive numerical model. The model was validated using an existing solar PV system in Kajiado County, comparing the predicted performance metrics with the actual characteristics of the system. Simulation procedures involved developing the model using module specifications and intermittency variables, and conducting simulations based on site-specific data. The results were analyzed, and the accuracy of the predictive model was assessed. The model demonstrated that solar PV systems perform well at low Nominal Operating Cell Temperature (NOCT) conditions of 30 °C. Based on the simulated data output, the PV module conversion efficiency varies between 20.32% and 16.72%. This differs from the expected efficiency value, which in laboratory circumstances is 21.00%. The simulated power output values had a deviation of between 0.68% and 10.68% in comparison to experimental data from a site specific location in Kajiado County, Kenya. The study concluded that the developed predictive numerical system accurately predicts the performance of solar PV systems, and that the predicted power based on laboratory test conditions is more than the real power based on real site conditions. The findings provide valuable insights for decision-making in the design, operation, and management of solar PV systems. The research recommends further model refinement, expanded validation, real-time monitoring, collaboration, and policy support to enhance the effectiveness and applicability of the predictive numerical system in the renewable energy sector.***

Keywords: Module Output, Module Conversion Efficiency, Nominal Operating Cell Temperature Intermittency, Predictive Model

1. Introduction

Access to clean and affordable energy has been a challenging goal to developing countries. According to recent statistics, 9% of the world's population lacks access to electricity, with Sub-Saharan Africa having the least amount of access [1]. It is economically unfeasible to connect sparse and far flank regions using the national grid. Sustainable development goals (SDGs) have been devised to help address these issues, which pose a challenge to the entire world. SDG 7 promotes the use of clean, cheap energy. It aims to provide everyone with access to modern, clean, inexpensive energy. Sub-Saharan Africa countries are signatory to these goals and they have put in place efforts to ensure universal access. Kenya launched Vision 2030, whose key objective is to help her transform into an industrializing, middle-income country. This will provide high quality of life to all its citizens by 2030 in a clean and secure environment.

Use of off-grid systems, that incorporate renewable energy sources, promise solutions to this problem. These systems operate independently and are not connected to the national electricity grid. They are thus known as 'off-grid systems' [2]. Solar PV is quite flexible and therefore, it has been a helpful resource for off-grid systems. Two main approaches under these systems can be conducted to ensure electrification reaches all areas. They include mini-grids and stand-alone systems. Off-grid systems, which offers environmentally friendly solutions for energy access, still has challenges attached to it [3]. These challenges include; dependency on weather conditions that bring about intermittency issues, high initial investment costs, and high costs related to energy storage.

Intermittency is a challenge since it affects solar PV off-grid systems to a large extent. The predictability of peak sun hours, due to changes in weather patterns would mean that electrical energy generated is limited. The varying output will in turn be a drawback since the fluctuating electricity demands shall not be met. Different sun positions within the year and cloud cover also bring out the limitation of consistently using Solar PV as an electricity resource. Furthermore, what is promised in the lab and shown on the data sheet is not what is generated in specific locations. The data sheets are used to plan and develop photovoltaic systems. The market does not receive the promised production after installation, which undermines the effort to provide everyone with access to energy. We are also unsure about the degree of this performance's deviance.

The limitations caused by intermittency causes challenges for power system reliability of the customers on off-grid systems. A study was done for this purpose, and a predictive model that evaluates the performance of solar PV systems in Kenya under specific geographic conditions was developed. The predictive model is developed using governing equations with intermittency variables that have a significant impact on Solar PV output.

Grid extension and the incorporation of off-grid systems in the country has led to the increase in access to electricity. Different organizations like The World bank has funded the Kenya Off-grid Solar Access Project (KOSAP). The study will fast-track electrification of underserved regions in the country. With all this at hand, the predictive model will assist such agencies and organizations in decision making on designing the off-grid systems.

Modeling of energy demand with a view of getting optimal results from off-grid Solar PV while ensuring that the environment is sustained, is a notable research area that would bring in benefits to the Kenyan economy, Sub-Saharan Africa and the whole world in general. Since little is known on the degree of intermittency of solar in countries along the equator, the findings of the study will be an addition to the pool of knowledge in this area. Having this in view, information on the degree of intermittency will be useful for design of future systems to improve reliability of the off-grid solar PV systems.

2. Theoretical Background

Solar PV system performance models include quantitative analyses of PV-system electrical output in relation to system components, design, and installation climatic conditions. This includes the yield of a module, the system efficiency, the performance ratio, the solar fraction, the short circuit current, the open circuit voltage, the fill factor, the capacity factor, and the performance index.

Solar PV System Performance Parameters

The short-circuit current, I_{SC}, is the current that flows through the solar cell while the voltage across it is zero. It is the current produced when a solar cell is short circuited. The generation and collecting of light-generated carriers causes the short-circuit current. The short-circuit current and the light-generated current are same for a perfect solar cell with most moderate resistive loss mechanisms. As a result, the short-circuit current is the maximum current that can be pulled from the solar cell. [4]. The open-circuit voltage, V_{OC}, is the maximum voltage available from a solar cell when no current is applied. The open-circuit voltage is proportional to the amount of forward bias on the solar cell caused by the solar cell junction's bias with the light-generated current. [5].

The maximum current and voltage from a solar cell are the short-circuit current and open-circuit voltage, respectively. However, the power from the solar cell is zero at both of these operating points. The fill factor (FF) is a quantity that, along with V_{OC} and I_{SC}, determines the maximum power output of a solar cell. The FF is defined as the ratio of maximum solar cell power to the product of V_{OC} and I_{SC} [4]. System efficiency is the ratio of the PV system's output energy to the energy of the incoming irradiation incident on the same PV panel area. [6].

When compared to other conventional power generators, the efficiency of a PV system is low. It is heavily dependent on PV panel efficiency, which ranges from 14% to 17% under conventional test circumstances, and inverter efficiency, which ranges from 95% to 98% under actual operating conditions [6]. This method is beneficial when comparing the various designs and brands of PV systems. However, from the perspective of the end user, this method of assessment is not a good tool for comparing power system performance because conventional power units have much higher energy conversion efficiency than solar energy systems.

Intermittent Solar PV Variables

The outputs of the described PV systems are influenced by a variety of environmental or meteorological factors. They may differ depending on geographical location and time of year. The fluctuating conditions cause intermittent difficulties. Irradiance, peak sun hours, temperature, angle of inclination, shade, and dust are among the underlying variables. The PV panel manufacturer's operating data, such as the open circuit voltage, short circuit current, maximum power current, maximum power voltage, temperature coefficients at open circuit voltage and short circuit, and nominal operating cell temperature (NOCT), is limited [7]. The fluctuating situation also results in output that differs from what is expected from the data sheet.

In terms of temperature, humidity, wind velocity, and irradiation, meteorological conditions vary geographically. The relationship between PV-system components and environmental temperature leads to the conclusion that modules must be suitable for the ambient temperature of the area in order to operate well. Modules that perform well in Europe may not perform well in Africa. Monocrystalline modules, for example, are less impacted by high temperatures and hence suitable for sites near the equator. Polycrystalline modules are temperature sensitive and may not produce the optimum electrical energy output. [8]. Temperature has an impact on all devices, including solar panels. The panels create less voltage and become less efficient in producing electricity as the temperature rises.

PV module energy conversion efficiency is typically a non-linear function of irradiance and module temperature, falling for low irradiances as well as high temperatures. The solar irradiation level influences the current and voltage produced by the PV module. According to the findings, open circuit voltage and short circuit current are closely related to sun irradiation. The open circuit voltage and short circuit current both decrease when sun irradiation decreases. [8]. Poor radiation received by solar panels is frequently caused by incorrect inclination angles. If the tilt and orientation were incorrectly computed during the design stage, the optimal position of the PV-system in regard to the direction of solar radiation could not be reached. If there are data collection mistakes in the irradiance measurements, performance parameters such as yield will give minimal results. [7].

The length of testing, angle of tilt, orientation factor, and geographic latitude all contribute to differences in photovoltaic output performance. This means that the solar panel's power output is proportional to its photovoltaic efficiency. The photovoltaic tilt angle is critical for increasing the overall efficiency of the solar panel array system. Some solar panel installations incorporate the use of tracking devices that are meant to move with the Sun as it travels over the horizon in relation to the earth's movement. When compared to the fixed stand-alone counterpart, these installations have been shown to produce higher energy yields. It has been accepted, however, that these Sun monitoring systems are expensive and will typically require continuous maintenance to keep them operating optimally. As a result, when considering a stand-alone arrangement, all parameters on the solar panel must be optimized to offer optimal energy yield. [9].

The parameters affected by the intermittency variables can be determined using Equations (1), (2), and (3) [10], [11].

$$Cell\ Temperature: T_C = T_A + \left[\frac{NOCT - 20}{800}\right].R_t \ (1)$$

$$Module\ Conversion\ Efficiency: \eta_{PV} = \eta_{r-PV}.\eta_{PC}\left[1 - N_T\left(T_{C-}T_{ref}\right)\right] \ (2)$$

$$Solar\ PV\ Output\ P_{PV}(t) = R_t \eta_{PV} A_{PV} f_{PV}(W) \ (3)$$

Where T_A is the Ambient temperature, NOCT is the Nominal Operating Cell Temperature, R_t is Solar Radiation, $\eta_{r\text{-}pv}$ is the efficiency of the reference module, η_{pc} is the power conditioning (Inverter) efficiency, N_T is the efficiency temperature factor of the Photovoltaic collector (-3.7×10^{-3}). T_c is the PV Cell Temperature, T_{ref} is the reference cell Temperature (25℃), η_{pv} is the efficiency of the PV module, A_{pv} is the Surface area of the PV module, and f_{pv} is the derating factor of the modules.

Summary of related studies

Research on solar PV systems has been done previously conducted by researchers in the world. The main goal is to identify the best way of ensuring electrification is achieved. This has been shown by recent studies on how best solar PV systems can work best in different regions and how the cost of energy can be economically feasible. Modeling and simulation of these systems have also been done to project how best these systems can function and what conditions can be improved to ensure increased energy production.

Simulation and optimization techniques and existing tools have been generated to simulate and design stand-alone hybrid systems for the generation of electricity. Different software and tools have been programed to design the models of these systems to view the best approach that can be taken in terms of merging technologies that can produce the highest energy yield. This has been highlighted in the study conducted by [12].

Tools like HOMER® Pro, HYBRID2®, TRNSYS®, HOGA®, ARES®, HYDROGEMS®, INSEL®, RAPSIM®, SOMES® and SOLSIM®, were showcased as some of the tools used for simulation and optimization. The study concluded that stand-alone hybrid systems are more suitable than systems that have only one energy source for the supply of electricity to off-grid applications. Remote areas with difficult access was the study area. It also stated that the design, control and optimization of hybrid systems are usually very complex tasks and would require much work. This work is important in informing scientists on the various tools for simulation and optimization. However, the study did not highlight on how simulation and design can be conducted and the expected results.

In order to have a hybrid scheme with minimal costs and maximum reliability, optimum design is essential for predicting energy production. This is highlighted in the work by [10], who showcases how optimization of hybrid renewable energy schemes is done while incorporating load demand forecasting. An improved system configuration was defined along with its mode of operation and a theoretical modeling. The load forecasting involved collection of hourly data of wind speed, air temperature, and solar radiation at particular locations and load demand for the studied site.

Modeling and simulation was done using Tabu search which is a global optimization method for monitoring an embedded heuristic algorithm. For validation, harmony search and simulated annealing was used. The analysis for three hybrid systems based on wind energy, solar energy and battery energy storage was performed where MATLAB® software was used to implement the suggested approach. The study acts as a good reference more so on the incorporation of load demand forecasting in sizing. However, only the cost aspects of the hybrid renewable systems were highlighted.

In the study by [11], design of an off grid hybrid solar PV-Fuel cell system was done. The analysis was based on integrating modeling, simulation and optimization approaches. The main aim for the approach was to design and develop a dispatch control strategy for the system in order to meet the desired electric load of a residential community in a desert region. The cost of the system was also to be determined by the approach.

To bring out a scientific approach, the effects of temperature and dust accumulation on solar PV was investigated. The constraints that these effects would bring were also put into consideration. The analyses done would then give the best possible hybrid power system configuration based on the desired constraints at the lowest total net present cost. In as much as the system gave out the best possible system for power generation, an increase in the penetration of the renewable energy mix, and low energy costs, there were constraints. Power consumption by AC primary loads were not highlighted, which means, power losses in the inverter and other AC loads not being powered was expected.
Aspects of hybridization of a stand-alone Solar-Wind-Hydrogen system was studied by [13]. These aspects were to help overcome the variability and intermittency issues in solar and wind energy. The hybridization was also to help improve efficiency. To actualize the process, and to further

increase the accuracy of the optimization of the systems, more accurate weather forecasting data was used. They were used along with solar radiation data, ambient temperature data, and wind speed forecast data. Using the data at hand, the study sought to optimize the stand-alone system to meet the load demand in Eastern Iran. Simulation was done using the MATLAB® software. The simulated results showcased that the renewable energy forecasts are indeed a viable approach for obtaining data for optimization of Hybrid renewable energy systems. However, the continuous supply of energy to the loads, and how the life cycle costs that are subject to technical constraints were not considered.

[14] conducted a techno-economic research analysis of diesel-biogas hybrid micro grid system. They modeled, designed and simulated a micro grid system using MAT LAB® software, and performed system optimization using HOMER® Pro software. Load audits were conducted; whereby daily load profiles were obtained on power consumption which were calculated using HOMER®. Biogas system equations were then modeled in MATLAB® using the load profiles in order to determine the generator capacity. SIMULINK® was then used to design and simulate the generator, and to determine the machine output parameters. The results showed output variables of the synchronous generator. These include, terminal voltage, current of the actual speed of the rotor, field voltage and current, and the mechanical power. All these being functions of power output and input. The optimization was majorly for the purposes of maximizing generator power output at specific times, minimizing micro grid cost of operation and to minimize the environmental costs. With the above in mind, the system was designed to generate sufficient electricity by implementing the lowest cost of the system.

[15] optimized the design and performance of an off grid power system for a university building. The main goal of the study was to design a power system with a high renewable fraction, low greenhouse gas emissions, and low cost of energy. It was also coupled with a move away from coal and grid-tied fossil fuel power systems, to the use of cleaner renewable energy power systems. Challenges with regard to high dust accumulation on the solar PV panels, high energy demand, and high ambient temperatures that reduce power output from the PV modules were observed during the study. A detailed analysis on the challenges was performed in comparison to the power system's performance cost.

Modeling, simulation, optimization and design of a stand-alone power system using a solar PV and hydrogen fuel cells using an Optimization Search Space was conducted in the study. The optimization was based on the building's AC load, the distributed power generation system capacities, and the design constraints and challenges. Three design architectures were used in the study. Two renewable Energy sources (Solar PV and Fuel cell) and a back-up generator as the first scenario. The second scenario did not incorporate a back-up generator, while scenario three used solar PV and diesel. The results on the demand side gave a recommendation to reduce energy consumption by use of building energy monitoring, and using more energy efficient equipment. On the supply side, the recommendation was in line with developing and using new technologies for dust cleaning and solar PV module cooling, to help increase electricity generation.

[3] conducted a study on rural electrification, with a focus on a remote area in Kenya. It is based on modeling, computer simulation and optimization of a hybrid powered mini grid in Korr. The hybrid system consists of solar PV and wind, with the inclusion of battery storage and a diesel generator back-up. The main purpose of the study was to reveal the most cost effective energy system to provide sufficient and reliable electricity through renewable and non-renewable sources. HOMER® pro software was used to perform the design analysis of the proposed hybrid system. The variability of the available resources in the low income area and the energy consumption rate, based on the load profiles were used as a baseline data for the study for simulation purposes. The study was also limited to determining the best cost effective combination of electricity generation technology, as they explored optimization techniques to ensure the needs were met. Sensitivity analysis was also carried out in order to determine the accuracy of the simulation and optimization results. The analysis also checked on the viability of the system under actual conditions. The major outcome in terms of constraints on the best design still accrued. Despite giving a projection of low energy costs, considerable excess electricity generation was noted. Based on the load profile of the study area, wastage of power would not be avoided.

3. Methodology

The study was crafted using a combination of exploratory and predictive approaches, incorporating elements of descriptive and analytical research methodologies. The study began with an exploratory approach to understand the key factors that influence the performance of solar PV systems. This involved conducting a literature review, and examining existing research on solar PV system modeling and performance. Since the study's primary objective was to develop a predictive numerical model for solar PV systems, a predictive approach was used. It involved the use historical, site specific data to develop a model capable of forecasting the performance of solar PV systems based on various parameters and site-specific intermittency variables.

Analytical techniques were adopted during the model development and refinement processes using Equations (1), (2) and (3). These techniques involved analyzing the relationships between different parameters and identifying the factors that have the most significant impact on Solar PV system performance. In this case, irradiance and temperature were independent variables whereas module's power and module conversion efficiency were dependent variables. Numerical techniques, such as mathematical modeling and simulation, were also employed to predict and simulate the performance of Solar PV systems. These techniques allowed for the estimation of Solar PV power output, module efficiency, and other performance metrics based on site-specific intermittency variables.

The study also incorporated an experimental validation by comparing the predicted data of the developed numerical model with the performance characteristics of an existing

Solar PV system in Kajiado County. This validation helped assess the accuracy and reliability of the predictive numerical system. Overall, the study employed a combination of exploratory and predictive approaches, utilizing analytical and numerical techniques, to develop, simulate, and validate a predictive numerical system for solar PV systems.

4. Simulation Procedures

Model Development

To be able to predict the performance of Solar PV systems, a model was first developed in place of the real thing. It was needful in order to better comprehend the performance of the systems being studied. A 5 W Monocrystalline Silicon PV module was used as part of the resources for the model development. The main parameters that were of necessity included the cell technology, module surface area, maximum power output and the module's efficiency. Other useful simulation parameters are listed in Table 1.

Table 1: 5 W Module specifications

Model of the Module	ES5M36
Rated Max Power (P_{max}) [W]	5
Power Tolerance Range [%]	$\pm$ 3
Voltage at P_{max}(V_{mp}) [V]	18.5
Current at P_{max}(I_{mp}) [A]	0.29
Open-Circuit Voltage (V_{oc}) [V]	22.7
Short-Circuit Current (I_{sc}) [A]	0.30
Nominal Operating Cell Temp (NOCT) [℃]	50
Maximum System Voltage [V]	1000
Dimension [mm]	230 x 185 x 17
Cell Quantity and Array	36 (4 x 9)

Solar PV modules produce energy under site-specific varying conditions depending on the time of the day, month, and seasons. Irradiance, ambient temperature, NOCT, and other conditions such as humidity and soil content are the parameters that lead to varying power output. Table 2 outlines the intermittency parameters that were used for the model development.

Table 2: Parameters for Model Development

Parameter	DG-M30W
Solar Irradiance [W/m^2]	0 - 1800 [with intervals of 10 W/m^2]
Active Module Area [m^2]	0.0304
Reference Efficiency (Monocrystalline)	15- 25
Power Conditioning Efficiency [%]	95
Power Derating Factor [%]	68.5
Reference Cell Temperature [^{0}C]	25
Ambient Temperature [^{0}C]	20
(NOCT) [℃]	30, 50, 60
Efficiency Temperature Factor	-3.7 x 10^{-3}

The output of the 5 W PV module was predicted using equations (1), (2), and (3). This prediction made use of intermittency variables and PV parameter values that enabled forecasting of the PV module output.

Simulation of the Predictive Model

Simulation was used to better visualize the predictive model's operation. It was based on site-specific secondary data, with Kajiado county serving as the study's reference focal point. Photovoltaic Geographical Information System (PVGIS), an open source online platform that provides information on solar radiation and PV system performance for any location in the world, was used to obtain daily average irradiance and temperature data. The coordinates of the site in Kajiado county were recorded in order to acquire average data scenarios for the entire year.

For the same aim, a variety of Solar PV modules of different power ratings were chosen. Additionally, their rated power measurements, reference efficiency, and maximum power output values were noted. Table 3 outlines the specifications of the PV modules that were used.

Table 3: Module specifications for Simulation Input

Module Specifications			
Rated Max Power (P_{max}) [W]	40	200	440
Power Tolerance Range [%]	$\pm$ 3	$\pm$ 3	$\pm$ 3
Voltage at P_{max}(V_{mp}) [V]	16.8	24.1	40.63
Current at P_{max}(I_{mp}) [A]	2.37	8.29	10.83
Open-Circuit Voltage (V_{oc}) [V]	21.0	8.80	48.95
Short-Circuit Current (I_{sc}) [A]	2.58	29.5	11.29
Nominal Operating Cell Temp (NOCT) [℃]	47	50	50
Maximum System Voltage [V]	600	600	1000
Dimension [mm]	695 x 265	1260 x 950	2045 x 1005

Additional simulation-related parameters are outlined in Table 4. Simulations were performed after getting the necessary input parameters, timescale, and system size. The predictive modeling was performed done to understand the effects of temperature and irradiance, two prominent intermittent variables, and how they affect solar PV output in a specific location.

Table 4: Simulation Parameters

Parameter	DG-M30W
Solar Irradiance [W/m^2]	0 - 1500 [with intervals of 10 W/m^2]
Reference [%] Efficiency (M-Si) (P-Si)	(21) (15)
Power Conditioning Efficiency [%]	95
Power Derating Factor [%]	68.5
Reference Cell Temperature [^{0}C]	25
Ambient Temperature [^{0}C]	(14) (17)
(NOCT) [℃]	50
Efficiency Temperature Factor	-3.7 x 10^{-3}

Model Validation
Model Validation was performed to compare the output of the predictive model with the experimental data. This would help ascertain the accuracy and viability of the predictive numerical model. The study site, Ongata Rongai in Kajiado county was chosen as appropriate for the experimental setup to validate the predictive model developed.

Experimental Procedure
To ensure success of the validation process, a favourable site had to be identified. Ongata Rongai, Kajiado County was noted as a favourable spot due to its proximity to the Renewable Energy and Technology Research lab in Multimedia University of Kenya. The site also had reliable historical performance data that were used in the simulation process. A 30 W monocrystalline module was used in this phase. The PV module's ratings, based on the data sheet is as outlined in Table 5 below.

Table 5: 30 W Solar PV Module specifications

Module Specifications	DG-M30W
Rated Max Power (P_{max}) [W]	30
Power Tolerance Range [%]	$\pm$ 3
Voltage at P_{max}(V_{mp}) [V]	21.24
Current at P_{max}(I_{mp}) [A]	1.84
Open-Circuit Voltage (V_{oc}) [V]	18
Short-Circuit Current (I_{sc}) [A]	1.67
Nominal Operating Cell Temp (NOCT) [℃]	50
Maximum System Voltage [V]	1000
Test conditions	1000 W/m^2, 25℃, A.M 1.5
Dimension [mm]	618×324

Using a TRI-KA PV analyzer and TRI-SEN PV analyzer, the following procedure was used. We first measured the 30 W module's surfcae temperature using TRI-SEN PV analyzer. The TRI-SEN PV analyzer is also installed at the same level as the module in order to capture and measure the irradiance level at the measurement time. By the use of TRI-KA PV analyzer, the off-load voltage and the shortcircuit current was measure. The TRI-KA PV analyzer also helps to determine the current/voltage characteristic curve of the system. As part of the experiment, there is a wireless transmission of the data from the TRI-SEN PV analyzer to the TRI-KA PV analyzer. In the three month data collection period, these tools were effective since they also had a provision for data storage which would be analyzed at a later stage.

Study set-up and assumptions
The experimental set-up involved having the 30 W module on site for purposes of collecting relevant data, validating the predictive numerical model, evaluating performance metrics, and drawing conclusions based on the findings. Figures 1, 2, and 3 show the experimental set-up for measurement purposes.

Figure 1: Experimental Set-up for Measurement

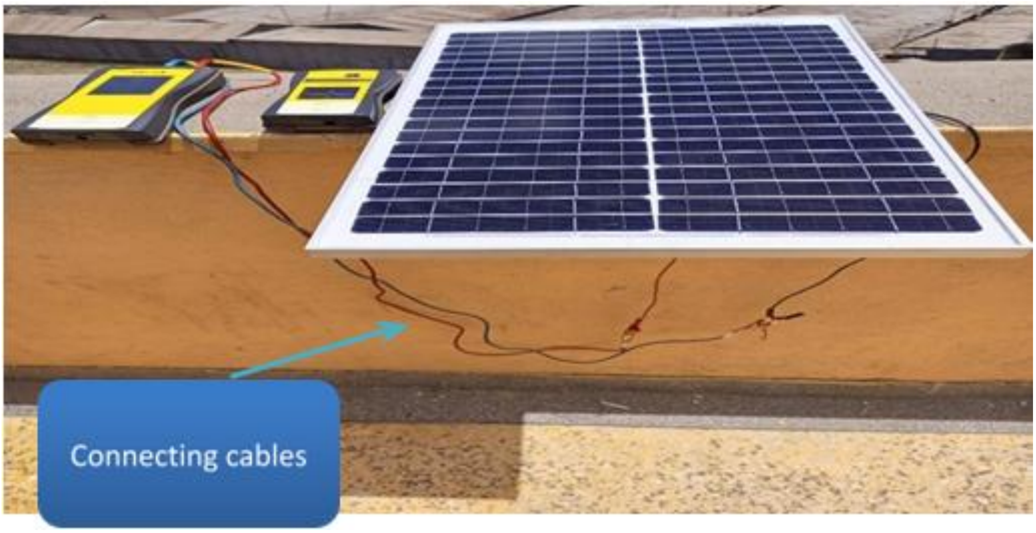

Figure 2: PV Output Data Collection

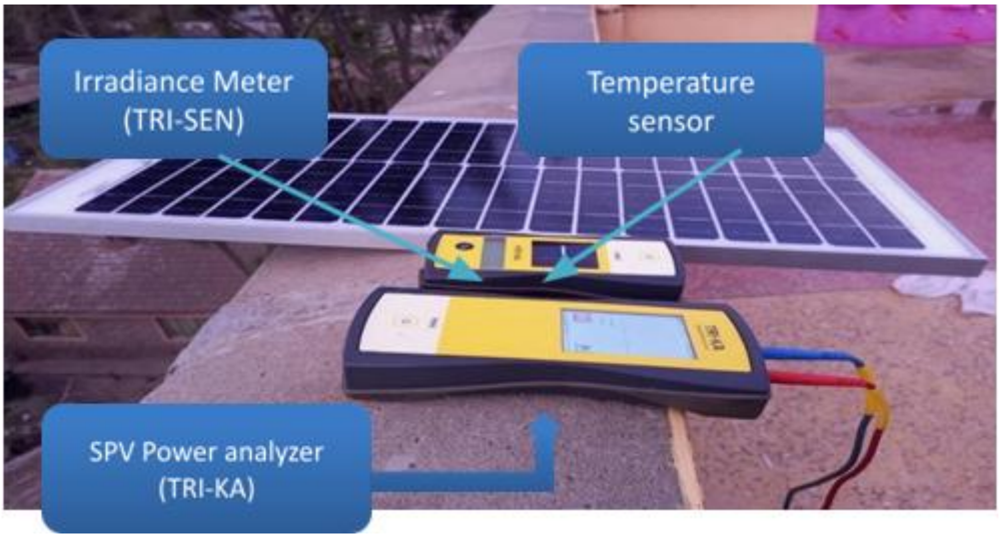

Figure 3: Real-time Temperature and Irradiance data collection

In the context of PV module installation, factors that can impact its performance were considered. Three assumptions that are often made when designing a solar panel installation are the module inclination angle, azimuth angle, and installation type. A 10° inclination angle was chosen to act as a basis of power optimization. Ensuring that solar panels are oriented correctly and have a suitable tilt will assist ensure that they produce the most energy since they are exposed to the most intense sunlight for the longest length of time.

An azimuth angle of 0° was also used since the study is set-up in the Southern hemisphere. This orientation maximizes the amount of sunlight the panel receives throughout the day. Finally, it was assumed that the installation type is roof-mounted, implying the modules were installed on the roof of the building. However, it's important to note that these assumptions may not be applicable to all solar PV module installations. In addition, the optimal module inclination angle and azimuth angle may vary depending on the location and specific requirements of the installation.

Research Instruments

After setting up the experiment, instruments for measurement were used. The major focus was on the measurement of Irradiance, voltage, current, and power output, and cell temperature. The following research instruments were required for the attainment of the research objectives. TRI-KA PV analyzer (model no: X0220113242737), TRI-SEN PV analyzer (model no: X0220113242737), four connecting cords/wires, ten 30 W 21 V m-Si PV modules with dimensions 324 mm by 618 mm. Table 6 gives an overview of the research instruments.

Table 6: Instrument Technical Specifications

Tool	Model	Range	Accuracy	Measurement Output
TRI-KA	TRI-KA S/N: X0220113242737	1.0 – 1000 V	(< ± 1%)	Voltage Measurement
TRI-KA	TRI-KA S/N: X0220113242737	0.1 – 15.0 A	(< ± 1%)	Current measurement
Irradiance meter	TRI-SEN S/N: X0220113242737	0 – 1200 W/m^2	± 5%	Irradiance
Temperature sensor	TRI-SEN S/N: X0220113242737	0 – 100 °C	± 3%	Cell temperature

Data analysis and processing

To analyze and process the data collected for the study, various tools and techniques were employed. The data collected and stored by the TRI-KA PV analyzer was first cleaned and sorted in the TRI-KA PC software. The software has an allowance of data visualization, data cleaning, and sorting of the relevant data that would be used in validation. Missing values were Identified and handled to ensure consistency and standardization of data formats across the different variables.

The cleaned data was then transferred to Microsoft Excel where the predictive model was developed. The developed model was then trained and validated using the collected data. Simulations were then conducted by inputting site-specific intermittency variables into the developed model inorder to generate the predictions for Solar PV system performance metrics. The simulation corresponded to the input parameters of the 30 W module that was used. Model evaluation and data visualization using plots, charts, and graphs to aid in the interpretation and presentation of findings were conducted in Excel. This enabled the visualization of the simulated performance of solar PV systems, comparing the predicted and actual performance metrics.

By leveraging various tools and software packages as stated above, the data was effectively analyzed and processed. Model development, simulation, model performance evaluation, and data visualization were also conducted, thus enabling a comprehensive understanding of Solar PV system performance and the effectiveness of the predictive model.

5. Results and Discussion

After running the predictive model, various results were obtained based on the effects of temperature and irradiance on the module's output. Validation of the prediction model was also done using experimental data to ascertain the accuracy of the predictive model and to allow for further examination of the model. Simulated and experimental data outputs from the model validation were in agreement. However, there were slight variations attributable to unexpected cloud cover, dust, and higher temperatures. Figure 4 illustrates the validation of the predictive model using simulated and experimental power output data.

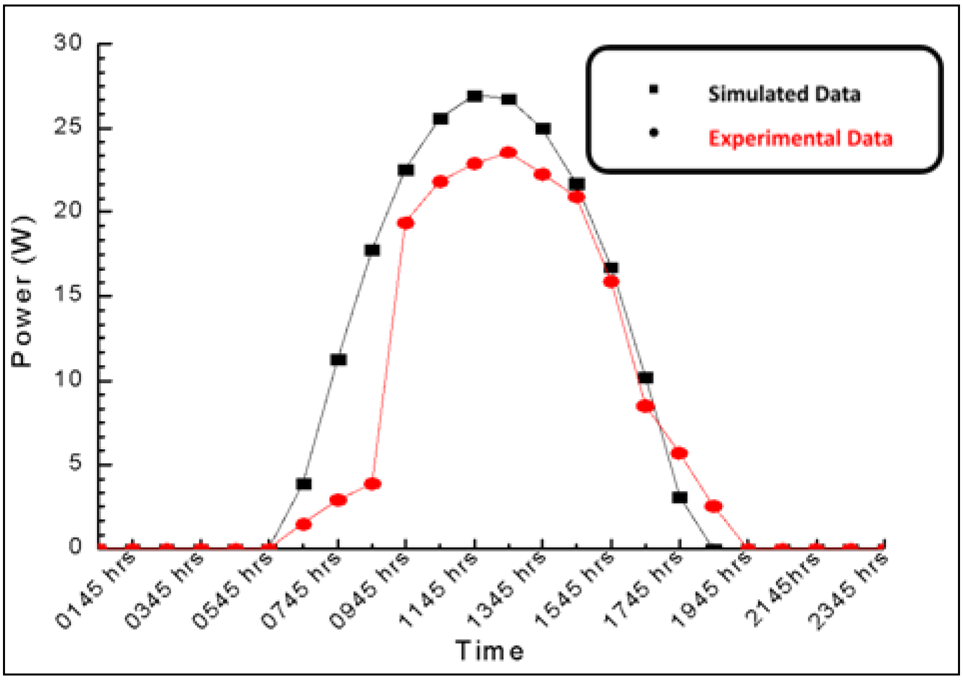

Figure 4: Data Validation between simulated and Experimental Data

First, a comparative analysis on temperature difference (Cell Temperature - Ambient Temperature) and increasing irradiance was performed using the Nominal Operating Cell Temperature scenarios.

Three scenarios were considered. The best case had a NOCT of 30 °C, the average ambient scenario had a NOCT of 50 °C, and the worst case was highlighted at 60 °C. Figure 5 outlines how these cases affect the cell temperature differences when compared with varying irradiance.

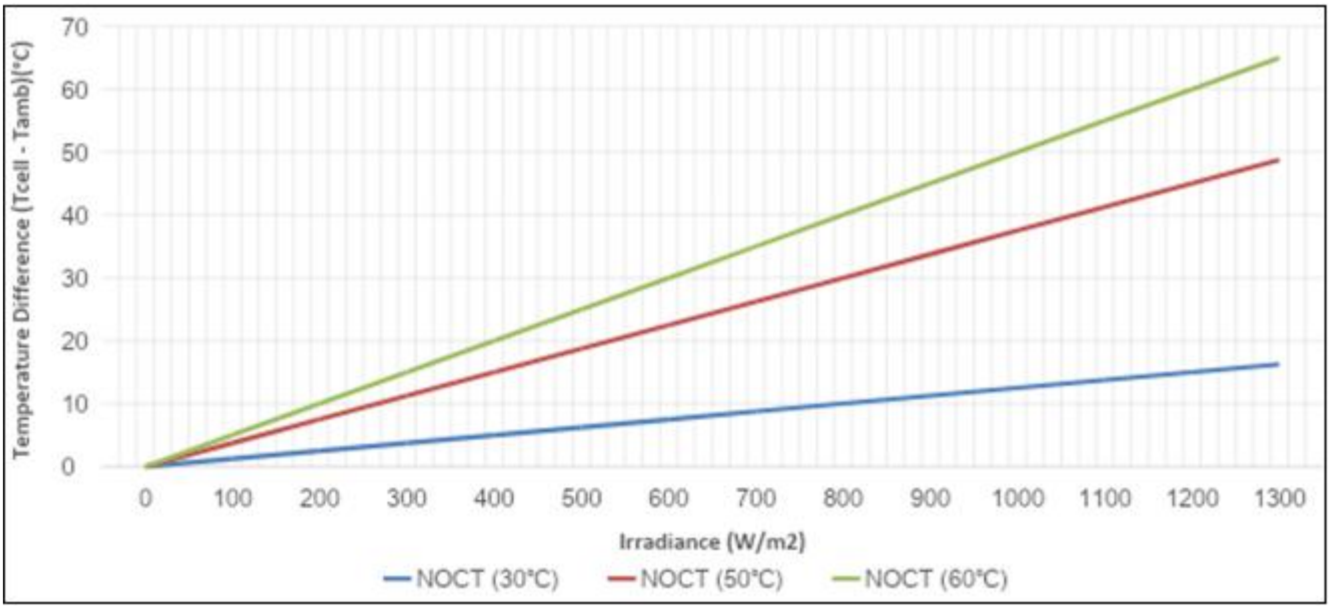

Figure 5: Temperature difference in NOCT Scenario Cases against varying Irradiance

The best case, 30 °C NOCT, has the least temperature differences when compared to the other two scenarios. Equations (1), (2), and (3) were then used to predict the cell temperature, module conversion efficiency, and power output in each of the three scenarios. Table 7, 8, and 9 shows extracts from the obtained results.

Table 7: Power output of a 5 W PV with reference to ambient Temperature of 20 °C and NOCT of 30 °C.

Irradiance $[W/m^2]$	Temperature Difference $(T_{mod}- T_{Amb})$[°C]	Module Conversion Efficiency[%]	Solar PV Power Output[W]
100	1.25	20.23	0.4212
500	6.25	19.86	2.0676
1000	12.50	19.40	4.0391
1250	15.63	19.17	4.9888

Table 8: Power output of the 5 W PV with reference to ambient Temperature of 20 °C and NOCT of 50 °C.

Irradiance $[W/m^2]$	Temperature Difference $(T_{mod}- T_{Amb})$[°C]	Module Conversion Efficiency[%]	Solar PV Power Output[W]
100	3.75	20.04	0.4174
500	18.75	18.94	1.9715
1000	37.50	17.55	3.6548
1250	55.50	16.22	4.9996

Table 9: Power output of the 5 W PV with reference to ambient Temperature of 20 °C and NOCT of 60 °C.

Irradiance $[W/m^2]$	Temperature Difference $(T_{mod}- T_{Amb})$[°C]	Module Conversion Efficiency[%]	Solar PV Power Output[W]
100	5.00	19.95	0.4154
500	25.00	18.47	1.9235
1000	50.00	16.63	3.4627
1250	85.50	14.01	4.9881

The efficiency of solar panels decreases as cell temperature increases. The performance and longevity of the panel are negatively impacted by increased temperatures. To lessen these consequences, it is therefore preferable to operate solar PV modules at low cell temperatures. On the other hand, as predicted by the model, an increase in irradiance leads to an increase in PV power output.

The key to achieving increased output, is to figure out how to sustain higher irradiance levels while making sure that there is a constant cooling strategy. However, contrary to what the model predicts, irradiance does not remain constant in the real-world setting. To further evaluate the predictive numerical model, simulation utilizing real-world data from PVGIS was conducted. This was to help improve the output from the model based on the challenge noted.

When the ambient temperature (T_a) varies while the Cell temperature (T_c) remains constant, a comparison of power output was performed. T_c was calculated using Equation (1). Figure 6 depicts the power output for a 440 W module using a predictive numerical model.

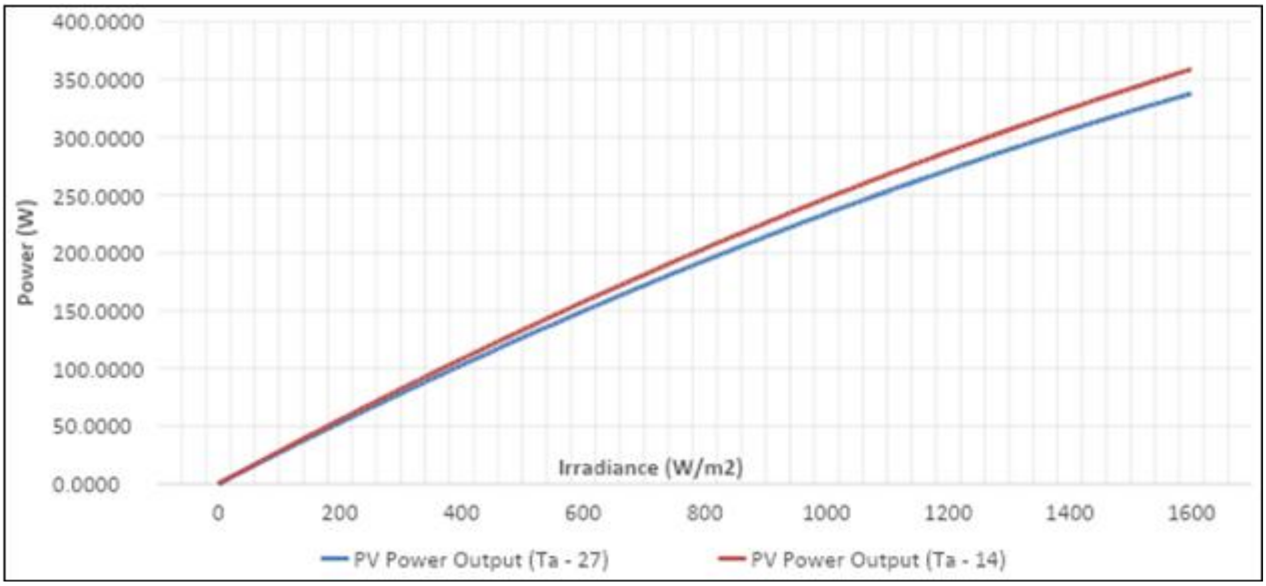

Figure 6: Simulation power output for a 440 W module using a predictive numerical model

Observe from Figure 4.3 that, the higher the T_c in the ambient conditions, the lower the power output. To confirm the case scenario in terms of temperature, a simulation using a 440 W module was used. For this purpose, two different ambient temperature scenarios were used. When temperatures are higher, the expected power output is lower than when temperatures are lower. For this reason, it is recommended that cooling mechanisms be used in order for the system to function optimally. The variations caused by the temperature differences are noted in Tables 10 and 11.

Table 10: Simulation output for a 440 W module using a predictive numerical model - Extrapolations at 14°C

Irradiance $[W/m^2]$	Temperature Difference $(T_{mod} - T_{Amb})$[°C]	Module Conversion Efficiency[%]	Solar PV Power Output[W]
100	3.75	20.49	28.1348
500	18.75	19.38	133.0707
1000	37.50	17.99	247.1328
1250	46.88	17.30	297.0355

Table 11: Simulation output for a 440 W module using a predictive numerical model - Extrapolations at 27°C

Irradiance $[W/m^2]$	Temperature Difference $(T_{mod} - T_{Amb})$[°C]	Module Conversion Efficiency[%]	Solar PV Power Output[W]
100	3.75	19.53	26.8169
500	18.75	18.42	126.4810
1000	37.50	17.03	233.9534
1250	46.88	16.34	280.5614

Secondary data from PVGIS was used to predict how a 440 W Monocrystalline module would perform. In this simulation scenario, clear sky irradiation data was used. The average ambient temperature for the Kajiado County site was also used. Figure 7 showcases the predicted monthly power output of the 440 W module.

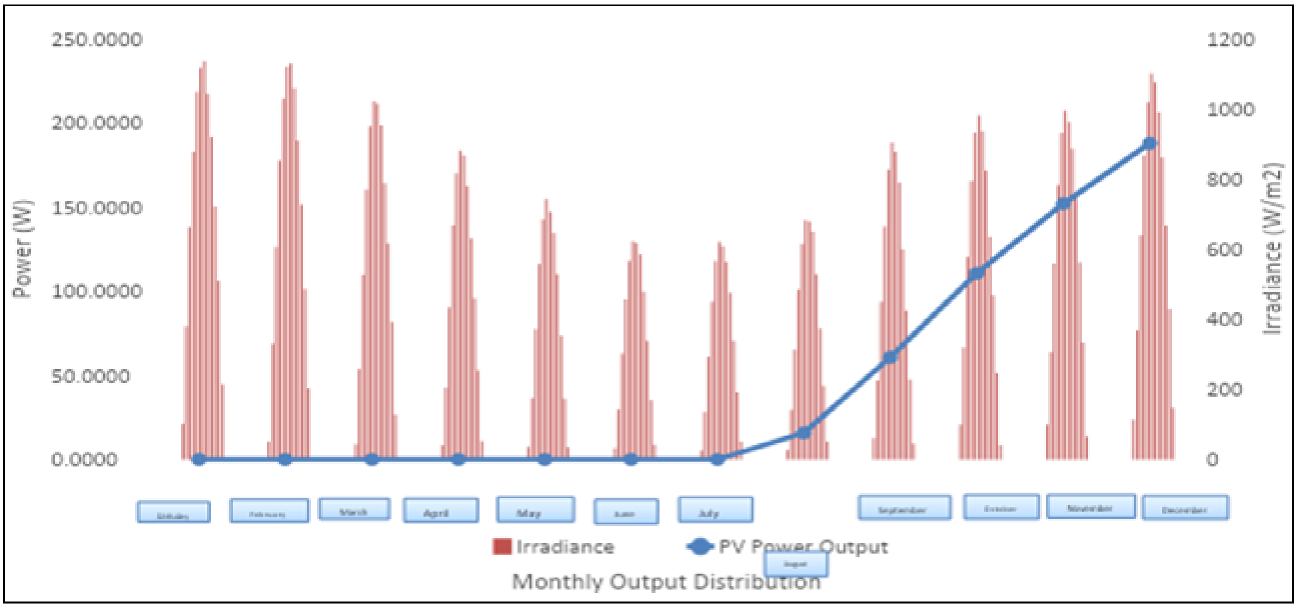

Figure 7: Monthly Representation of the average Solar PV output of a 440 Watt Module in a year

The module conversion efficiency was discovered to have a variance of between 20.32% and 16.72% after additional computation of the simulated output. The percentage variance for the power output ranged from 0.6795% to 10.6756%. The variation from the mean for the power output was therefore calculated to be 5.1622%.

Since data was collected for three months, the comparative analysis of the solar PV power output was also generated. Figure 4.5 illustrates the simulated power output of the three months under study.

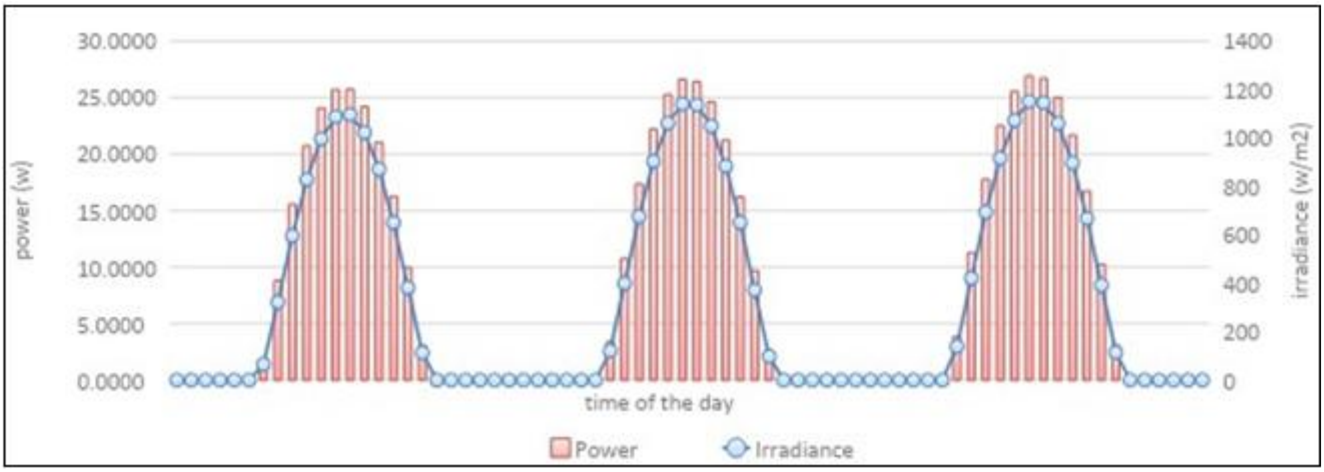

Figure 8: Output of the simulated data under site specific conditions

Figure 9 illustrates the power output of the experimental set-up under real-time weather conditions for the three months under study.

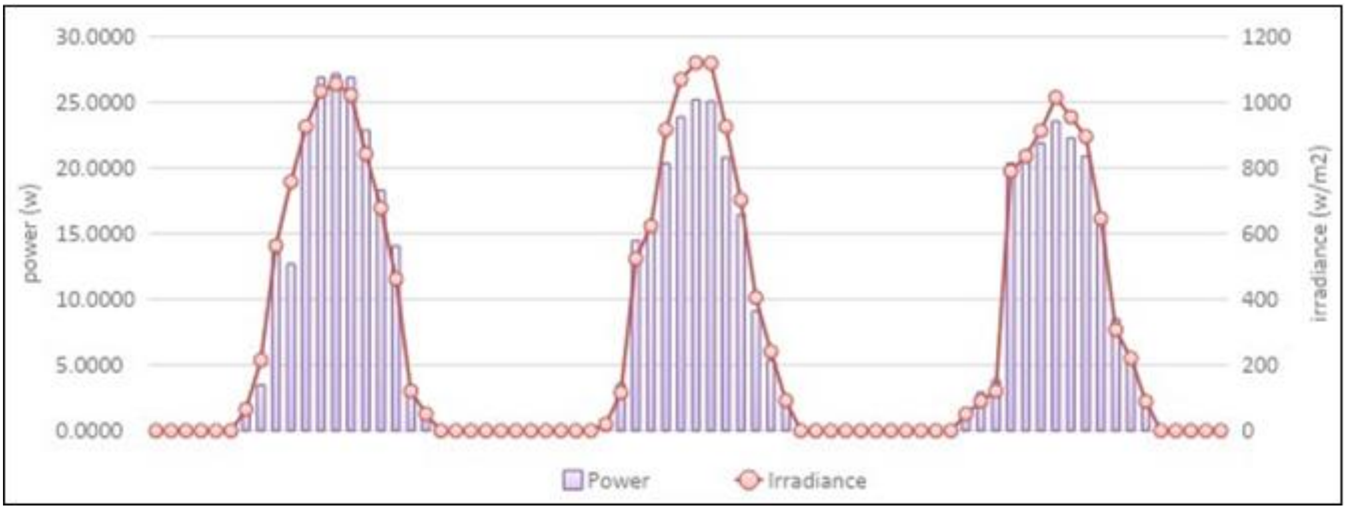

Figure 9: Output of the experimental data under site specific conditions

It is observed from Figures 8 and 9 that there are slight differences in terms of Solar PV output. The PV output and irradiance values also varied monthly during the study.

Observe in Figures 10 and 11, that the I -V and P -V curves were also generated in order to get an in-depth analysis of the experimental data output.

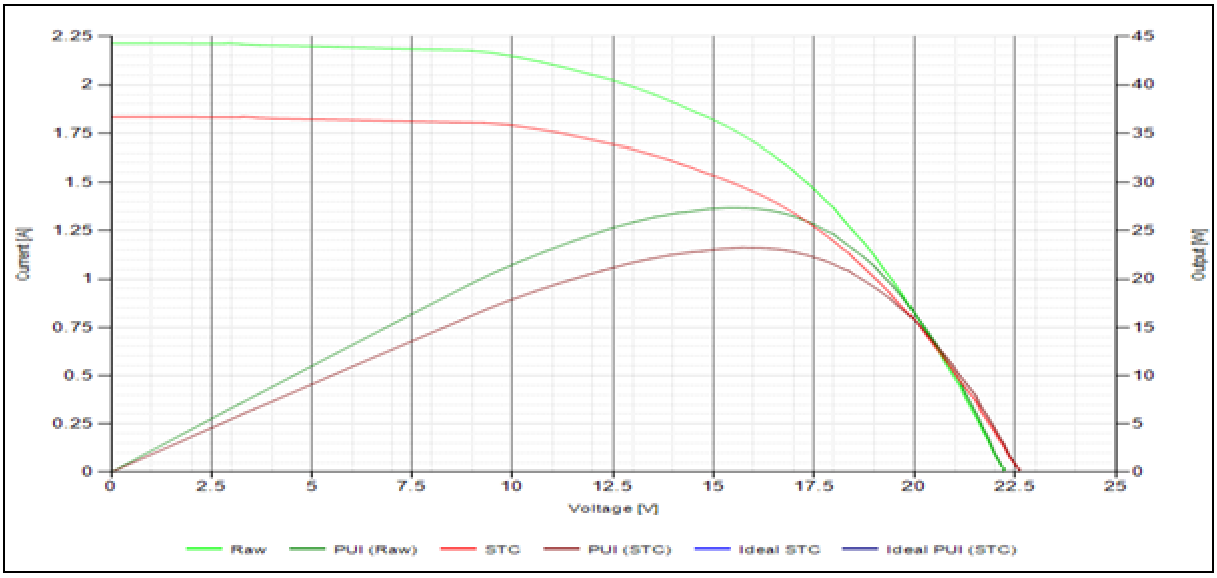

Figure 10: I-V & P-V Curve For a Peak Irradiance Level – October

Figure 10 illustrates the I-V characteristic curves for peak irradiance levels in the month of October, 2022. The curve describes the 30 W PV module's power conversion capability at the existing conditions of irradiance and temperature. Despite having a higher irradiance of 1208 W/m^2, and a relatively lower temperature, the expected 30 W power output was not achieved. Figure 11 demonstrates the peak irradiance data for the month of November, 2022.

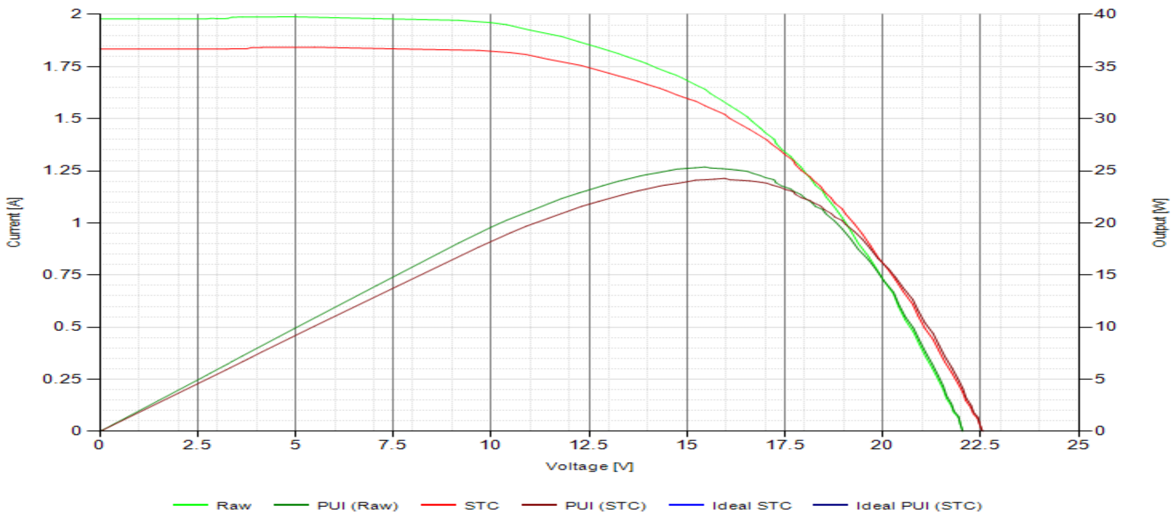

Figure 11: I-V & P-V Curve for a Peak Irradiance Level – November

It is observed from Figures 10 and 11 that the short circuit current (I_{SC}) is overwhelmed by the drop in the open circuit voltage (V_{OC}). As a result, a decrease in the rated power, module conversion efficiency, and fill factor were noted. The PV module's power conversion efficiency also drops when surface temperature rises. This has an adverse effect on the module's performance and lifespan.

6. Conclusion

The study successfully developed a predictive numerical model for Solar PV systems considering parameters such as solar radiation, temperature, module efficiency, and inverter efficiency. The predictive model demonstrated the ability to capture the complex interactions between these parameters and accurately predicted solar PV system performance. The predictive model was tested with different module sizes and results revealed that the PV module's efficiency drops when surface cell temperature rises. The model also demonstrated that solar PV systems perform optimally at low NOCT of 30 °C.

The simulations reveal valuable insights into the performance of Solar PV systems under varying site-specific intermittency variables. The simulations highlighted the impact of weather patterns, cloud cover, dust accumulation, shading, tilt angle, azimuth, and other factors on energy generation and system efficiency. Based on the simulated data output, the PV module conversion efficiency varied between 20.32% and 16.72%. The simulated power outputs revealed a percentage deviation of between 0.6795% and 10.6756% in comparison to experimental data from a site specific location in Kajiado County, Kenya. The average module conversion efficiency for simulated data was calculated to be 18.33%.

The validation process demonstrated a good level of agreement between the predicted performance metrics generated by the model and the actual performance characteristics of the existing Solar PV system in Kajiado County. The validation confirmed the accuracy and reliability of the developed predictive numerical model in predicting energy generation and module conversion efficiency. After a three-month data collection and validation period, the module conversion efficiency was calculated to be 12.26%. It is noteworthy that the negative effects of shading and high temperatures were not explicitly accounted for in the model's development. This is attributable to the variations in module conversion efficiency and solar PV output.

7. Future Work

Despite the promising results generated by aforementioned findings emerging from the study, we observed the following important issues that might be recommended for future work:

1) Further model refinement – This would involve continuously refining and improving the predictive numerical model by incorporating additional variables and optimizing model parameters. It may also explore the potential integration of advanced machine learning algorithms or data-driven approaches to enhance the accuracy and robustness of the model.
2) Expanded validation – Validating the predictive numerical system using performance data from a broader range of Solar PV systems in different geographical locations. Multiple case studies may be incorporated to assess the model's applicability across various system sizes, technologies, and environmental conditions.
3) Real-time monitoring and feedback – Implementing a real-time monitoring system that continuously collects performance data from Solar PV systems is recommended for further studies. The collected data is to be integrated into the predictive numerical system to provide real-time feedback and updates, enabling adaptive predictions and performance optimization.
4) Policy and decision Support – Advocating for the integration of predictive numerical systems into renewable energy policies and decision-making processes to enhance the accuracy of solar energy forecasts, inform energy planning, and optimize system performance.

By implementing the suggested recommendations, the accuracy, reliability, and applicability of the predictive numerical system will be enhanced, contributing to improved planning, operation, and performance optimization of Solar PV systems. This will facilitate the broader adoption of solar energy and support the transition to a sustainable and renewable energy future.

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