

HYBRID ENERGY HARVESTING SYSTEM DESIGN AND OPTIMIZATION FOR SEISMIC NETWORK

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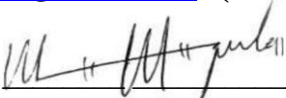
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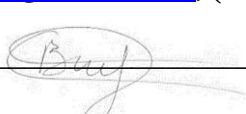
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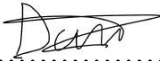
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CERTIFICATION

The undersigned certifies that he/she has read and hereby recommend for acceptance by the Faculty of Engineering a thesis titled: ***Hybrid Energy Harvesting System Design and Optimization for Seismic Networks***, in fulfilment of the requirements for the degree of Doctor of Philosophy in Electrical and Electronics Engineering in BIUST.



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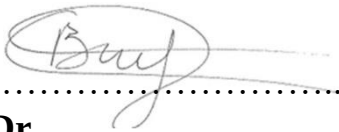
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DEDICATION

This thesis is dedicated to Almighty God for His favour and sustenance.

ABSTRACT

Remote seismic nodes frequently experience failure because of the short lifecycle of lead–acid batteries. Even the use of solar cells is insufficient because these cells have low energy conversion and requires the deployment of relatively expensive solar energy harvesting systems at the node. The conventional solar energy harvesting system requires hardware upgrades and charging to sustain the power at the remote seismic node. Lead–acid batteries and Direct Current–Direct Current (DC–DC) converters lose electrical energy due to low energy conversion, energy leakage, and shorter lifecycle. This study aims to develop an energy harvesting system with hybrid energy storage characterized by optimized constraints to enable the creation of a continuous and long-term remote seismic node database. This is anticipated to aid in the near real-time monitoring of the seismicity of an area and prediction of earthquakes. A single-diode model of the solar cell and photovoltaic module was adopted and developed in MATLAB, Simulink, and PSIM programs based on fundamental equations. The output observations of voltage, current, and power were measured, compared, and presented in graphs and tabulated forms. A Maximum Power Point Tracking (MPPT) algorithm is required to interface with the DC–DC converter for optimal solar energy conversion; rapid changes in irradiance and temperature influence the effectiveness of the algorithm. However, conventional algorithms inaccurately respond under these environmental conditions and change the duty cycle levels across the converter. They exhibit steady-state oscillations that cause continuous power losses while tracking possible Maximum Power Points (MPPs). Alternatively, an algorithm capable of managing the irregularities of inputs and nonlinearities of the photovoltaic module using curve fitting equations derived from the parameters of the selected module is adopted. The three-dimensional lookup table function yields the optimal photovoltaic voltage, current, and power outputs. The table requires a low computational process, and low oscillations at maximum voltage, current and power points are observed. The table consists of precomputed and possible combinations of optimal targets and input variables transformed by the artificial neural network model to supply maximum power levels. The proposed approach is simulated and tabulated by employing a single 120-W photovoltaic module. The algorithm, encoded using C programming, is embedded in an 8-bit microcontroller to feed optimal duty cycle levels across the pulse width modulation of the DC–DC converter. To improve the efficiency beyond 5 %, a synchronous buck DC–DC converter is adopted in this research. In the DC–DC converter, the investigation targets achieving a 0.1-ms processing time with an input voltage between 12.5 and 13.5 V. The fixed output voltage is 12 V through all responses while it is interfaced with the photovoltaic module. The converter simulations were performed in PSIM and Proteus environments with a remote seismic node mimicked with a drawn load current level of 0.8 A. The synchronous DC–DC buck converter is connected to the hybrid energy storage of the lead–acid battery and supercapacitor via a shunt connection of the converter. The novelty of this research is its delivery of two power solutions at the remote seismic node: (1) low computational effort and a low-cost MPP algorithm by adopting a lookup table and the curve fitting equations of a selected photovoltaic module; (2) a hybrid of lead–acid battery and supercapacitor with a synchronous buck converter to extend the lifecycle and ensure continuous current flow through the remote seismic node. The proposed approach was evaluated and verified along with the computer-controlled photovoltaic system. Based on tabulated results and graphs, the deviation

was between 2.5 % and 5 %. The results show that the proposed MPPT algorithm has less complexities, and the supercapacitor serves as buffer for the lead–acid battery to achieve an efficiency level of approximately 75 %.

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LIST OF ABBREVIATIONS

ANN:	Artificial Neural Network
C:	Capacitor
D:	Diode
E_C :	Energy Consumed
E_S :	Energy Source
ESR:	Equivalent Series Resistance
FLC:	Fuzzy Logic Control
FPGA:	Field-programmable Gate Array
G:	Irradiance
GPS:	Global Positioning System
I_B :	Battery Current
I_{Load} :	Load Current
I_{MAX} :	Current at P_{MAX}
I_o :	Output Current
IoT:	Internet of Things
I_{sc} :	Short-circuit Current
I_{scap} :	Supercapacitor Current
L:	Inductor
LDR:	Light-Dependent Resistor
MOSFET:	Metal Oxide Semiconductor Field Effect Transistor
MSE:	Mean Square Error
MPPT:	Maximum Power Point Tracking
P and O:	Perturb and Observe
PI:	Proportional Integral
PV:	Photovoltaic
PWM:	Pulse Width Modulation
R_{Bat} :	Internal Resistance of battery

RMSE:	Root Mean Square Error
R_{Scap} :	Internal Resistance of Supercapacitor
SASSCAL:	Southern African Science Service Centre for Climate Change and Adaptive Land Management
SOC:	State of Charge
STC:	Standard Testing Condition
SW:	Switch
T:	Temperature
V_{Bat} :	Battery Voltage
V_{Load}	Voltage across load
V_{MAX} :	Voltage at P_{MAX}
V_O :	Voltage Output
V_{OC} :	Open-circuit Voltage
V_s :	Voltage Source

CHAPTER 1

INTRODUCTION

1.0 INTRODUCTION

Data acquired from remote seismic nodes have proven to be the most valuable measurements that reveal the earth's dynamism as they aid in analyzing and investigating seismic activities, which can cause natural disasters [1]. Typical energy harvesting systems utilized to power these remote seismic nodes are characterized by low efficiency (less than 15 %) [2, 3]. This inefficiency has led to operational failure, degradation of seismic instrumentation, and undue routine cost expenses. A seismic node is designed to operate in remote areas; consequently, its energy harvesting system, which is its power source, is of primary concern among seismic operators. A reliable and continuous energy harvesting system for powering remote seismic nodes is significant in seismic deployments [4]. Usually, remote seismic nodes are energized by a PV system and a single energy storage as primary and secondary sources, respectively. One of the most challenging tasks is to manage photovoltaic system throughout daytime and ensuring energy storage is optimally charged to support remote node at night. The overall optimization of the solar energy harvesting system needs to be developed to able reliable and continuous power flow across the remote seismic node. To meet the demand of continuous seismic data acquisition even during shaded and partial shaded periods as well as in the night. Also, the battery is combined with supercapacitor as hybrid energy storage to become obvious power solutions. Supercapacitor is a promising energy storage, for integration of battery and other energy storage, employing supercapacitor addresses the issues of shorter lifecycle and adverse temperature effects of the battery [5, 6, 7]. This combination delivers optimal hybrid energy storage with solar energy harvesting system at remote seismic node.

The hybrid PV system that integrates, optimizes, and provides more benefits especially in the nights and lifetime cost in comparison with single system [8]. The hybridization allows utilization of the two energy storages in full capacity, as each other constraints are relatively enhanced by the other and a superior option to increase the electrical energy harvested is developed.

These nodes require an energy storage buffer for continuous power, enabling unending seismic data acquisition operations in an area. Lead-acid battery is frequently used as energy storage; however, it is problematic because it is slow to recharge, leading to frequent failures, poor performance, and relatively short runtime. Moreover, its shorter lifecycle, limited power density, and relatively high routine cost [9] are setbacks to remote seismic nodes. In contrast,

other energy storage systems, such as supercapacitors, are more durable and relatively inexpensive as well as have large power density [10, 11, 12].

A seismic node is a relatively low-power sensing instrument consisting of a seismometer, a seismic data acquisition system, and occasionally, GPS; however, it has no telecommunication backbone, as shown in Figure 1.1. Seismic network operators prefer to deploy seismic nodes in remote areas where human activities are limited for the instrument to distinctly sense seismic signals. This requires the energy harvesting system of a remote node to be reliable, continuous, and robust. The preferred features of a remote seismic node are low-power consumption, remote deployability, continuous operation, and long-term database storage. To reduce the running cost and sustain its operation, optimizing the energy harvesting system is critical. Power conversion optimization is one of the most vital considerations in any energy harvesting system design to attain maximum electrical energy conversion at the node.

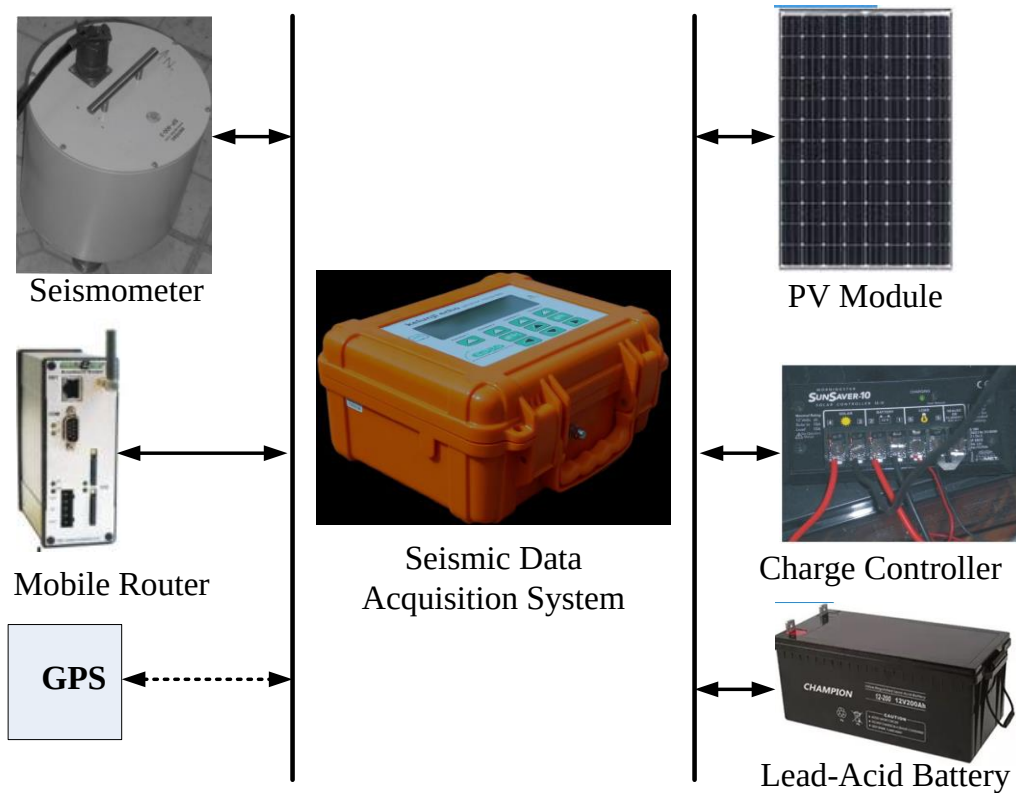


Figure 1.1: Typical Seismic Node energized by Solar Energy Harvesting System.

Several renewable energy sources are available for energizing seismic nodes. Among these, solar energy is the most functional and viable to utilize [13]. It can be harvested and subsequently converted into electrical energy to power the seismic node. However, the solar energy conversion yielded by the PV technique is typically less than 15 % [14] due to irregular input parameters and the non-linear nature of solar energy transducers. Nevertheless, various approaches are available to deliver optimal output levels and improve efficiency, employing

either tracking rotation or fixed position (using maximum power point tracking (MPPT) algorithms) methods for the PV module. The energy conversion rate of solar cells is low and relatively unavoidable. An option for improving the electrical output levels of solar energy harvesting systems is to employ an optimal Direct Current–Direct Current (DC–DC) converter. A typical converter, such as buck converter, experiences power losses due to a considerable forward voltage drop from the freewheel diode, eventually affecting the total efficiency of the solar energy harvesting system. To reduce the forward voltage drop, a synchronous buck DC–DC converter employs a Metal Oxide Semiconductor Field Effect Transistor (MOSFET) to replace the free-wheel diode. For improving overall efficiency, the low-side MOSFET replacing the diode is virtually lossless and switches function with another MOSFET, the high-side switch.

The DC–DC converter, usually connected across the PV module, requires an MPPT algorithm to monitor the optimal output level of the PV module. It maximizes the output power, extends the runtime, and reduces the installation cost of an energy harvesting system at the seismic node. Figure 1.2 shows an implementation of MPPT technique and a direct coupling of energy harvesting system across a load. While its output power values vary proportionally with respect to MPP values and its output voltage is a logarithmic function of the power. The direct couple system only tracked 56.25 % of the power from the energy transducer, whereas the MPPT-implemented system acquired 87.5 %. The operating points of the direct coupling of the energy harvesting system can fall at any point along the curve (power–voltage (P–V) plot characteristics) [15].

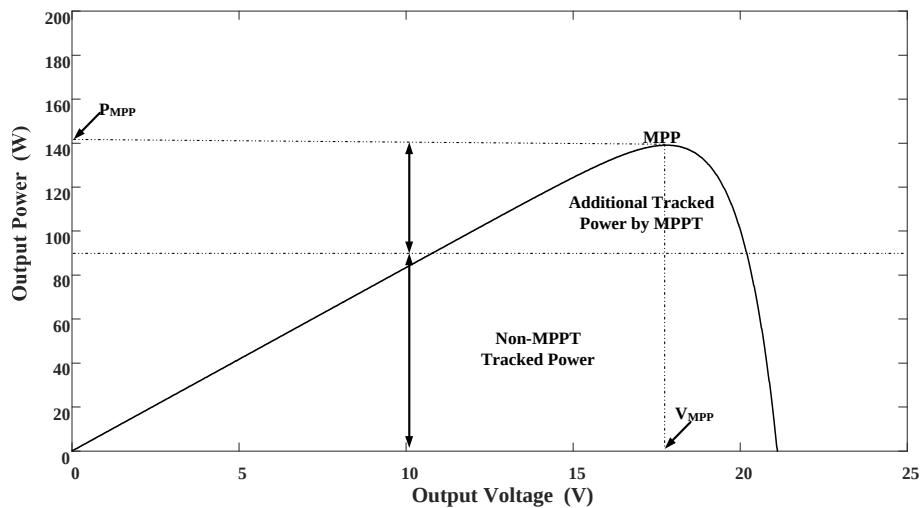


Figure 1.2: Implementation of the MPPT Technique and the Direct Coupling of the Energy Harvesting System across the Load.

Numerous MPPT algorithms can deliver the maximum possible power from the module that varies the duty cycle of the regime. Among these, the most common are the perturb and observe (P and O) [16, 17] and incremental conductance [18] algorithms. However, the P and O MPPT experiences high oscillation ranges, convergence instabilities near the maximum operating points under rapid irregular PV module inputs, and inaccurate tracking [19, 20]. Although the incremental conductance technique can be employed to reduce oscillations, a more complex circuit is required to attain the maximum operating point [21]. These MPPT algorithms experience setbacks because of the rapid changes in input levels and non-linearities of solar cells, which limit their accuracy. Recently, intelligent and knowledge-based MPPT algorithms have been utilized to predict duty cycle levels across pulse width modulation (PWM) to drive the DC–DC converter to deliver optimal electrical output levels. To deal with the rapid input changes in the solar cell and its non-linear nature, some of the MPPT algorithms employed are artificial neural network (ANN) and Fuzzy Logic Control (FLC). The ANN model handles multiple inputs and mapping to a single output process with highly accurate predictions. The FLC utilizes the excellent knowledge interpretation and deduction capabilities of fuzzy logic to handle sudden input level changes and non-linearities of solar cells. These approaches achieve relatively fast convergence speed and considerable accuracy [22, 23]. However, these techniques rely on complex software applications, which are math-intensive in nature and composed of voluminous computing instructions. The instructions also depend on numerous functions as well as several processing levels and cycles based on complex arithmetic calculations [24]. An example of this arithmetic calculation, which describes the relationship between temperature and voltage across temperature sensor. Considering the sensor connected to a circuit in Figure 1.3 as a medical-grade thermometer and observations populated in Table 1.1.

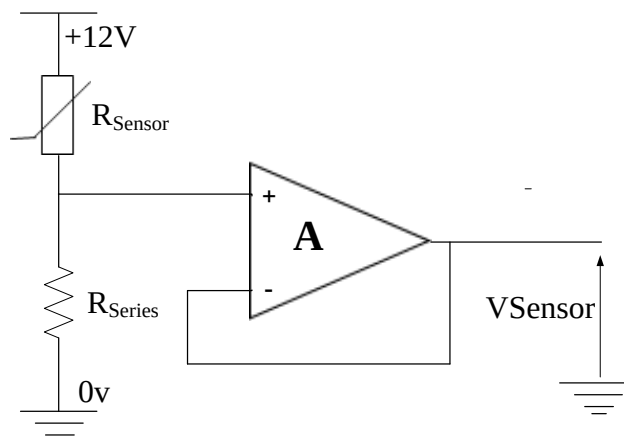


Figure 1.3: Temperature Sensor connected with Circuit.

Table 1.1: Relationship between Temperature, Resistance and Voltage Using Medical-grade Thermometer

Temperature (°C)	Resistance (Ω)	Generated Voltage (V)
10	3.07	3.07
20	2.60	2.60
30	2.13	2.13
40	1.70	1.70
50	1.33	1.33
60	1.02	1.02
70	0.78	0.78

The MPPT technique utilizes a lookup table through interpolation to derive results. The technique is based on a dataset acquired from an experiment and stored in memory. When a target query is entered, an output is issued; the overall accuracy is determined according to the transformed data that populate the table. These MPPT algorithms are implemented with microcontrollers or digital signal processors, which tend to demand numerous functions and high computational processes or numerous gates.

Conventional MPPT algorithms are simple and reach incorrect decisions, consequently delivering inefficient output levels. In contrast, intelligent and knowledge-based MPPT algorithms yield optimal results; however, they demand numerous functions and high computational processes or many logic gates. Consequently, the solar energy harvesting system underperforms at the remote seismic node, or the use of a high-power microcontroller is necessary to deliver optimal outputs. To identify the constraints and parameters to optimize, literature was reviewed, and an experimental study of remote seismic nodes was performed. Then, reference was made to a lookup table consisting of possible combinations of optimal targets and input variables precomputed by an ANN model to derive results. The neural network model addresses the non-linear nature of solar cells and their rapid changes in ambient irradiance and temperature level to deliver the optimal duty cycles across the PWM.

1.1 BACKGROUND

A seismic network is a linked or unlinked system that collects and analyzes seismic data as well as locates seismic events [25]. Typical remote seismic nodes are energized by a single energy source, which frequently experiences power failures; consequently, the seismic instrumentation function is relegated. Due to the variations in ambient irradiance and temperature levels, which irregularly occur, lead-acid batteries with limited lifecycle and low

power density are frequently employed. In seismology, the continuous acquisition of seismic data without gaps in the database enables the identification of the comprehensive seismicity of an area. All seismic network operators target the prevention of power intermittency and discontinuity based on seismic data acquisition to enable the assembly of continuous and long-term databases for accurate earthquake predictions.

To track optimal power output levels from the energy harvesting system of a remote seismic node at different environmental situations, particularly when rapid variations occur, an energy transducer is employed. The use of conventional DC–DC converters for energy transformation is equally challenging because these devices sustain power losses. The MPPT algorithms are implemented between the energy transducer and converter, making incorrect decisions. To overcome such problems, the energy transducer, DC–DC converter, and energy storage constraints are optimized. To predict the optimal duty cycle levels across the PWM to drive the converter, the advantages of the lookup table and ANN algorithms can be leveraged. This enables a machine learning algorithm to transform the lookup table and avoids running multiple function and several processing levels, thus reducing cost. The use of single-energy sources and storage results in outsized hardware and increased running costs [26]. In contrast, by employing more than one energy source, each source complements the limitations of each other to deliver continuous and reliable power solutions. Accordingly, a hybrid combination of lead–acid battery and supercapacitor with a shunt circuit to improve the lifecycle of energy storage at the remote node is adopted in this study. The constraints of subsystems are modeled and simulated in the PSIM, Simulink, Proteus, and MATLAB programs; the overall design is implemented in the Proteus environment. The Proteus environment is adopted for the implementation, so that the hardware and software components can be thoroughly tested side by side before carrying out the physical prototype.

1.1.1 REMOTE SEISMIC NODE

By convention, a remote seismic node is an electronic device equipped with seismometers for sensing ground motion when perturbed; it outputs voltage levels using a broadband seismometer [4]. A seismometer is a low-power electronic device with a control circuit that uses logical gates to calibrate pulse sequences. It converts incoming ground motion signals into electrical signals and amplifies as well as manipulates them into frequency-modulated carriers. The modulated signals are transmitted across the acquisition system for logging, as shown in Figure 1.4. The figure indicates that the acquisition system is equipped with a microcontroller

for coordinating processes, signal sensing and conditioning, signal processing, signal timing, and communication.

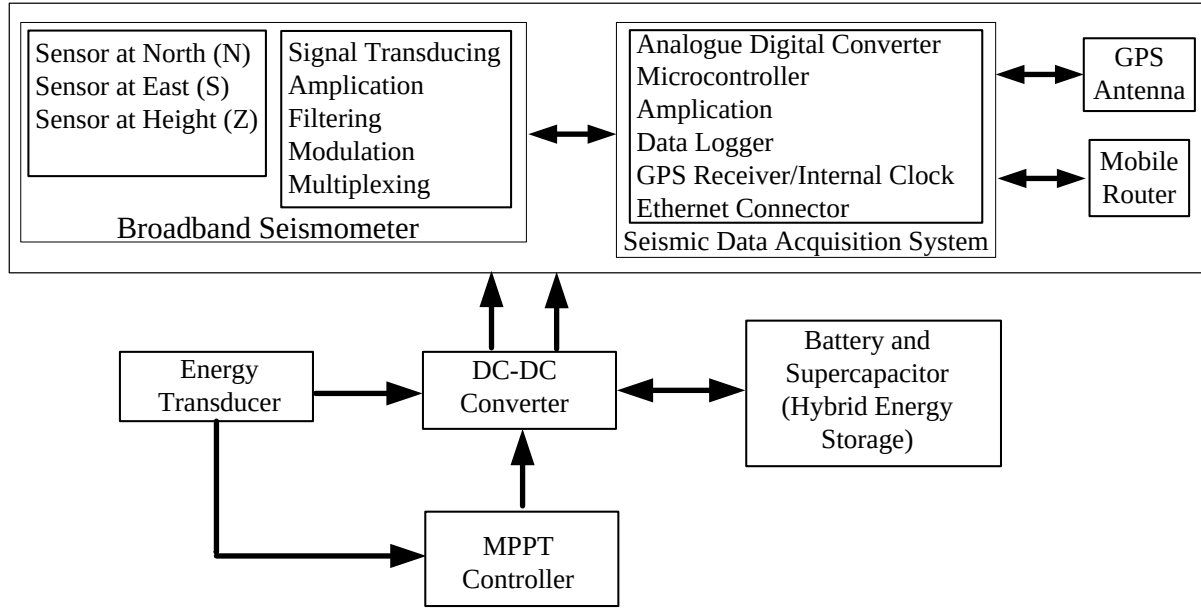


Figure 1.4: Generic Remote Seismic Node powered by Optimal Hybrid Energy Harvesting System.

1.1.2 ENERGY HARVESTING SYSTEM

Energy harvesting involves harnessing and converting ambient energy to a functional form [27]. Assume that the energy consumed by a load is $E_C(t)$, the time that the energy is utilized is t , and the energy source can consistently deliver the energy, $E_S(t)$, at all times during t . In one case, if only the energy transducer of the energy harvesting system can provide energy to the load, i.e., $E_C(t) \leq E_S(t)$, then the energy harvesting system can operate without energy storage. In this case, the harvested energy of the solar DC water pumping machine required during the daytime, $E_S(t) - E_C(t)$, is wasted. In another case, when $E_C(t) \geq E_S(t)$ and the source is not continuously available during t , a power converter and an energy storage device are required to augment and control the energy harvesting system. A typical case is a remote seismic node that requires continuous electrical energy to acquire seismic data for interpreting and analyzing the earth's subsurface. A single energy source is erratic and unstable. In contrast, multiply energy sources are regarded as relatively reliable for a remote node [28]. Moreover, optimizing the hybrid constraints of two or more energy conversion devices ensures continuous and dependable power supply for the electrical load. In this research, solar energy is the primary energy source, whereas the hybrid combination of lead-acid battery and supercapacitor functions as the secondary source.

Several energy harvesting methods, such as piezoelectric, thermoelectric, radio frequency, and PV, convert ambient energy to functional forms. Significant advances have been achieved using each technique, and the energy conversion topology enables optimal, reliable, and continuous energy harvesting across their loads. Solar, thermal, vibration, and radio frequency are conventional energy sources. They differ in ambient density, technique type employed, and manner of electrical output (i.e., AC or DC). DC sources are from PV and thermoelectric techniques, and AC sources are from radio frequency and piezoelectric transducers.

1.1.2.1 PIEZOELECTRIC ENERGY HARVESTING SYSTEM

Piezoelectric energy harvesting converts ambient energy from natural vibration into an electrical signal. It is a process whereby the electric field is generated from mechanical strain due to the inherent polarization characteristics of certain materials when deformed. As shown in Figure 1.5, when a crystalline material is deformed, AC voltage is generated and then converted to usable DC voltage. The material regularly degrades, resulting in low energy conversion, decreased efficiency [29], and failure or downgrade of load operation. It is more difficult for a remote seismic node that requires a DC source to use this power because several low-efficiency conversions are involved in the piezoelectric technique.

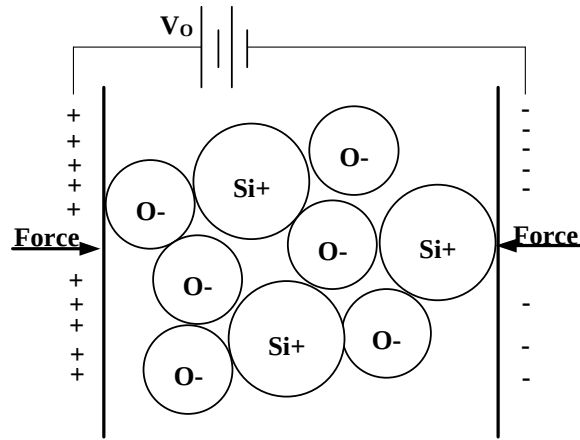


Figure 1.5: Piezoelectric Effects due Deformation of Crystalline Material.

1.1.2.2 RADIO FREQUENCY ENERGY HARVESTING SYSTEM

In this system, the radio frequencies of Wi-Fi routers, Bluetooth, global navigation satellite system, mobile communications, and radar stations sources are converted into electricity. The AC signal is subsequently converted to DC voltage for the load, as shown in Figure 1.6. In this approach, the subsystems involved in the energy conversion are receiving antenna, matching circuit, rectifier, and power converter. Radio frequency sources usually generate noise and introduce them into the data acquired by the node from the ambient environment. The radio

frequency energy harvesting system is useful for systems that require a relatively low electrical load, such as a wireless sensor node [25]. The processes involved in radio frequency energy harvesting systems are problematic and yield extremely low power. The primary energy of radio frequency (RF) sources is relatively low and insufficient to energize a remote seismic node, which requires reliable and continuous power supply.

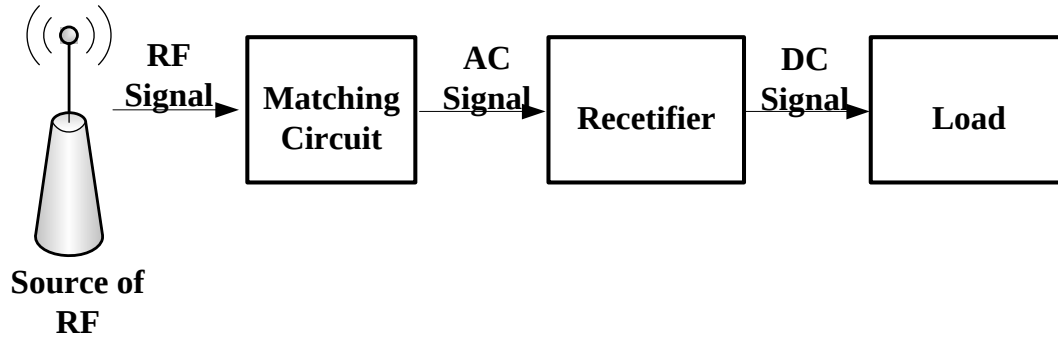


Figure 1.6: Basic Block Diagram of RF Energy Harvesting System.

1.1.2.3 THERMOELECTRIC ENERGY HARVESTING SYSTEM

The electrical voltage generated from a thermoelectric energy harvesting system is due to the thermal gradient between the two sides of a thermoelectric material and depends on the Seebeck effect [30]. The thermoelectric energy transducer is doped with P and N semiconductors, which are electrically and thermally connected in series and in parallel, respectively, as shown in Figure 1.7. Thermal energy is conducted from the hot side to the cold side, generating voltage across the transducer. The voltage magnitude depends on the semiconductor material and optimization technique employed [31]. Thermoelectric energy transducers are difficult to integrate. Moreover, they are characterized by low energy conversion and low efficiency of approximately 3 % [32] because the ambient thermal gradient is usually inconsiderable. Consequently, the foregoing has deterred the use of thermoelectric transducers for more applications [33]. They are only suitable for extremely low-power electronic devices, such as those deployed in the Internet of Things (IoT) [34]. Energy transducers naturally output DC voltage.

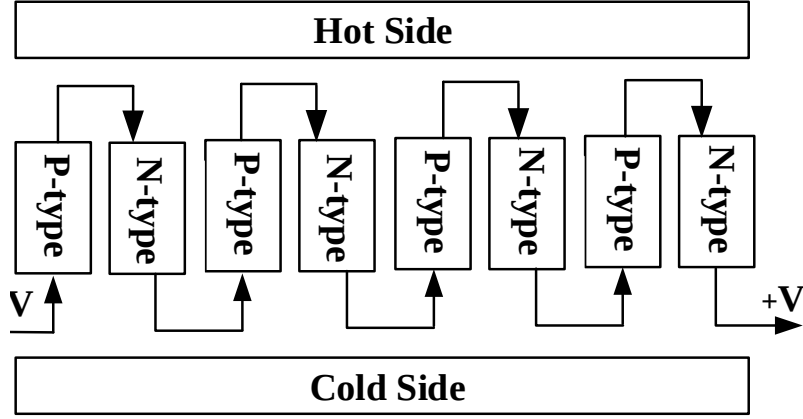


Figure 1.7: Basic Diagram of Thermoelectric Energy Transducer.

1.1.2.4 WIND ENERGY HARVESTING SYSTEM

In energy harvesting system solutions, wind and solar renewable approaches have been extensively investigated and deployed [35, 36]. While, wind energy harvesting system is relatively sustainable energy source [37, 38, 39], and its constraints have been optimized through several methods to improve its energy conversion [40, 41, 42]. Wind is generated due to uneven heating of the surface of the earth and transferred into the air. It is made up of energy capable of converting into electrical energy using wind turbines, and the output power depends mainly on the wind speed and other parameters. But the secured ways to deliver maximum power is by interfacing the wind energy harvesting system with MPPT algorithms. However, in remote nodes, energy harvesting system from solar irradiance is deployed more frequently than wind source. Simply because PV module requires less maintenance than wind turbine where the blade is expected to be repaired or replaced frequently. Also, wind turbine generates AC power output and electrical load such as seismic node operates using DC power. Figure 1.8 represents basic wind energy harvesting system consisting of wind turbine permanent magnet synchronous generator, AC-DC rectifier, DC-DC converter, and electrical load, R_{Load} . The energy E_{KE} obtainable in the ambient wind is kinetic energy(KE) in moving air and can be expressed in Eq. 1.1 [43], where m is the air mass and V is the mean wind speed over a suitable period. While the available wind power is the differentiation of E_{KE} in the wind with respect to time t as expressed in Eq. 1.2.

$$E_{KE} = \frac{1}{2}mV^2 \quad (1.1)$$

$$P_{KE} = \frac{dE_{KE}}{dt} \quad (1.2)$$

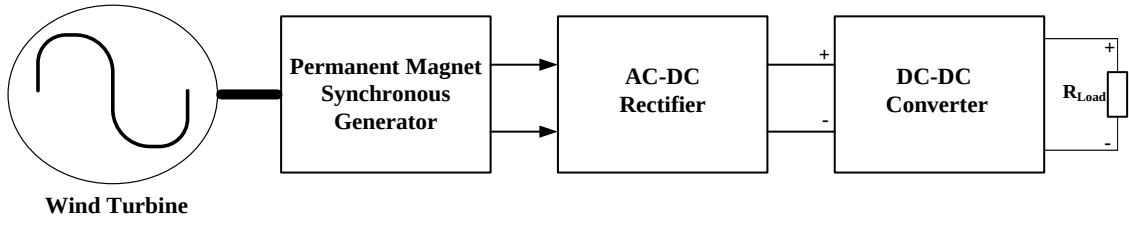


Figure 1.8: Basic Diagram of Wind Energy Harvesting System.

In seismology, typical seismic signal frequency falls between 10-80 Hz [44] and study has demonstrated that wind turbines introduce seismic noise levels in a frequency around 10 Hz at remote seismic nodes [45, 46, 47, 48]. Hence, the generation of electrical energy using wind energy harvesting system can considerably interfere with the seismic data and monitoring of earthquake activities at the seismic node will suffer.

1.1.2.5 SOLAR ENERGY HARVESTING SYSTEM

The energy source of a solar energy harvesting system is inexhaustible and typically reaches its highest power density during daytime [49, 50]; it is reliable and consistent [51]. A solar cell is a PN junction that produces electric current through PV effects when exposed to solar energy. Its output is DC in nature, rendering it an appropriate energy source for remote seismic nodes. However, the solar energy source is irregular, and no energy is received at night, thus affecting the operational cycle of unattended nodes, such as remote seismic nodes. In view of these, designing a solar energy harvesting system that can extract maximum power at any point in time to energize remote seismic node is challenging. The energy storage (e.g., lead-acid battery and supercapacitor) and electrical power conditioning must be optimized to maintain the operational cycle of nodes. Typically, remote seismic nodes are located where adequate solar energy is available. When solar cells are connected in series or parallel, a PV module is formed; several modules form a PV array, as shown in Figure 1.9.

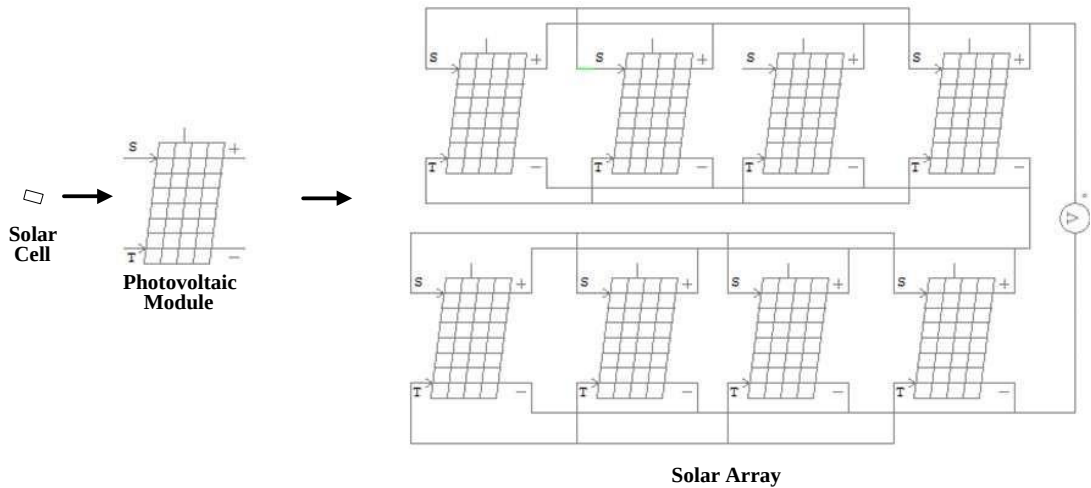


Figure 1.9: Solar Cell, PV Module, and Solar Array.

1.1.2.6 DC–DC CONVERTER

The basic DC–DC converter is a power converter that transforms a DC signal to different DC signal levels. It could be a DC–DC linear, switched-mode, magnetic, or capacitive topology form. A switched-mode DC–DC converter consists of a switch (SW), a filter, and an electrical load. The four topologies are the buck, boost, buck–boost, and Ćuk converters, each of which influences the output parameters in different ways [52]. This study adopts the buck converter topology, which reduces the DC voltage by engaging a MOSFET to control an inductor, as shown in Figure 1.10. The buck converter swings between the voltage source (V_s), inductor (L), and capacitor (C) and discharges the energy in the inductor and capacitor across the load, as illustrated in Figure 1.10. In contrast, a freewheeling diode (D) circulates the DC when the SW is off, and the buck converter controlled by a duty cycle α generated in MPPT controller.

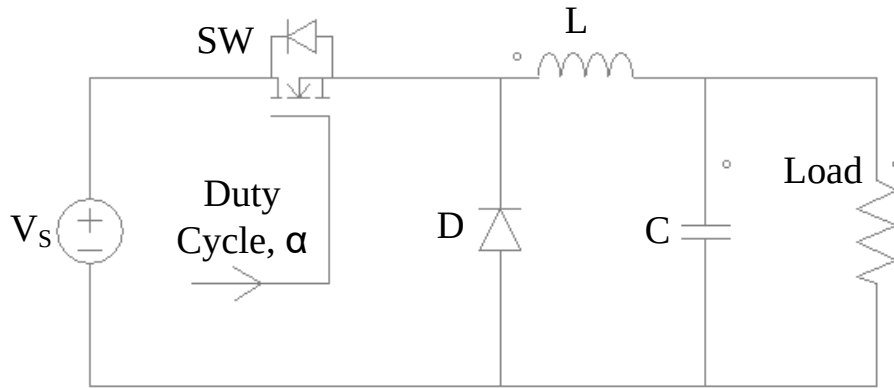


Figure 1.10: Basic Buck Switched-mode DC–DC Converter.

1.1.2.7 MPPT Algorithm

The ambient inputs of energy transducers in energy harvesting systems are usually irregular, and the extraction of maximum possible power levels is difficult. The system power level must be between those of the energy transducer and electrical conditioning subsystems to determine the optimal point of maximum output power levels. To achieve the maximum output levels, the MPPT algorithm is usually employed. Numerous MPPT algorithms, such as P and O, incremental conductance, FLC, and ANN algorithm based MPPT, have been proposed and implemented in designs [53]. This study adopts the indirect lookup table MPPT technique by first generating input and output datasets using an ANN model to populate the lookup table. The outputs of the MPPT model are the duty cycle levels to be applied across the PWM to drive the DC–DC converter.

1.1.2.8 HYBRID ENERGY STORAGE

To continuously operate a solar harvesting system at a remote seismic node, including the dark hours of a day when the solar energy source is virtually zero, energy storage (e.g., lead–acid

battery or supercapacitor) is required. These storage systems accumulate and discharge electrical energy during the day and at night, respectively, to sustain node operations throughout its lifetime. The key factors affecting energy storage are energy and power densities, which determine the extent of runtime.

A lead–acid battery is usually employed as energy storage because it is inexpensive, readily available, and characterized by high energy density and relatively low power density. However, it is not the best secondary energy source for solar energy harvesting systems because of its slow charge and discharge rates as well as low power density [54]. A supercapacitor has a higher power density and longer lifecycles than a lead–acid battery to supply current to nodes [55]. By integrating a lead–acid battery and supercapacitor, longer energy storage at the node is achieved [56]. The combination provides relatively larger energy and power density magnitudes to resolve the frequent failure of lead–acid batteries at remote seismic nodes.

A shunt connection of supercapacitor across the battery’s terminals is also an option; the battery connected in parallel to the load is shown in Figure 1.11. The shunt connection is adopted because of low resistance path between the battery and supercapacitor, which makes it the best option for this research. The shunt connection is possible by implementing PWM and buck DC–DC converter configuration to regulate the battery. This increases the battery’s operational time, reduces complexities, and prolongs the lifecycle [57]. Consequently, intermittent power in the energy harvesting system at the remote seismic node is avoided. Moreover, energy conversion and electrical conditioning are implemented, prolonging the current flow to the load. The topology of the hybrid may be passive or active, as shown in Figure 1.11.

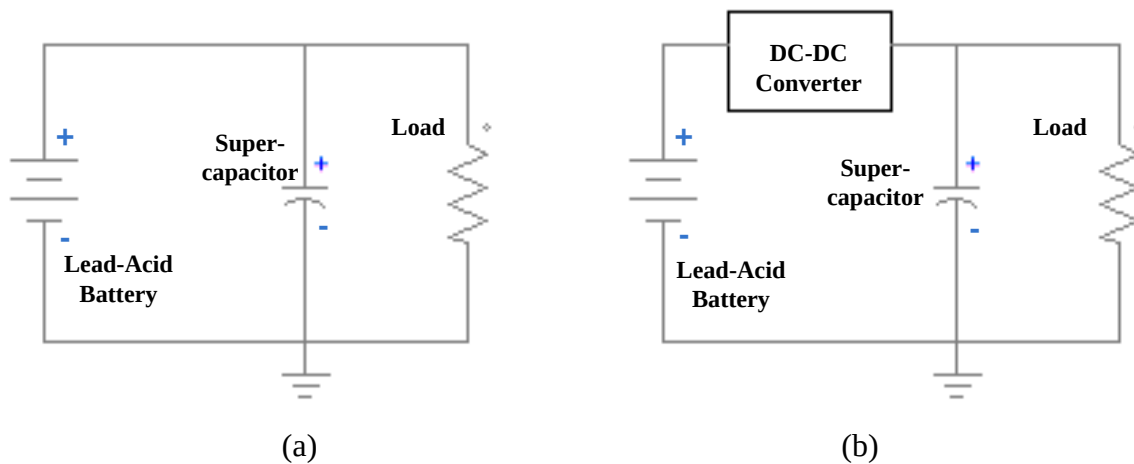


Figure 1.11: Topology of (a) Passive and (b) Active hybrids of Lead–acid Battery and Supercapacitor.

1.1.2.9 HYBRID ENERGY HARVESTING SYSTEM

Solar energy sources are intermittent, and the attainment of continuous current flow is difficult, particularly at unattended remote nodes. Thus, the integration of two or more energy sources is vital. The combination of energy sources, such as energy storage and ambient solar energy sources, as a hybrid energy source is necessary to render the energy harvesting system at remote seismic node dependable. This approach is similar to overcoming the constraints of irregularities in solar energy sources (resulting from the use a single energy source) by integrating a hybrid of lead–acid battery and supercapacitors for energy storage. This leverages the possibility of providing a reliable and continuously operating energy harvesting system at the remote seismic node.

Figure 1.12 shows the topology of a hybrid energy harvesting system using a PV module to charge the hybrid energy storage and load node simultaneously. In Figure 1.12, the output current (I_O) flows through the load as an aggregate of the battery current (I_{Bat}) and supercapacitor current (I_{Scap}) based on Kirchhoff's principle. Equations (1.1) and (1.2) express the aggregate current and voltage obtainable at the node, respectively. The battery voltage (V_{Bat}), supercapacitor voltage (V_{Scap}), internal resistance of the battery (R_{Bat}), and supercapacitor (R_{Scap}) involved in the foregoing equations are shown in the equivalent circuit of Figure 1.12. The passive topology of the battery and supercapacitor has simple implementation and cheap, however, its load voltage, V_O is not regulated, and complementing the two energy storages is limited. To optimize and complement the energy storages, power electronics circuit is introduced in the energy harvesting system. In this research, the output power of PV module is used to charge the hybrid energy storage via a synchronous buck DC-DC converter. To aid in harnessing the benefits of the battery and supercapacitor as well as regulate the output parameters of the energy harvesting system.

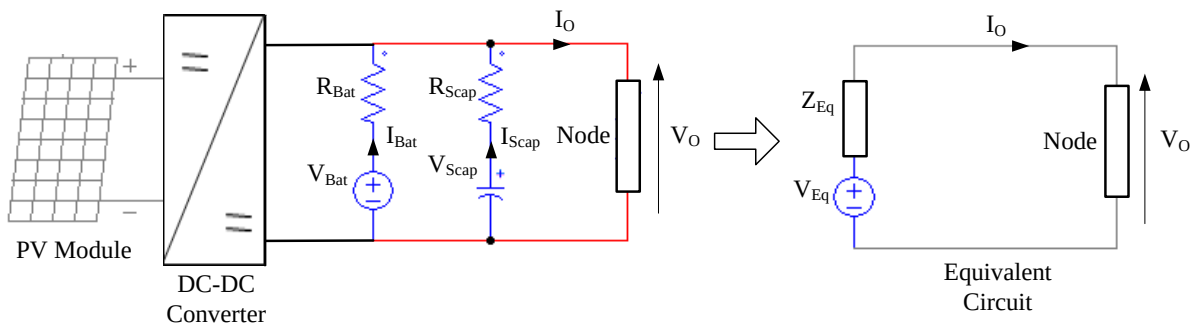


Figure 1.12: Topology of Hybrid Energy Harvesting System of Battery and Supercapacitor powered by PV Module.

The impedances of the energy storages are formed into frequency domain and expressed in Eq. 1.1 derived from Figure 1.12 and expressed in equivalent impedance as $Z_{Eq}(S)$. The equivalent impedance of the hybrid energy storage appears to be less than individual impedances due to parallel connection, enabling more current to be available at the node. The internal resistance R_{Scap} of the supercapacitor is much smaller than the battery [58], where a significant part of the output current I_O is supplied by the supercapacitor in the system. Hence, the hybrid of supercapacitor and lead-acid battery exhibits relatively small internal resistance and essentially reduced power losses. Figure 1.13 demonstrates the simulation results of I_{Scap} , I_{Bat} and I_O for the energy storages varying with time in seconds, where the I_O levels are derived from the circuit in Figure 1.12 as well as Equations (1.3) and (1.4).

$$Z_{Eq}(S) = \frac{R_{Bat} * R_{Scap} + \frac{R_{Bat}}{S_{cap}}}{(R_B + R_{Scap}) + \frac{1}{S_{cap}}} \quad (1.3)$$

$$I_{Bat} + I_{Scap} = I_O \quad (1.4)$$

$$V_O = V_{Eq} - Z_{Eq} * I_O \quad (1.5)$$

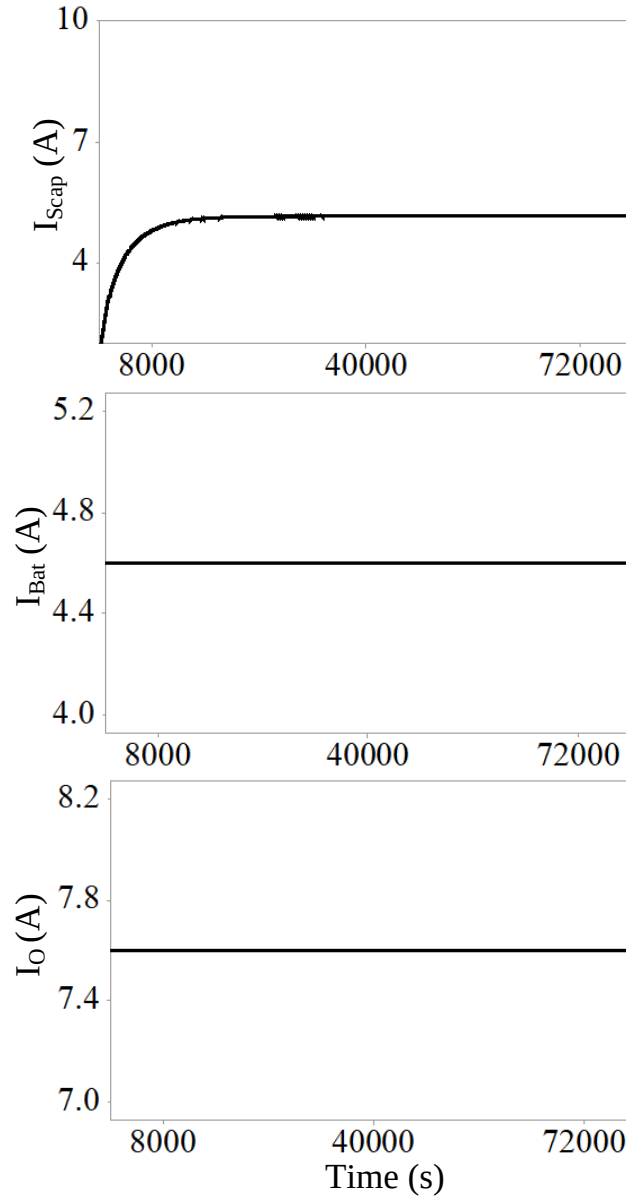


Figure 1.13: Waveforms of I_{Scap} , I_{Bat} and overall Output Current I_o .

1.1.2.10 REQUIRED ENERGY HARVESTING SYSTEM AT REMOTE SEISMIC NODE

The typical frequency of subsurface seismic signals is approximately 1 kHz, and that of surface seismic signals is 10–80 Hz [44]. Seismic operators prefer avoiding low-frequency noise, which interferes with seismic signals and adversely affects the analysis and interpretation of the seismicity of an area. A high-pass filter is integrated with the seismic node to differentiate between the actual seismic data and preferred data [59]. Although a switched-mode DC–DC converter is highly efficient, its generation of high-frequency noise during energy conversion is a major disadvantage [60, 61, 62]. As mentioned, low-frequency levels can include noise, and high frequency levels can be managed and traded with a high energy conversion rate when a seismic node is deployed. Consequently, more electrical power is available, and the DC–DC

converter can achieve a high energy conversion rate, implying high efficiencies in cost and operation.

Notably, the energy harvesting system for powering remote seismic nodes significantly differs from the conventional electrical power source in remote areas in terms of continuity and reliability. The seismic monitoring targets achieving continuity to better understand a region's seismicity [63]. This requires continuous operation to acquire seismic data over considerably long periods of time for earth scientists to analyze and interpret the deformation of the earth's subsurface. Over a longterm operational cycle of a remote seismic node, the electrical conditioning unit of the energy harvesting system shown in Figure 1.13 must be efficient in converting and storing energy. The electrical conditioning unit is one of the essential parts of an energy harvesting system for tracking the maximum power from the source. The synchronous buck converter and indirect lookup table based MPPT model exhibit high efficiency and are appropriate for remote seismic nodes.

A typical seismic node housing a broadband seismometer, data acquisition system, GPS, and mobile router consumes about 10 W of 12 V DC as the terminal voltage draws a current of 0.8 A, as shown in Figure 1.13. Typical seismic node operates continuously for 24 hours in a day for accurate analysis and comprehensive seismicity of an area [64, 65]. The solar energy harvesting system for the node requires a regular 18 hours back up for continuous seismic operations, thus 172.8 Wh(18 h*0.8A*12V) per day for the node. With 86 %(172.8 Ah) of the lead-acid battery of 200 Ah needed to back up the remote seismic node.

The DC-DC The DC–DC power converter losses (P_L) due to inductor conduction, MOSFET switching, and MOSFET conduction [66] are ignored and expressed by Eq. (1.5). The degradation of the PV module's short-circuit current (I_{sc}), which increases with ambient temperature, is also neglected. The losses in the power converter are given by the following:

$$P_L = I_{L(rms)}^2 * R_{L(DC)} \quad (1.5)$$

Where

I_L = Inductor current

$R_{L(DC)}$ = DC Resistance of the Inductor

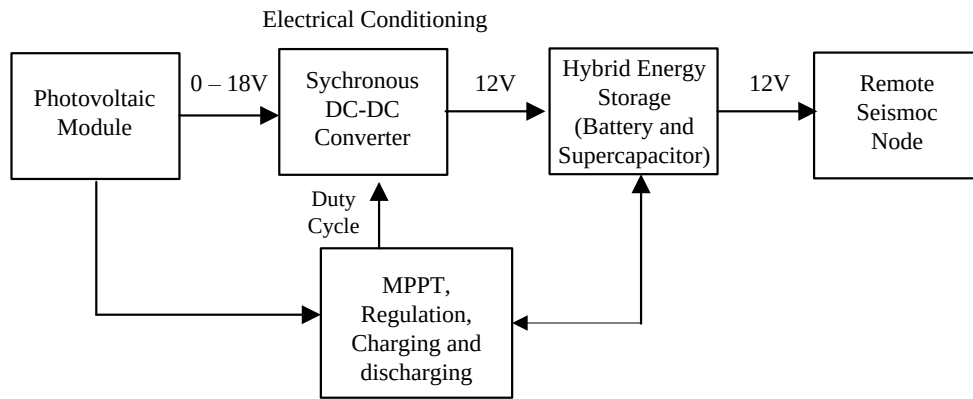


Figure 1.14: Block Diagram of Solar Harvesting System with Hybrid Energy Storage to energize Remote Seismic Node.

1.2 MOTIVATION

In recent times, micro-earthquakes have been observed in areas where seismic activities are inactive. Accordingly, scientists and engineers have to prepare and design efficient seismic instrumentation such that they can gather continuous seismic data to better understand and predict earthquakes. Although earthquakes cannot be avoided [67], damage can be reduced. This requires the installation of seismic nodes that continuously operate over relatively long periods of time without power failure such that a long-term seismic database can be acquired for accurate analysis, interpretation, and monitoring of seismic trends in an area. Accordingly, an optimal energy harvesting system is required to continuously and steadily power a remote seismic node over a relatively long time. The modeling of the subsystems of the optimal energy harvesting system is challenging in PSIM, Simulink, and MATLAB simulating environments because each program has one or more drawbacks. Based on a literature review, the algorithms designed to track the optimal power output levels using conventional techniques are either extremely complex (requiring high-power computational processes for microcontrollers) or simple, leading to incorrect decisions. Moreover, converting the models to conform with hardware implementation is equally challenging because balancing the functions of PV modules, microcontrollers, and accessories is difficult at the development stage. A typical microcontroller with a Light-Dependent resistor (LDR) used to replace a commercial meter for sensing irradiance levels affords several advantages that can be exploited with the lookup table interface. The optimal duty cycle levels can be predicted based on the ambient irradiance sensed by the LDR across a DC–DC converter. The mining sectors and Botswana Geoscience Institute can considerably benefit from this research because they continuously monitor the seismic and micro-seismic activities in the mines and country

1.3 PROBLEM STATEMENT

The survey conducted on the reviews of remote seismic nodes shows that most nodes severely exhaust their batteries each year, and their lifetime is reduced. This causes discontinuities in the seismic database and relegates seismic instrumentation performance. The investigation of reviews indicates the lack of optimization of subsystems under energy harvesting systems for energizing remote seismic nodes. The relationship between power, current, and voltage in the PV module is non-linear, rendering the tracking of maximum power under ambient conditions challenging. If the foregoing constraints are ignored and the electrical ratings of energy sources are upgraded, the losses further increase, and untimely energy storage failure occurs; consequently, greater costs are incurred. The implementation of an intelligent algorithm between energy transducers and storage is necessary for controlling the electrical variables to enable the transfer of maximum power. Several algorithms are available; however, these are characterized by slow tracking speed, oscillations around the maximum operating points, inaccurate responses to the outputs of the module, and circuit complexities. An algorithm based on ANN is explored and implemented to transform data for the lookup table. The dataset populates the lookup table and delivers optimal duty cycle levels as outputs derived by interpolation. This technique functions as an indirect lookup table MPPT system for solar energy harvesting. The lookup table stores corresponding ambient irradiance and temperature variables as inputs and duty cycle levels as outputs transformed by the neural network model. This approach requires no voltage and current sensors; nevertheless, relatively optimal power outputs are achieved. Challenges associated with training the algorithm are also encountered; these include the influence of the transfer function on input dataset responses and the training stability of ANN. Literature reviews show that two transfer functions are involved: Gaussian basis and sigmoid functions. Second, the limited lifecycle of lead–acid batteries impacts the discontinuities of the electrical power source, resulting in gaps in seismic databases, and hindering the feasibility of earthquake predictions. In the study, PWM and synchronous buck DC–DC converter configuration are employed to check the limits of the battery in which the lead–acid battery and supercapacitor are shunt-connected. The voltage rating of the supercapacitor is matched with the battery, and the battery is connected across the load. This increases the lifecycle and cost effectiveness of energy storage at remote seismic nodes in the long term.

1.4 RESEARCH AIM

This research aims to design, simulate, and implement an energy harvesting system characterized by relative simplicity and low cost that can be used for energizing remote seismic nodes to improve the continuity and assembly of long-term seismic databases.

1.5 OBJECTIVES

The objectives of the research are as follows:

- i. to review and compare models and designs of solar energy harvesting systems, their energy storage devices, progress, and prospects as well as the challenges confronting them at remote seismic nodes;
- ii. to conduct experimental studies and observations at permanent operational seismic nodes and obtain baseline data;
- iii. to propose a new lookup table function and curve fitting equations for selected PV module based MPPT algorithms for tracking and obtaining accurate responses during rapid changes in ambient irradiance and temperature variables with minimal computations;
- iv. to design, model, and simulate the integration of a PV module and hybrid energy storage of lead–acid and supercapacitor to power remote seismic nodes; and
- v. to test, implement, and evaluate the performance of hybrid subsystems.

1.6 CONTRIBUTIONS

The contribution of this research is significant in two ways.

- i. Developed and optimized energy conversion in solar energy harvesting systems by employing curve fitting equations, a lookup table, and an 8-bit microcontroller at a remote seismic node.
- ii. Developed a hybrid energy storage of lead–acid battery and supercapacitor with a synchronous buck DC–DC converter via a shunt connection circuit for powering remote seismic nodes.

1.7 RESEARCH QUESTIONS

Based on the literature review and realizing that a gap has to be filled, the research questions of this study are as follows.

1. How can an MPPT model be designed without voltage and current sensors with relatively less computations and then interface it with a solar energy harvesting system to power and deliver continuous and reliable power solutions to remote seismic nodes?

2. How can curve fitting equations considering the environmental conditions of selected PV module characteristics be developed? How can the relationship between environmental conditions and duty cycle levels across a DC–DC converter be formulated to deliver a simple and inexpensive irradiance meter to mimic ambient irradiance variations?
3. How can the lifecycle of a lead–acid battery be extended to ensure continuous and longterm processes at the remote seismic node?

1.8 SIGNIFICANCE OF STUDY

As justified in the literature review, the energy harvesting systems used at typical remote seismic nodes are not continuous and reliable, leading to discontinuities in seismic databases. The study considers the intermittency and fluctuation of both energy source and storage at remote nodes. The non-linearities of power, current, and voltage relationships at different ambient irradiance and temperature levels render tracking maximum power levels problematic. The constraints of the tracking algorithm are identified and optimized to provide the best impedance matching between the energy source and its load. Most tracking algorithms are complex, involving high-power computational processes or inaccurate yet straightforward decisions. The lookup table is interfaced with an LDR to eliminate high computational processes using transformed ANN data to populate the table and derive inexpensive power solutions at the remote seismic node. Solar source and hybrid lead–acid battery with supercapacitor are adopted as primary and secondary energy sources. The main research contributions are as follows.

- i. This research proposes and designs optimal hybrid energy harvesting solutions to reduce the intermittency of the PV module and constrained lead–acid battery at remote seismic nodes. The conventional MPPT algorithm requires voltage and current sensors to compute the duty cycle across the DC–DC converter, causing complexities and oscillations. This study formulates a lookup table and ANN algorithms (employing Levenberg–Marquardt back-propagation algorithm) to train the ambient irradiance and temperature dataset layers. Further, the log-sigmoid transfer function of ANN techniques is implemented to transform the lookup table content, forming pre-computed possible combinations of irradiance and temperature variables to provide the desired duty cycle variables.
- ii. Model curve fitting equations to correlate ambient irradiance and temperature levels with duty cycle levels are formulated using selected PV module characteristics. These equations are embedded in an 8-bit microcontroller algorithm to transform ambient

irradiance and temperature levels into optimal duty cycles. An inexpensive LDR and a temperature sensor are employed to detect variations in irradiance and temperature levels, respectively. These avoid the repeated ANN algorithm computations and allow the lookup table to assign duty cycles based on ambient irradiance and temperature values.

- iii. A synchronous buck DC–DC converter configuration is designed with PWM to check the lead–acid battery limits and connect the supercapacitor using a shunt connection. This extends the lifecycle and reduces the mechanical stress on the battery, thus improving the energy storage efficiency at remote seismic nodes.

1.9 RESEARCH PUBLICATIONS

- D. Duncan, A. M. Zungeru, M Mangwala, B. Diarra, B. Mtengi, T. Semong, and J.M. Chuma, “Power-Efficient Hybrid Energy Storage System for Seismic Nodes,” *Journal of Engineering*, Hindawi, **vol. 2020, Article ID 3652848, 21 pages. ISI/Scopus Indexed. <https://doi.org/10.1155/2020/3652848>**
- D. Duncan, M. Mangwala, B. Mtengi, A. M. Zungeru, B. Diarra, and J.M. Chuma, “Hybridization of Photovoltaic and Thermoelectric Energy Harvesting Systems at Seismic Nodes,” *International Journal of Engineering Research and Technology (IJERT)*, International Research Publication House, **vol. 13, Issue 9, pp. 2417-2428, 2020. ISI/Scopus Indexed. DOI: <https://doi.org/10.37624/ijert/13.9.2020.2417-2428>**
- D. Duncan, A. M. Zungeru, M. Mangwala, B. Diarra, J. M. Chuma, and B. Mtengi, “Optimizing Energy Harvesting System at Seismic Node: A Case of NNNSS Nodes,” *International Journal of Engineering Research and Technology (IJERT)*, International Research Publication House, **vol. 13, Issue 9, pp. 2409-2416, 2020. ISI/Scopus Indexed. DOI: <https://doi.org/10.37624/ijert/13.9.2020.2409-2416>**
- D. Duncan, A. M. Zungeru, M. Mangwala, B. Diarra, J. Chuma and M. Bokani, "Enhancing Maximum Power Point Tracking of Solar Energy Harvester to Energize Seismic Node: A Case of NNNSS Nodes," 2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies (CSUDET), Penang, Malaysia, 2019, pp. 224-229. **ISI/Scopus Indexed. DOI: <https://doi.org/10.1109/CSUDET47057.2019.9214628>**
- D. Duncan, A.M. Zungeru, M. Mangwala, B. Diarra, J.M. Chuma, B. Mtengi, “Optimal Power Management for Seismic Network”, In *International Journal of Engineering Research in Africa (JERA)*, vol. 56, pp. 162-181, 2021. **ISI/Scopus Indexed. <https://www.scientific.net/JERA.56.162.pdf>**
- A.M. Zungeru, D. Duncan, B. Diarra, J.M. Chuma, M. Mosalaosi, B. Mtengi, J. Gaboitaolelwe, C. Lebekwe, “Design and Simulation of an Off-Grid Photovoltaic System with Duty Cycle Prediction using Neural Network Controller”, In *International Journal of Engineering Research in Africa (JERA)*, vol. 57, pp 181-210, 2021. **ISI/Scopus Indexed. <https://www.scientific.net/JERA.57.181.pdf>**

- A.M. Zungeru, J.M. Chuma, D. Duncan, B. Diarra, M. Mosalaosi, B. Mtengi, J. Gaboitaolelewe, "Design of Photovoltaic System for IoT Devices," In: Green Internet of Things Sensor Networks- Applications, Communication Technologies, and Security Challenges. A.M. Zungeru et al. (Eds.): Chapter 4, pp. 55-81. Springer Nature Switzerland AG Gewerbestrasse 11, 6330 Cham, Switzerland, 2020. **ISI/Scopus Indexed**. DOI: http://dx.doi.org/10.1007/978-3-030-54983-1_4
- D. Duncan, A.M. Zungeru, M. Mangwala, S.R.S. Prabakaran, B. Diarra, "Optimal Photovoltaic Energy Harvesting System at Remote Seismic Node", International Transactions on Electrical Energy Systems, Hindawi, February 2022. Under 2nd revision.

1.10 THESIS LAYOUT

The thesis is structured into six chapters and subdivided into related subsections, and the remainder of the thesis is outlined as follows:

1.10.1 Chapter 2: Energy Harvesting System for Seismic Network

This chapter examines existing literature and specifies a review of the most popular energy harvesting systems, PV models, DC–DC converters, and energy storage. The constraints, capabilities, and advantages are highlighted; these subsystems are modeled in Simulink, PSIM, and MATLAB.

1.10.2 Chapter 3: Optimization of Solar Energy Harvesting System at Remote Seismic Node

This chapter outlines the structure used in implementing the proposed research. It presents the modeling approach to achieve a simple, fast, and relatively accurate tracking of the maximum power outputs in PSIM, MATLAB, and Proteus programs.

1.10.3 Chapter 4: Hybrid Energy Storage

This chapter describes and presents the investigation of the benefits afforded by the supercapacitor to the lead–acid battery when integrated as hybrid energy storage at the remote seismic station.

The design of hybrid energy storage is performed in the PSIM program.

1.10.4 Chapter 5: Results and Analysis

Chapter 5 presents the theoretical examination, simulations, and results from the PV module, synchronous buck DC–DC converter, and the hybrid of lead–acid battery and supercapacitor models. It further discusses the results and analysis of the ANN model, lookup table. This chapter also presents the comparison conducted to validate the proposed research.

1.10.5 Chapter 6: Conclusions

This chapter concludes the research, presenting a brief analysis of the study as well as recommendations for future work.

CHAPTER 2 ENERGY HARVESTING SYSTEM FOR SEISMIC NETWORK

2.1 INTRODUCTION

An energy harvesting system is deployed at a remote seismic node as a power solution to sustain long-term operations. It comprises an energy transducer and power conditioning unit, which convert the ambient energy to suitable electrical form and magnitude for the electrical load and energy storage to utilize. The impedance matching of the load to the energy transducer is the key to optimal energy transfer; hence, suitable electronic circuits and algorithms must be developed. The energy harvesting system captures and then processes the ambient energy, such as solar irradiance, vibration, heat, and radio frequency, into a usable form. These energy sources have been investigated along with their power densities and processes [68, 69, 70, 71]. Ambient irradiance is abundant at remote deployments and easy to extract as well as utilize [72]. This chapter explains the research methodology used to design, model, and simulate a typical energy harvesting system at a remote seismic node. In this research, the development of subsystems is approached theoretically by appreciating the concepts and models and then simulating the subsystems in the PSIM, MATLAB, and Simulink environments.

2.2 ENERGY HARVESTING SYSTEM

The energy harvesting system converts ambient energy into electrical energy and applies it across an electrical load and energy storage to power a remote seismic node, as shown in Figure 2.1. In this research, solar irradiance is the ambient energy utilized due to its prominence, abundance, and most importantly, its relative predictability throughout each season [50].

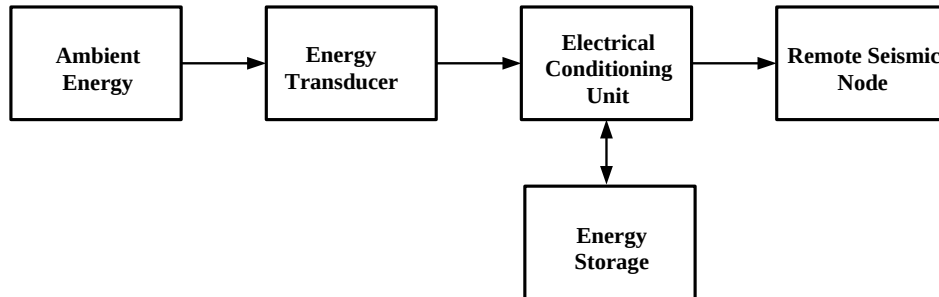


Figure 2.1: Energization process of Remote Seismic Node.

However, the conventional energy harvesting system, which employs ambient irradiance at the remote seismic node, wastes energy in the conversion and storage processes. This requires the node to use higher-rating PV modules or operate below optimal standards. In Figure 2.2(a) [73], only area B can sufficiently power the load and charge the energy storage for approximately 9 h/d; during the remaining hours, the load suffers. In addition, temperature varies throughout the day, as shown in Figure 2.2(b) [73]. The variation in ambient temperature

and irradiance changes the output of the PV module [74, 75]. It is essential to include the MPPT subsystem between the energy transducer and electrical conditioning unit [76]. An optimal energy harvesting system enables longer operational time and retards the energy storage aging process.

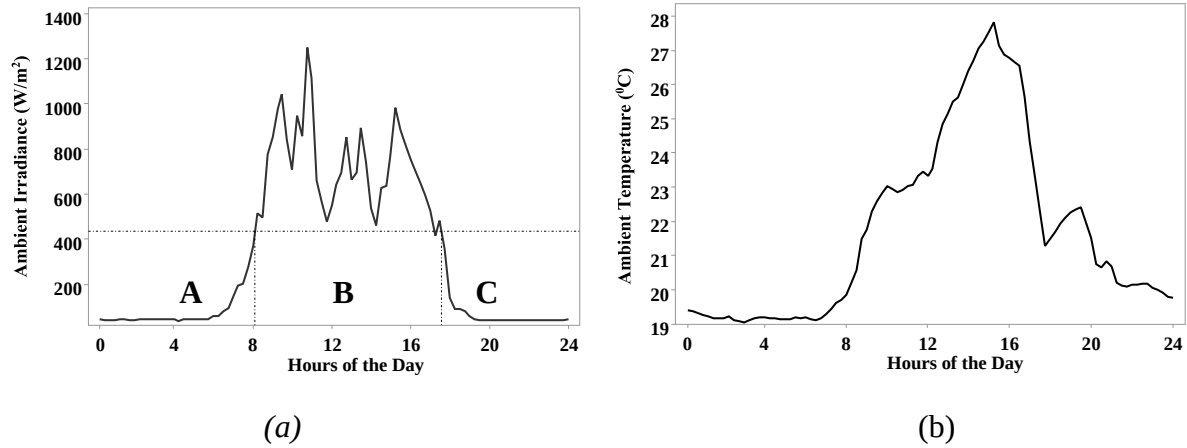


Figure 2.2: Plots of Ambient (a) Irradiance and (b) Temperature during Typical Day in Palapye.

In an energy harvesting system, the relationship between the current and voltage of the PV module can be formulated, and the characteristics of the plot are optimized to attain maximum power points (MPPs) [76]. In the proposed approach, a feedback control is introduced to compare the output of the PV module and reference voltage, developing a duty cycle across the PWM to drive the DC–DC converter to deliver maximum power.

2.2.1 ACQUISITION OF REAL DATA

Real data containing ambient irradiance and temperature measurements were acquired from the Southern African Science Service Centre for Climate Change and Adaptive Land Management. The data are measurements obtained on January 1, 2019 in Palapye at 23.1078°S 26.8321°E for 24 h as external parameters of the PV module. The data shown in Figure 2.2 represent the 24-h ambient irradiance and temperature measurements, which are vital for designing, modeling, and simulating the solar energy harvesting system.

2.2.2 PV MODELING

2.2.2.1 SOLAR CELL

Ambient irradiance (an excess renewable form of energy) is the input required by solar cells. These cells are the fundamental units of the PV module that convert irradiance into electrical energy using PV principles. They are made by depositing thin films of cadmium telluride, copper indium gallium arsenide, amorphous silicon, and micromorphous silicon on a substrate. A solar cell has an abundant and inexhaustible energy source to utilize. Moreover, it has no moving parts that can adversely affect its application and load [77]. However, it exhibits low

efficiency; thus, it requires optimization to deliver optimal power outputs. When irradiance passes through the PN junction, light travels in packets of energy (called photons), free electrons, and holes, which acquire sufficient energy to enable them to escape from the depletion zone, as shown in Figure 2.3. The free electrons in the zone quickly travel to the n side of the junction, whereas the holes head for the p side. As soon as the free electrons leave for the n side, a barrier potential, V_L , is created, and current, I_L , flows through the junction. If the resistor, R_L , is short-circuited without resistance, the generated holes and electrons produce I_{SC} . The highest potential that can break the depletion zone for current to flow through the junction is the open-circuit voltage (V_{OC}). Usually, the I_{SC} and V_{OC} (at 25 °C, the standard temperature) parameters are supplied by the vendor.

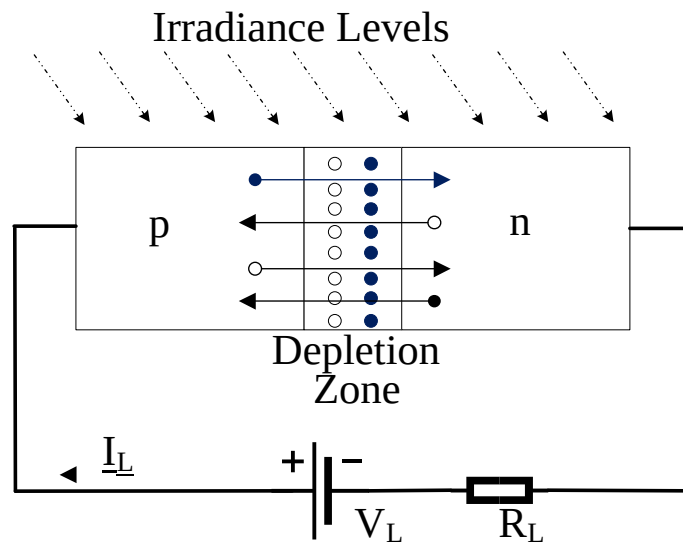


Figure 2.3: Basic PN Junction of Solar Cell.

Figure 2.4 shows the equivalent circuit of a solar cell, consisting of the current source (I_{PV}), diode (D), series resistor (R_S), and shunt resistor (I_{SH}). It generates the output current (I_O) and voltage (V_O). By applying Kirchhoff's law to the circuit shown in Figure 2.4, Eq. (2.1) [78] is derived.

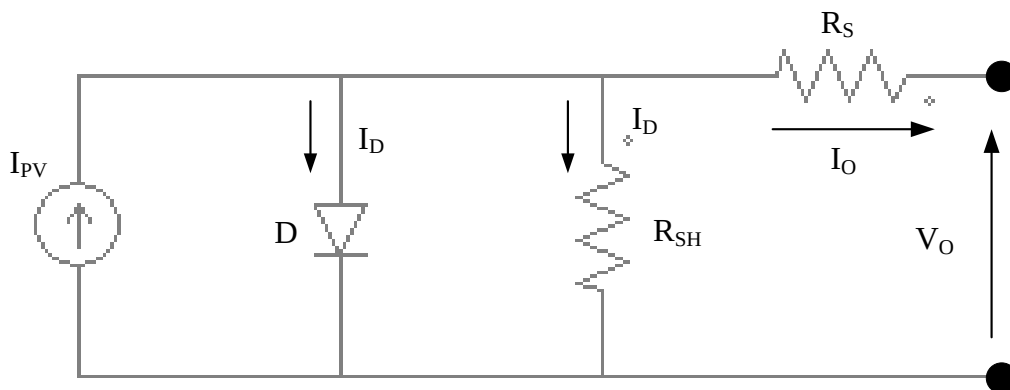


Figure 2.4: Equivalent Solar Cell Circuit.

$$I_O = I_{PV} - I_D - I_{SH} \quad (2.1)$$

The current source, I_{PV} , mainly depends on the set of ambient operating irradiance, G ; reference irradiance, G_{REF} ; set of ambient operating temperature, T ; k_i (temperature coefficient of short circuit current, I_{SC}); and reference temperature, T_{REF} . It is mathematically expressed by Eq. (2.2) [79], as follows.

$$I_{PV} = [I_{SC} + k_i * (T - T_{REF})] * \frac{G}{G_{REF}} \quad (2.2)$$

The diode current, I_D , which exhibits its inherent characteristics at the operating temperature (T) due to the ideality factor (A), Boltzmann's constant (K), and electron charge (q), is expressed by Eq. (2.3) [80]. The saturation current, I_{SAT} , and reserve saturation current, I_{RS} , are characteristics of the diode, as demonstrated analytically by Eqs. (2.3) to (2.6) [81].

$$I_D = I_{SAT} * \left[\exp \left(q * \frac{(V_O + I_O * R_S)}{K * T * A} \right) - 1 \right] \quad (2.3)$$

$$I_{SH} = \frac{R_S * I + V_O}{R_{SH}} \quad (2.4)$$

$$I_{SAT} = I_{RS} * \left(\frac{T}{T_{REF}} \right)^3 * \exp \left[\left(\frac{q * E_G}{A * K} \right) \left(\frac{1}{T_{REF}} - \frac{1}{T} \right) \right] \quad (2.5)$$

$$I_{RS} = \frac{I_{SC}}{\left[\exp \left(\frac{q * V_{OC}}{N_s * K * T} \right) - 1 \right]} \quad (2.6)$$

N_s = total number of cells in the solar module series

The foregoing implies that the output current, I_O , can be rewritten as Eq. (2.7). Based on Eq. (2.2), the generated current, voltage, and power of the solar cell are functions of ambient irradiance and temperature. Equations (2.1)-(2.7) give the characteristics of solar cells (in series or in parallel), including inherent features, such as their series and shunt resistance. Moreover, Eq. (2.7) identifies the parameters affecting the generated current, I_O , in solar cells, showing how the shunt and series resistance magnitudes contribute to solar cell outputs. The equation defines the I-V and P-V relationship curves. Thus, to explore, model, and predict the output measurements of solar cells, these parameters cannot be ignored. Before modeling the PV module, internal parameters (i.e., V_{OC} , I_{SC} , I_{SH} , and I_D) are simulated to appreciate their behaviors.

$$I_O = I_{PV} - I_{SAT} * \left\{ \exp \left[\frac{q * (V_O + R_S * I_O)}{A * K * T} \right] - 1 \right\} - \frac{V_O + R_S * I_O}{R_{SH}} \quad (2.7)$$

Codes with the m-file in MATLAB were developed to compute and plot the curves in modeling the I-V and P-V curves and validate the results.

2.2.2.2 AMBIENT IRRADIANCE CONSIDERATIONS IN SOLAR CELLS

Solar cell essentially relies on ambient irradiance levels to produce electrical outputs because the variation in irradiance and slight changes in temperature cause the movement of energy photons in the cells [82]. Figure 2.5 and Figure 2.6 illustrate how ambient irradiance variations influence current, voltage, and power relationships, indicating that their influence affects the MPPs of solar cells. These plots are based on the selected real irradiance levels, i.e., 100–972 Wm^{-2} , at 25 °C observed in Palapye.

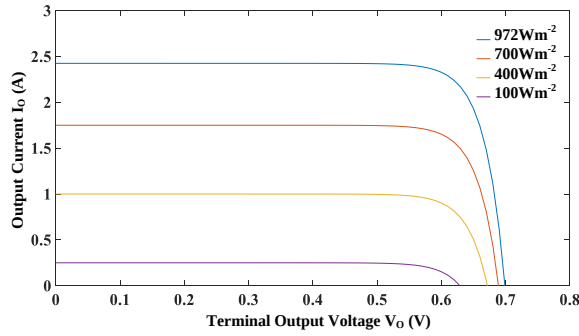


Figure 2.5: I-V Curve of Solar Cell varying Irradiance at fixed Temperature.

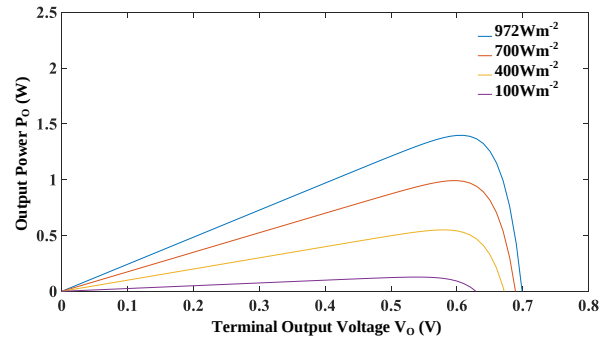


Figure 2.6: P-V Curve of Solar Cell varying Irradiance at fixed Temperature.

2.2.2.3 AMBIENT TEMPERATURE CONSIDERATIONS FOR SOLAR CELLS

The efficiency of solar cells decreases between 0.25 % and 0.45 % for every degree of rise in ambient temperature according to the energy conversion rate, which depends on the temperature and irradiance to deliver the electrical outputs. The I_{sc} measurements are virtually unaffected, as demonstrated in Figure 2.7; however, the V_{oc} measurements are affected, and the efficiency decreases. Equation (2.1) indicates that output current measurements are obtained when the current due to the diode and shunt resistor is deducted from the source current, I_{pv} , of the solar cell. The diode causes current losses owing to the thermal voltage, V_T , of the PN junction, as expressed in Eq. (2.8) [83], resulting in the diode's non-linear nature, as given by Eqs. (2.5) and (2.6). Due to thermal voltage effects, the plots in Figures 2.7 and 2.8 clearly prove that the increment in temperature reduces the output voltage, V_o .

$$V_T = \frac{K * T}{q} \quad (2.8)$$

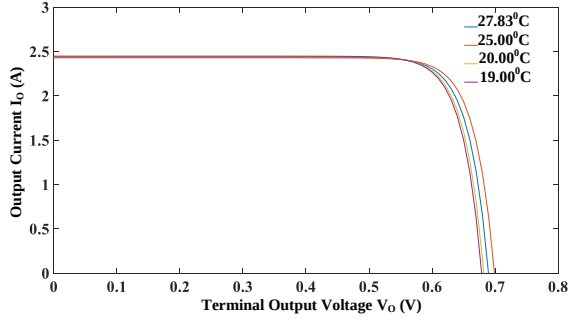


Figure 2.7: I-V Curve of Solar Cell varying Temperature with fixed Irradiance.

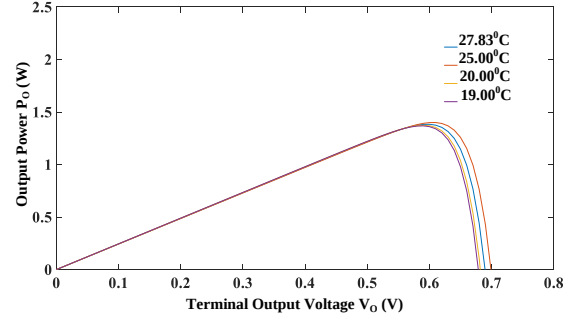


Figure 2.8: P-V Curve of Solar Cell varying Temperature with fixed Irradiance.

2.2.2.4 SERIES AND SHUNT RESISTANCE CONSIDERATIONS FOR SOLAR CELLS

The modeling of solar cells depends on the series and shunt resistances [84]; hence, the appreciation of these resistances is useful [82]. For simplicity, the shunt resistance is assumed to be infinite. For the series resistance, R_s , the curve characteristics of commercial PV modules are reduced to that of the resistance [85]. Thus, a series connection of solar cells results in resistive losses, which increase with the size of the PV module. Furthermore, shunt and series resistances are parasitic in nature, and the resistive effects decrease the efficiency of solar cells by dissipating energy. These adversely influence the energy conversion and efficiency of solar cells. The use of the increased series resistance and reduced shunt resistance leads to lower I_{sc} [66] and V_{oc} values [86]. In practical terms, the shunt resistance causes leakage current in parallel; its estimated value is specified by Eq. (2.9), which is the inverse of the slope of the curve shown Figure 2.7.

$$R_{SH} = \frac{dV_o}{dI_o} \quad (2.9)$$

2.2.2.5 SATURATION AND REVERSE CURRENT CONSIDERATIONS FOR SOLAR CELL

The saturation current, I_{SAT} , and reverse saturation current, I_{RS} , of solar cells are low-magnitude currents that result from ambient temperature and limit the performance of solar cells. The two parameters are added to I_D , as given by Eq. (2.1). Equations (2.2) and (2.3) and the simulation models are utilized to yield Figures 2.9 and 2.10.

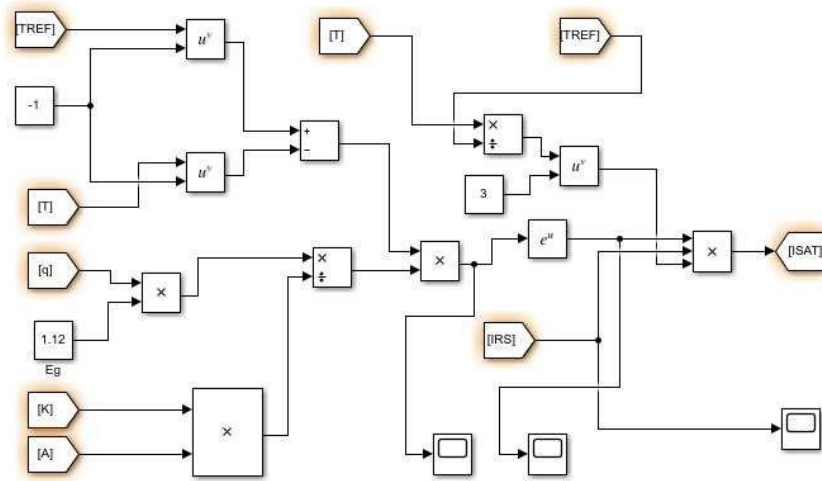


Figure 2.9: Simulink Modeling of Saturation Current (I_{SAT}) of Solar Cell.

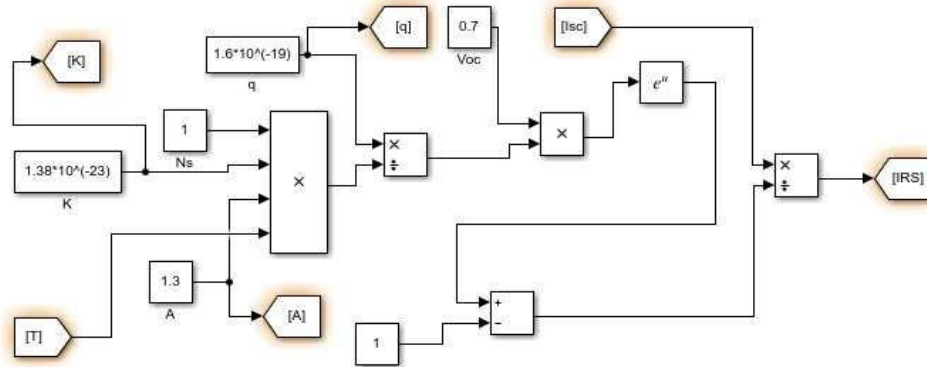


Figure 2.10: Simulink Modeling of Reverse Saturation Current (I_{RS}) of Solar Cell.

2.2.2.6 PHOTOCURRENT CONSIDERATIONS FOR SOLAR CELLS

The MATLAB model of the generated current, I_{PV} , is shown in Figure 2.11. The current is generated due to the changes in ambient irradiance and temperature, as expressed by Eq. (2.2). It is proportional to the ambient irradiance levels and relies on I_{sc} and its temperature coefficient, k_i .

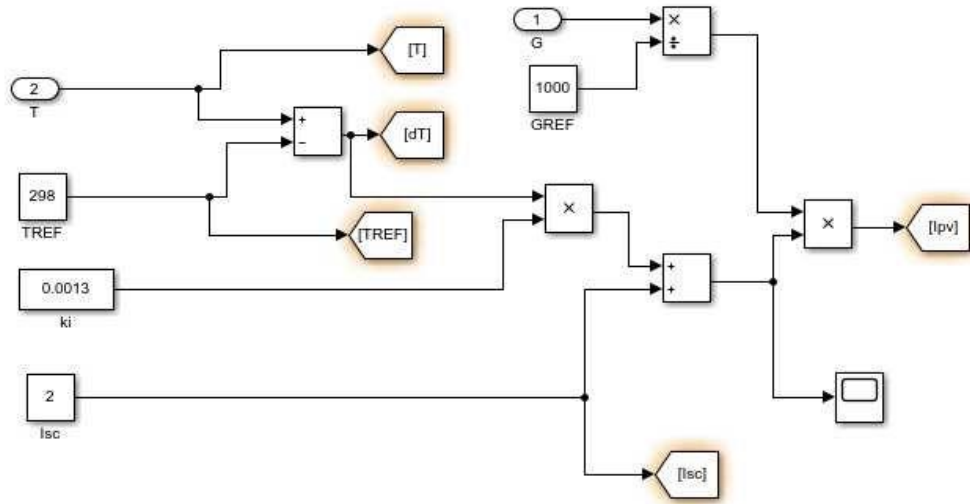


Figure 2.11: Simulink Modeling of Photocurrent, I_{pv} .

2.2.2.7 OUTPUT CURRENT CONSIDERATIONS FOR SOLAR CELLS

The model of the generated output current, I_O (Figure 2.12), demonstrates that I_O depends on all considered solar cell parameters (both external and inherent). Based on Eq. (2.2), ambient irradiance is directly proportional to I_O .

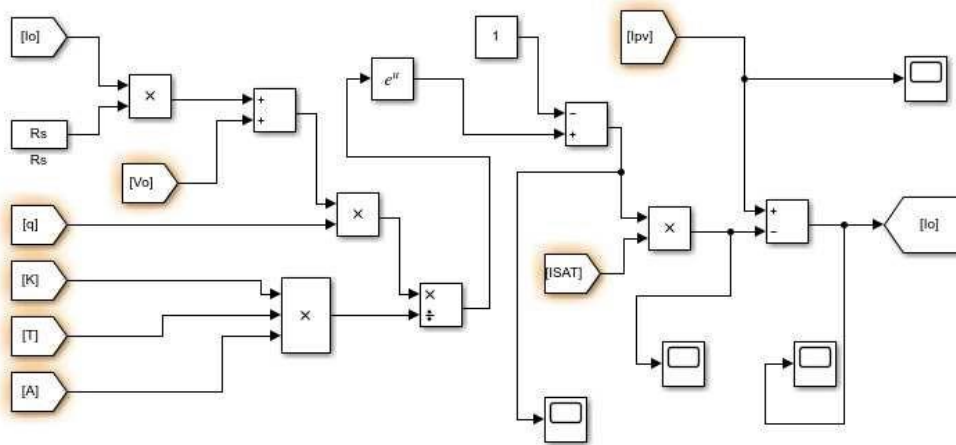


Figure 2.12: Simulink Modeling of Output Current, I_O .

2.2.3 MODELING OF PV MODULE

One of the goals of this study is to model an optimal and cost-effective PV module and implement it at a remote seismic node. The terminal voltage is typically 12 V DC, and the load is 10 Ω . Real observations of the ambient irradiance and temperature at Palapye are obtained and used, as summarized in Table 2.1, to model various subsystems. The PV module subsystems are modeled in Simulink [87, 88] and PSIM environments [89]. However, these simulation

environments can only accommodate an 8-bit microcontroller to implement the physical hardware design. In contrast, the Proteus environment can support this microcontroller; however, it is limited in simulating the PV module. Accordingly, PV module was simulated using both PSIM and Simulink tools to achieve more elaborate simulations and understand the module parameters. Equally, these tools were utilized to validate and test the performance of the developed model.

Table 2.1: Characteristics of Selected PV Module

Name	Value
Company	Atersa
Model	A-120P/A-127P
P_{MAX}	120 W
V_{OC}	21.9 V
I_{SC}	7.7 A
V_{MAX} , Voltage at P_{MAX}	17.2 V
I_{MAX} , Current at P_{MAX}	7 A
Temperature Coefficient of V_{OC}	$-0.00127 \text{ VA}/^{\circ}\text{C}$
Temperature Coefficient of I_{SC}	$0.0023 \text{ A}/^{\circ}\text{C}$
Temperature at V_{MAX} and I_{MAX}	25 $^{\circ}\text{C}$
P_M , Guaranteed Minimum Power	116 W

2.2.4 MODELING OF PV MODULE WITH SIMULINK

The Simulink models shown in Figures 2.13 and 2.14 are formulated using input parameters with varying magnitudes (irradiance ($100\text{--}972 \text{ Wm}^{-2}$) and temperature ($19\text{--}27.83 \text{ }^{\circ}\text{C}$)) based on the model equation, Eq. (2.2). The I–V and P–V curves show the electrical characteristics of the solar module outputs; the expected results are confirmed and found feasible to achieve.

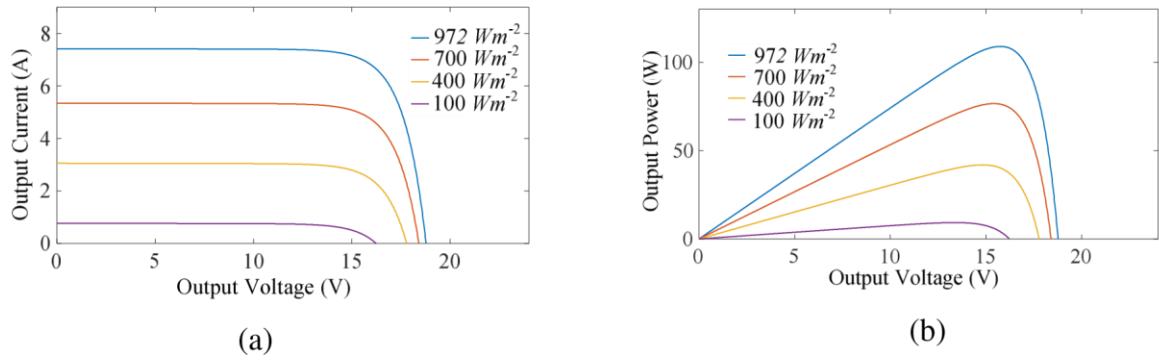


Figure 2.13: Plot of (a) I–V and (b) P–V Characteristics of 120-W PV Module with varying Irradiance using Simulink.

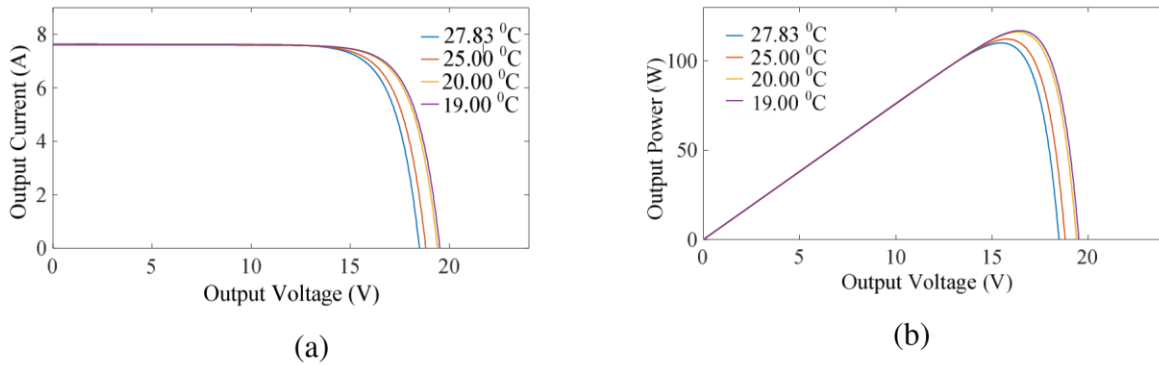


Figure 2.14: Plot of (a) I–V and (b) Characteristics of 120-W PV Module with varying Temperature using Simulink.

Using the model equations (Eqs. (2.1)–(2.7)) in Simulink, a model of the 120-W PV module is formulated, as shown in Figure 2.15; the model characteristics are summarized in Table 2.1.

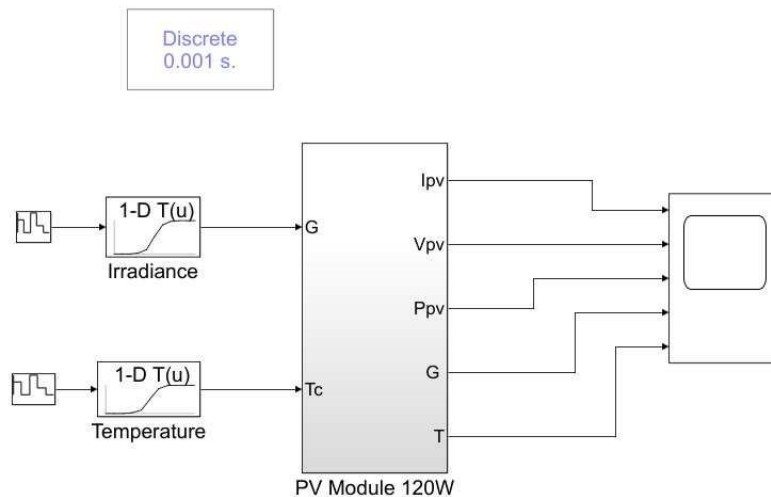


Figure 2.15: Model of 120-W PV Module in Simulink.

2.2.5 MODELING OF PV MODULE USING PSIM

Figure 2.16 presents the equivalent PV module circuit modeled using the PSIM derived from the models expressed by Eqs. (2.1)–(2.8).

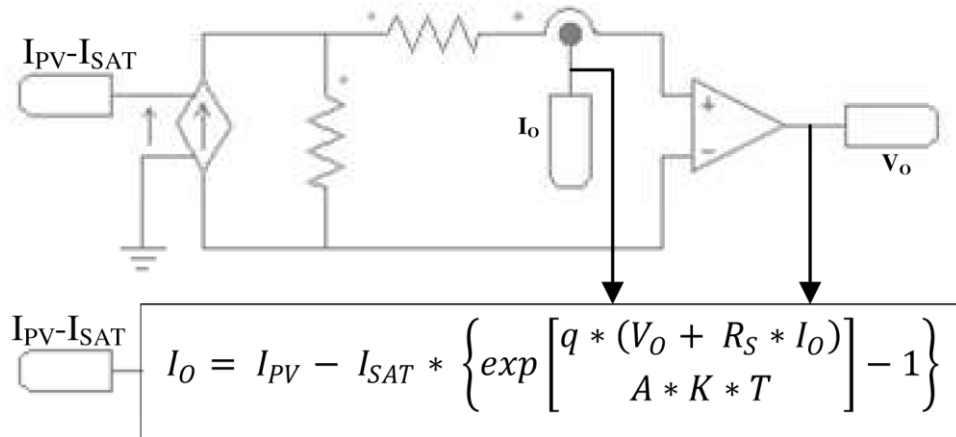


Figure 2.16: Equivalent PV Module Circuit.

Based on mathematical models given by Eqs. (2.1)–(2.7) and the characteristics listed in Table 2.1, the PV module characteristics are generated using PSIM, as shown in Figure 2.17. Moreover, the modeling of the module was designed in the PSIM environment, as shown in Figure 2.18. Based on the list in Table 2.1, Figures 2.19 and 2.20 demonstrate the variations in irradiance and temperature, respectively. The results conform with the principles of the PV module current, voltage, and power relationships and behaviors.

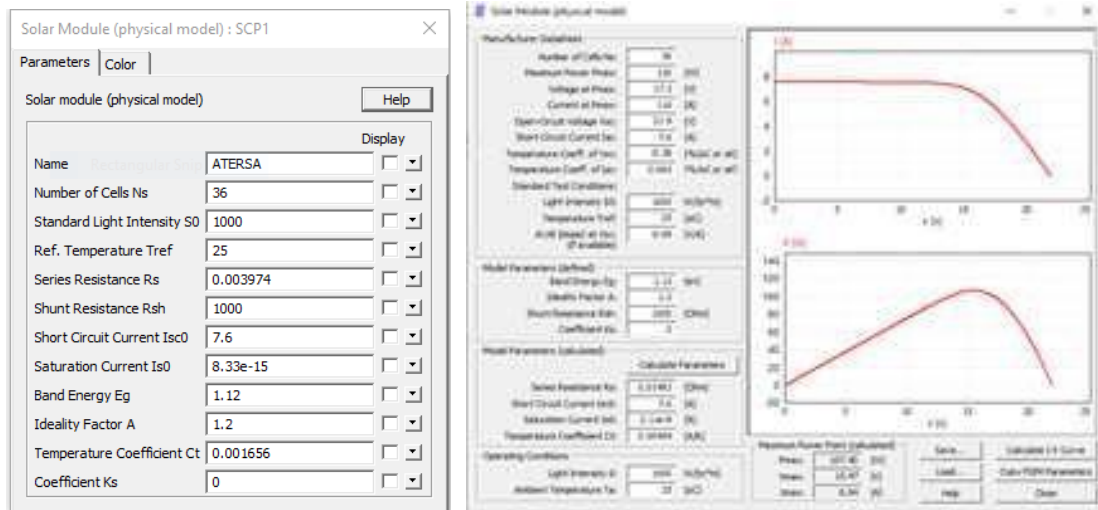


Figure 2.17: PV Module Characteristics generated by PSIM.

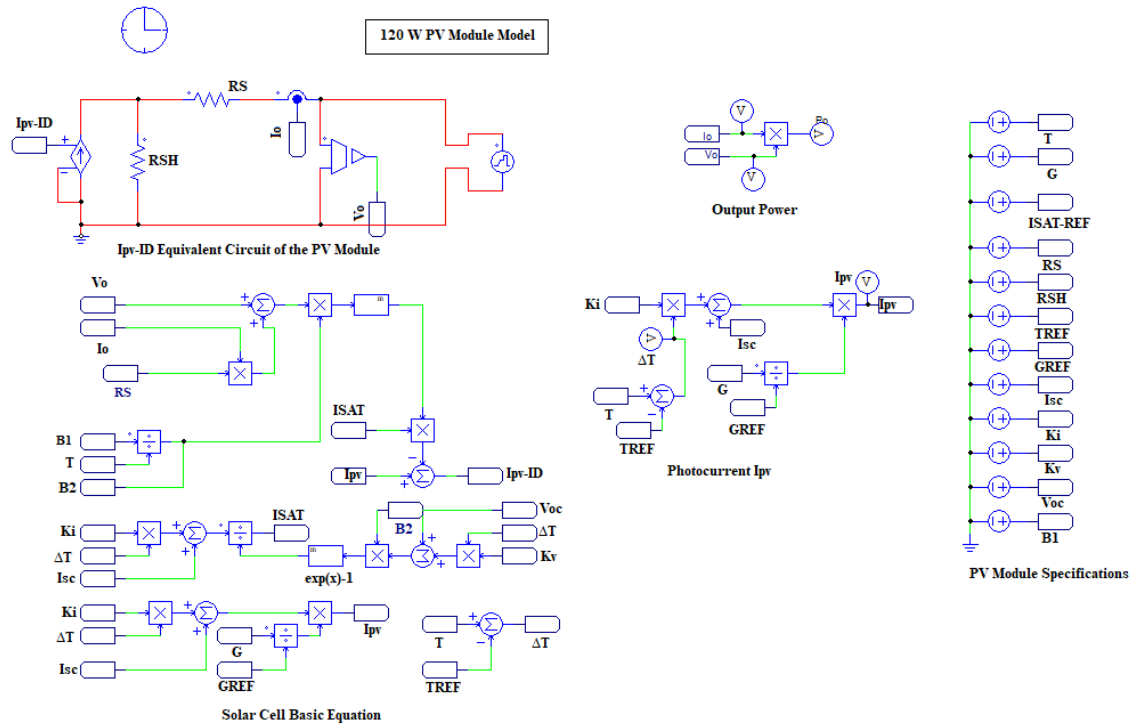


Figure 2.18: PV Module Modeling in PSIM.

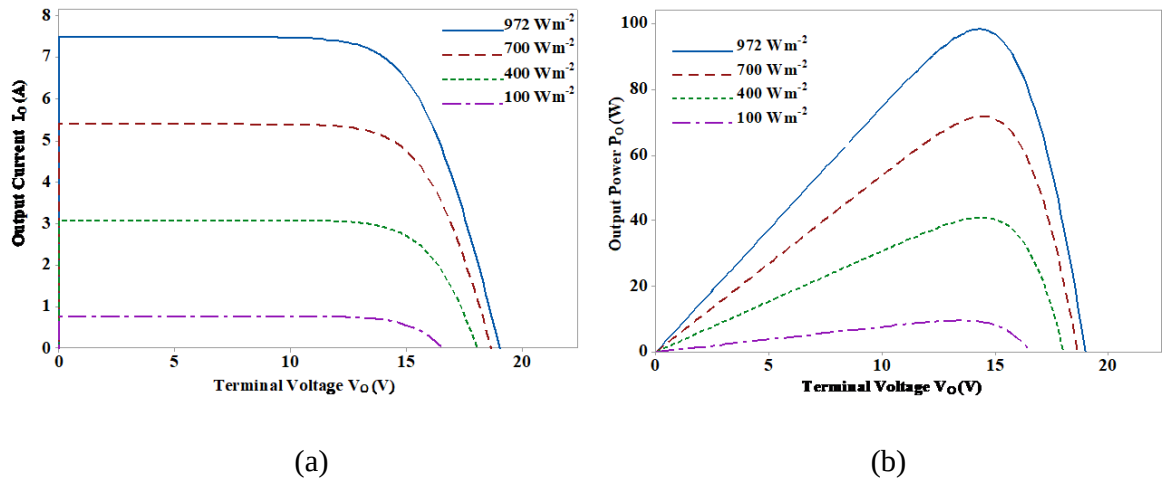


Figure 2.19: Plots of (a) I-V and (b) P-V Characteristics of 120 W PV Module with varying Irradiance using PSIM.

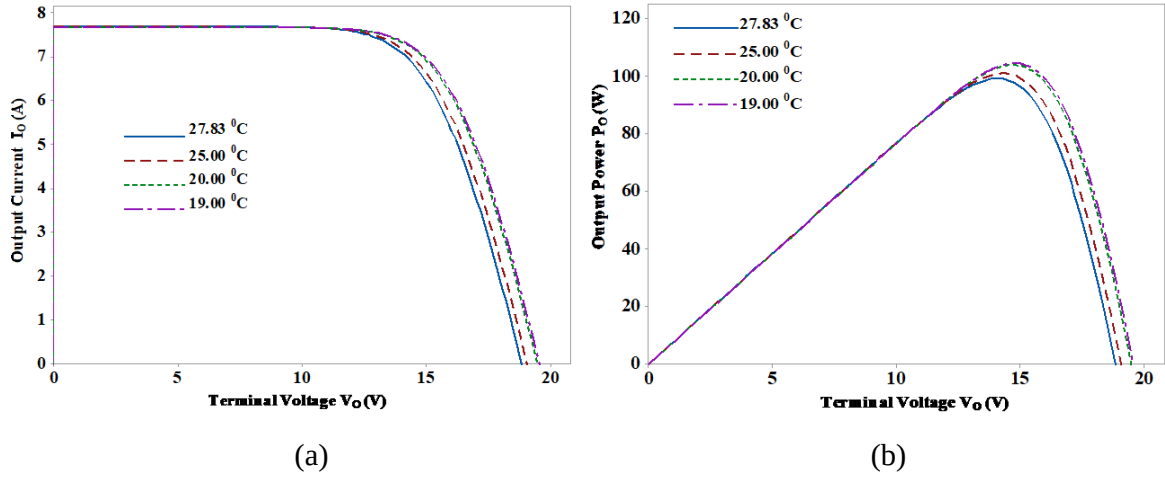


Figure 2.20: Plots of (a) I–V and (b) P–V Characteristics of 120 W PV Module with varying Temperature using PSIM.

2.3 DC–DC CONVERTER

Remote seismic nodes require DC signals to run their subsystems; hence, the DC–DC converter is vital in the solar energy harvesting system at seismic deployment. It controls the unregulated DC voltage by either increasing or decreasing the voltage magnitude, considering that the output voltage of the PV module varies. Usually, the remote seismic node requires a fixed voltage. To operate between the module and load, a power conversion process is necessary. In this regard, the DC–DC converter is an electrical conditioning device that converts the DC voltage to the desired voltage to feed the load. The key considerations in DC–DC conversion are the efficiency in energy conversion, cost, simplicity, and robustness. In seismic nodes, low-frequency noise is totally unacceptable due to the typically low frequency of actual seismic signals [44]. Hence, a low-frequency DC–DC converter is avoided, or a high-pass filter is employed across the output of the solar energy harvesting system to reject low-frequency noise.

The DC–DC converter may have a linear or switched-mode topology to achieve the desired voltage levels. The switched-mode topology utilizes power switching devices driven by the PWM control at a fixed frequency to regulate the output voltage levels. Usually, three types of switched-mode DC–DC converters can be implemented across PV modules: buck, boost, and buck–boost converters. In this research, the buck converter is adopted due to its simplicity and higher efficiency. Moreover, the lifecycle of batteries connected to it becomes more reliable [90]. The buck converter can also be easily integrated with the PV module and energy storage. It can conform with the electrical load characteristics of a remote seismic node.

In this study, synchronous buck DC–DC converter topology is proposed and adopted for the remote seismic node to improve the node's power and provide continuous current flow. The target is to improve the energy conversion rate through controller optimization and improve the lifetime of the lead–acid battery. Although conventional linear DC–DC converter controllers are simple to model and easy to implement, their efficiencies are low. In contrast, non-linear controllers, such as intelligent controllers, perform better [91, 92]. These controllers can continue to supply the desired output voltage levels for wide input levels. Accordingly, investigations have been conducted to enable these converters to deliver optimal outputs.

An optimal buck converter is required to simultaneously energize the load and control as well as charge the hybrid energy storage. Different energy sources are employed across DC–DC converters. Solar energy is mainly preferred because it is abundant and renewable as well as provides the highest power density [93]. Figure 2.21 is a basic buck converter with a switching device running at a fixed switching frequency during the period, T , and duty cycle α , (between 0 and 1), as defined by Eq. (2.10). It is used to control the PWM signal in switching the MOSFET of the converter.

$$\alpha = \frac{V_o}{V_{INS}} \quad (2.10)$$

The inductor (inductance: L) is assumed to be lossless and operates in conduction mode, whereas the ripple voltage across the capacitor is ignored. When the SW is on, current flows through the inductor and linearly increases; in contrast, the diode is in the reversed bias.

$$V_L = V_{IN} - V_o = L * \frac{dI_L}{dT} \quad (2.11)$$

$$\frac{dI_L}{dT} = \frac{V_{IN} - V_o}{L} \quad (2.12)$$

When the SW is off, the diode is in the forward bias to maintain the conduction mode of the inductor.

$$V_L = -V_o = L * \frac{dI_L}{dT} \quad (2.13)$$

$$\frac{dI_L}{dT} = -\frac{V_o}{L} \quad (2.14)$$

At steady state, the V_o can be expressed as follows.

$$(V_{IN} - V_o)dT = V_o(1 - d)T \quad (2.15)$$

$$V = dV_{IN} \quad (2.16)$$

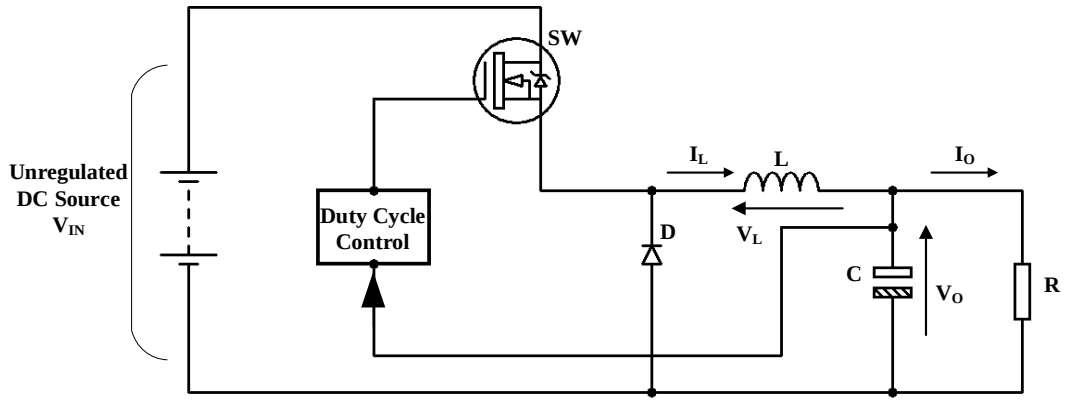


Figure 2.21: Basic Buck Converter with One Switch Device.

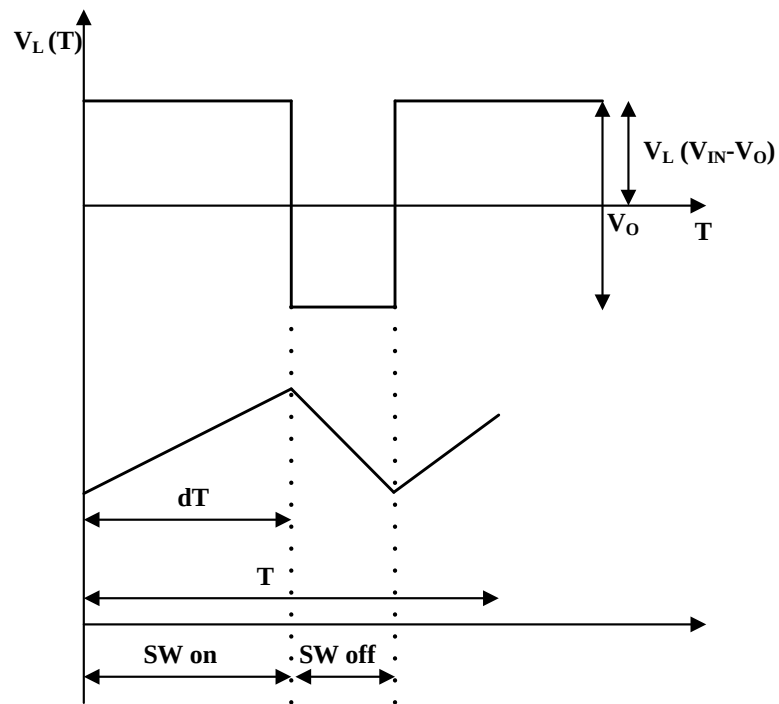


Figure 2.22: Waveforms obtained from Basic Buck Converter.

The technique where the converter uses a freewheeling diode is shown in Figure 2.23(a). As shown in Figure 2.23(b), the diode is replaced by another MOSFET. The MOSFET approaches an ideal condition in which power loss is extremely low. It also ensures the smooth transfer of current through it [94]; accordingly, it is adopted in this study. The use of a synchronous buck converter results in a relatively low voltage drop and ensures higher efficiency.

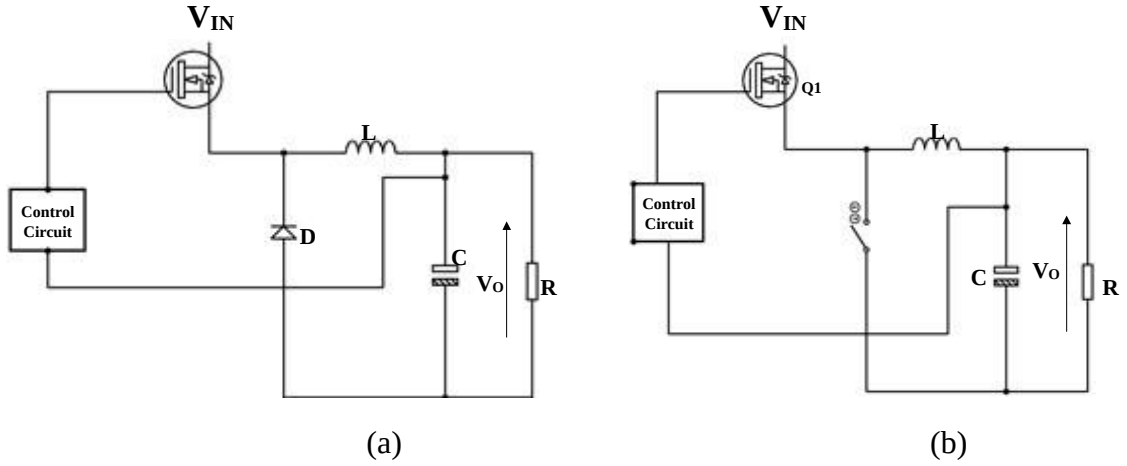


Figure 2.23: (a) Buck Converter with Freewheeling Diode; (b) Synchronous Buck Converter.

The two MOSFETs, Q_1 and Q_2 , are alternately switched on and off to control the output voltage levels in response to unregulated V_{IN} . In the synchronous circuit where the diode is replaced by MOSFET Q_2 , the switching signal regularly complements the signal of MOSFET Q_1 , as shown in Figure 2.24. A single MOSFET and diode topology of the converter are shown in Figure 2.23. The waveforms of the MOSFET during on and off periods for time duration T , is shown in Figure 2.22, the inductor current cannot be negative due to the reversed bias nature of the diode. In contrast, the negative current from the SW can flow through the inductor, as demonstrated by the waveforms shown in Figure 2.25 during on and off periods for time duration T . This tends to provide more energy for the load. A low-power electronic device, such as a remote seismic node, requires a synchronous buck converter to improve its efficiency, receive continuous power for the load, and achieve longer energy storage time [95].

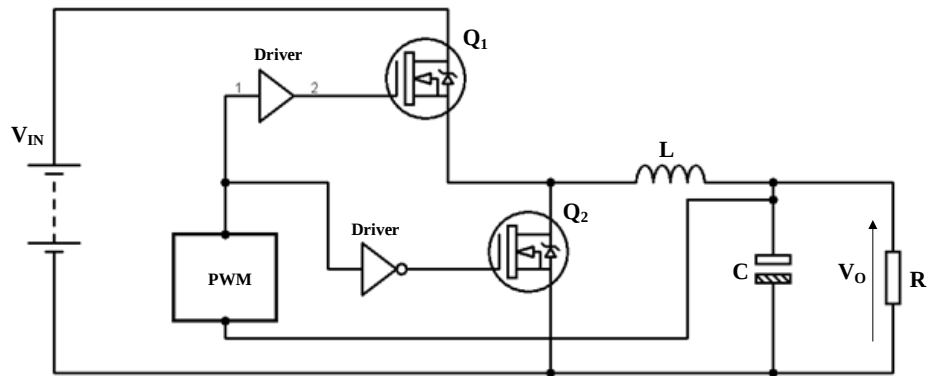


Figure 2.24: Basic Synchronous Buck Converter.

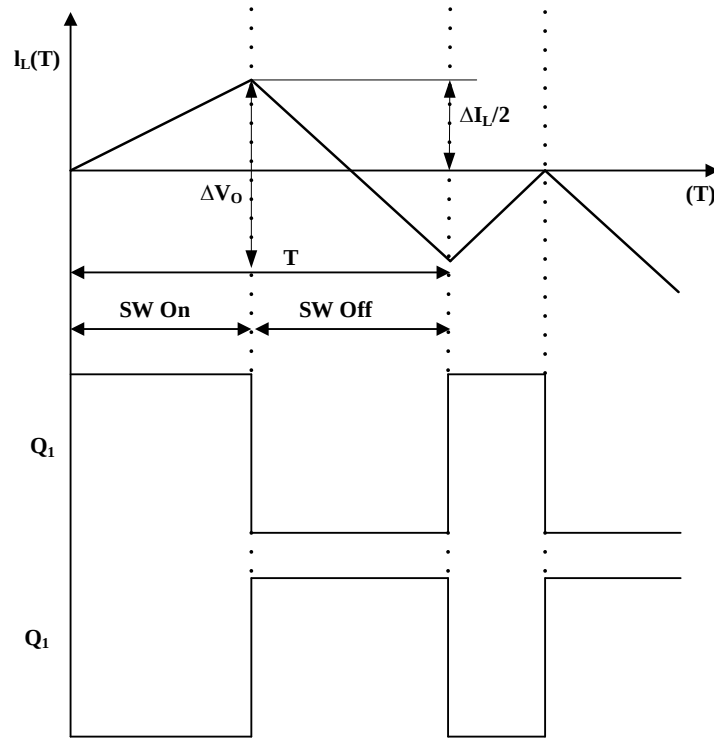


Figure 2.25: Waveforms obtained from Synchronous Buck Converter.

In addition to the number of SWs in the buck converter, the output variables are a function of the input voltage (V_{IN}), inductance (L), and duty cycle (D). When continuous current flow is required in the converter, the duty cycle levels are adjusted by increasing the fraction of the time that the converter is on to accommodate fluctuations. The PWM signal with the computed duty cycle drives the converter's SW to track the maximum possible power from the PV module. The two SWs alternately turn on and off to deliver different output power levels. The buck synchronous DC–DC converter has different topologies, which fundamentally differ in terms of applications where they are employed; controllers are used to vary the input voltages.

2.4 DC–DC CONVERTER BASED ON PV SYSTEM WITH MPPT

The PV module delivers the energy based on the availability of ambient irradiance and temperature levels. It is connected to a DC–DC converter where the switching signal is controlled by the duty cycle levels to feed the PWM, driving the converter (Figure 2.26) to track the maximum power. The duty cycle levels could be computed directly using a proportional–integral controller to regulate the PWM signal and then provide a constant value based on the average voltage or current output levels of the converter. This technique is relatively simple and reduces computational time. However, due to the non-linearity of

solar cells and irregularity of inputs, these controllers have inadequate power conversion [96].

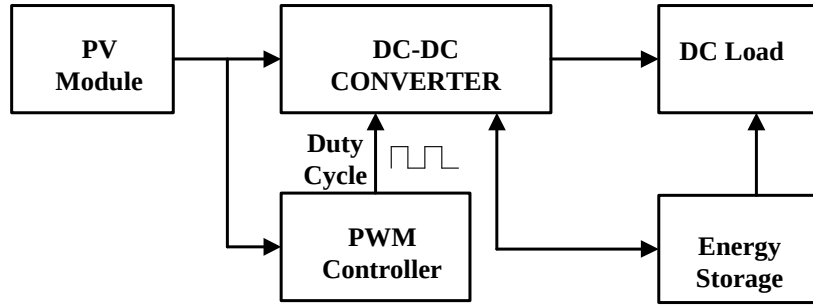


Figure 2.26: Block Diagram of PV Module and PWM Controller of DC–DC Converter.

With the microcontroller’s computing power, the constraints of the MPPT controller in the DC–DC converter can be optimized, thus obtaining the best results from the PV modules. Consequently, the non-linearity of the PV module and irregularities of the ambient irradiance and temperature levels can be managed [97, 98]. In the conventional MPPT controllers of the DC–DC converter, the use of current or voltage sensors is typical. However, they can be avoided, and energy conversion can be improved [99] by reducing the power losses; moreover, constraints can be eliminated through the artificial intelligence technique. For instance, setting the rapid variations in ambient irradiance and temperature levels as input parameters is acceptable due to the adaptive characteristics of the algorithm [100]. In contrast, output measurements may be used as voltage and current variables of the PV module, and control attributes of interest may be selected [101]. The literature review has shown that the power regulation of an energy harvesting system across any load is the most significant practical challenge that influences the conversion of power from the source to the load.

2.4.1 VARIATIONS IN MPPT ALGORITHM BASED ON FEATURES

The MPPT algorithms vary according to the type of sensors used, convergence rate, frequency of use, complexity, and most importantly, efficiency. For remote seismic nodes, the proposed requirements are simple implementation, relative inexpensiveness, and efficiency; these advantages are afforded by the algorithm [102, 103].

2.4.1.1 SENSOR TYPE USED

Sensors are involved in most MPPT technique implementations to measure voltage, current, irradiance, and temperature, which are used to compute the corresponding I_{MAX} and V_{MAX} levels. Hence, the type of sensor employed influences the effectiveness of the MPPT algorithm. Typically, sensors are relatively expensive and bulky. They can also cause

complexities in circuit designs [104] and power oscillations near maximum operating points [105].

2.4.1.2 CIRCUIT COMPLEXITIES

The more the number of sensors employed in a circuit, the greater the circuit complexity [106], the lower the speed of convergence, and the higher the cost. Moreover, the effect of resolving the maximum operating points is more adverse [107, 108]. These imply that the designed circuit may have low efficiency and experience power losses. In energy harvesting systems, additional subsystems require more complexities to trade off and reconfigure the entire system [109]. In contrast, the implementation of a simple and functional algorithm depends on making the right choice.

2.4.1.3 HARDWARE IMPLEMENTATION

The hardware implementation footprint of a circuit entails the nature of the circuit, which can be analogue, digital, or both. The hardware of an MPPT unit of a solar energy harvesting system include voltage, current, irradiance, and temperature sensors. The presence of these sensors results in more complications [109], expenses, and power losses.

Different MPPT methods have been explored, and other techniques are appropriate for different electrical loads. For instance, satellite development and robotics require highly precise and complex MPPT algorithms. Consequently, high cost and increased complexities cannot be avoided. In contrast, the use of highly precise and complex microcontrollers to drive the MPPT algorithm in a seismic node, which is a low-budget and low-power system, may not be cost-effective. Most algorithms require complex sensing circuits to operate optimally. However, the proposed design requires no complex sensing circuit for the optimization.

2.4.1.4 CONVERGENCE RATE

The development of the MPPT algorithm is based on the convergence speed of the I_{MAX} and V_{MAX} measurements. Measurements require time [110], whereas effective MPPT techniques have a short convergence time. The shorter the time, the faster the periodic tuning reaches the maximum operating points; however, this varies from one technique to another.

2.4.2 P AND O MPPT ALGORITHM

The P and O algorithm is easy to implement and most frequently used. It operates by regularly increasing or decreasing the output parameters from the PV module and comparing them with those of the previous perturbation cycle. It continuously iterates the output parameter voltage ($V(k)$) and measures the current ($I(k)$) toward the MPP, as indicated by

the flowchart shown in Figure 2.27. In this figure, when the PV output measurements are perturbed, the output power, $P(k)$, is computed and compared with the previous measurements. If the change in power, ΔP , exceeds zero, further changes are implemented in the direction of V_{MAX} ; when $\Delta P < 0$, the direction is reversed to reach the maximum operating point, V_{MAX} , as illustrated in Figure 2.27. Then, the duty cycle of the PWM is modified to drive the power converter.

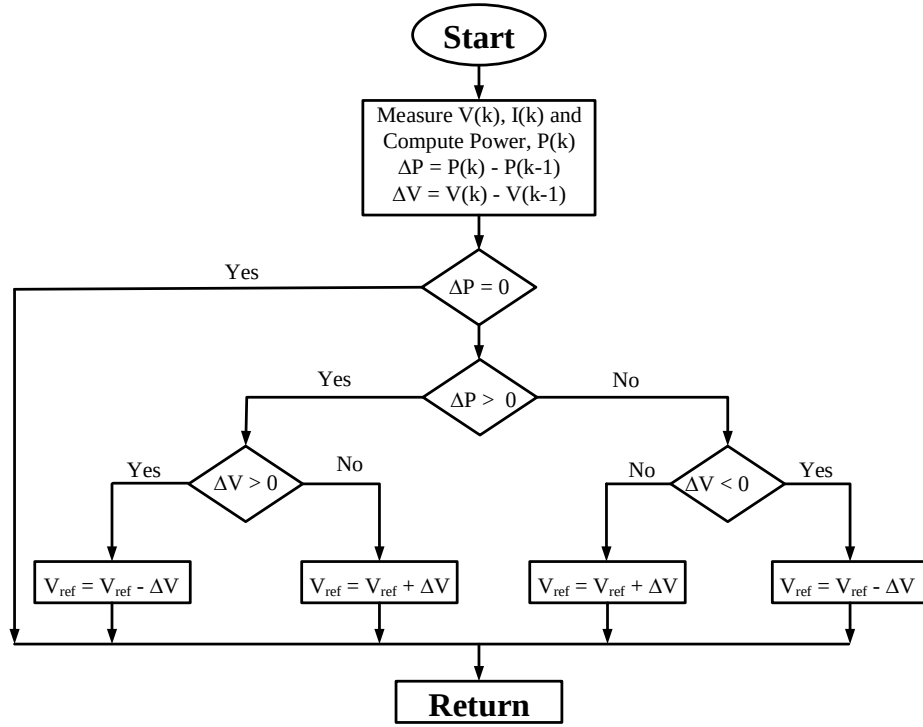


Figure 2.27: Basic P and O Algorithm Flowchart.

The usual P and O technique suffers high oscillations near maximum operating points [111]. This reduces the convergence rate [112], resulting in power losses and lower efficiency. Fast convergence is achieved when a large step size in voltage change is adopted [113, 114]. Moreover, the duty cycle levels of the DC–DC converter are perturbed instead of voltage measurements. However, in this technique, the step size of the PV output is usually constant; a larger size leads to more significant oscillations and lower efficiency [111]. In contrast, a smaller size generates lower oscillations near the operating points and fails under rapid changes in ambient irradiance and temperature levels [115, 116]. In the work reported in [117], the step sizes were set from 0.5 % to 10 % of the V_{OC} . Although preset steps were used, improvements were still observed. In this technique, the two significant features for improving the performance are changing the voltage step size and perturbing the frequency [16, 17, 118].

2.4.3 INCREMENTAL CONDUCTANCE MPPT ALGORITHM

This approach uses derivatives of the electrical conductance to arrive at MPPs where the slope of the power–voltage curve of the PV module is zero [119]. The implementation of an adaptive voltage step size in the solar MPPT controller is the key to improve the PV module efficiency. In this regard, the incremental conductance algorithm can employ an adaptive voltage step size [120]. The algorithm and curve shown in Figure 2.28 can be mathematically expressed by Eq. (2.17).

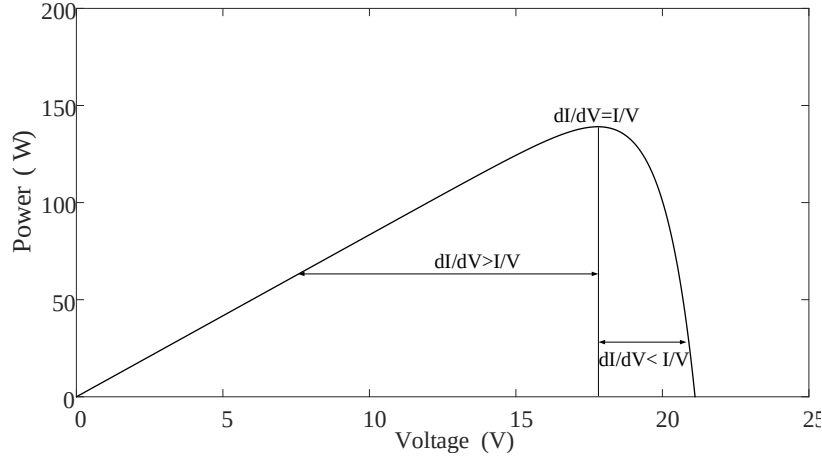


Figure 2.28: Basic Incremental Conductance Algorithm Iterations in P-V Curve.

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = I \frac{dV}{dV} + \frac{dI}{dV} = I + V \frac{dI}{dV} \quad (2.17)$$

In the curve shown in Figure 2.28, at zero gradients, Eq. (2.17) becomes Eq. (2.18) when the MPP is reached, and the change in output conductance is equal to the negative of the output conductance of the PV module.

$$\frac{dI}{dV} = -\frac{I}{V} \quad (2.18)$$

The P and O algorithm and that of incremental conductance are hill-climbing approaches for tracking the MPP and barely follow the same iteration of satisfying the following condition.

$$\frac{dP}{dV} = 0 \quad (2.19)$$

Figure 2.29 demonstrates the iterations of the incremental conductance algorithm by measuring the output voltage and current levels of the PV module. The incremental changes, ΔI and ΔV , are computed, and the algorithm is continued as shown in Figure 2.29 until the condition given by Eq. (2.19) is achieved. Then, the necessary impedance and voltage levels are adjusted to set the duty cycle across the power converter. The comparative analysis between the two hill-climbing approaches determines the direction where the voltage perturbation turns. In the incremental conductance algorithm, if the change in conductance,

$\frac{dI}{dV}$ equals the static conductance, $\frac{I}{V}$ then the maximum operating point has reached the conduction, as expressed by Eq. 2.19 [121] as described in Figure 2.29. The incremental conductance technique is characterized by lower oscillations; however, a relatively complex circuit is necessary to achieve them. The two techniques perform well under normal ambient irradiance and temperature levels, whereas efficiency suffers when the levels are irregular and rapid [122]. They oscillate at maximum operating points, they are sluggish in convergence [123], and they make incorrect decisions under rapid irradiance disturbances [119].

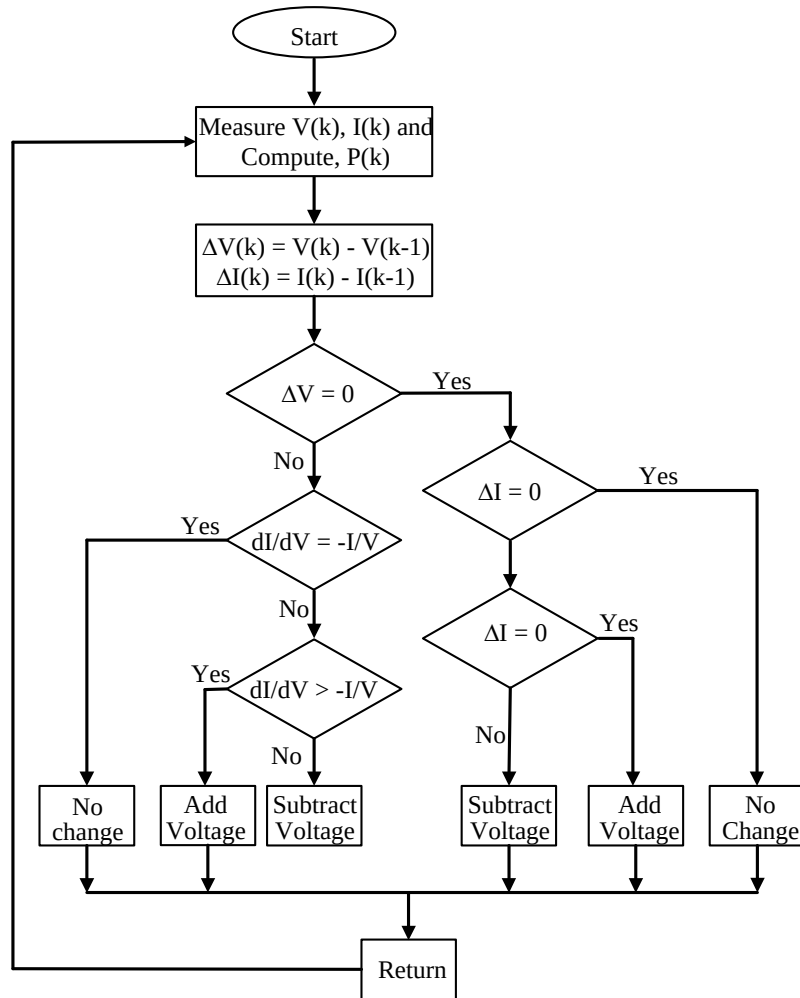


Figure 2.29: Basic Flowchart of Incremental Conductance MPPT Algorithm.

2.4.4 FUZZY LOGIC CONTROL MPPT ALGORITHM

The FLC-based MPPT algorithm is designed to be smart, intelligent, and relatively simple to implement by engaging the capabilities of a microcontroller with virtually no oscillations [124]. As indicated in Figure 2.30, it is a knowledge-based and rule-based algorithm that involves fuzzification and defuzzification [125]. It deals with problems that conventional

analytic formulae have been unable to resolve efficiently [126]. It equally manages imprecise and unclear information for non-linear measurements [127] and resolves the nonuniformities of ambient irradiance and temperature levels that hill-climbing techniques fail to handle [127, 128, 129]. It is employed in solar energy harvesting systems to deal with the non-uniformities of ambient irradiance and temperature levels to track the maximum power that hill-climbing techniques relatively failed to resolve [127, 128, 129]. Fuzzy logic controllers have been utilized in solar energy harvesting systems [130, 131, 132] and are observed to exhibit flexibility and simplicity. However, the FLC technique requires a personal computer or the integration of microcontrollers and digital signal processors [133]. This involves several subsystems, rendering the technique unsuitable or uneconomical for remote nodes. Furthermore, stability is uncertain due to its trial-and-error approach for optimization [134], resulting in ambiguities and divergences.

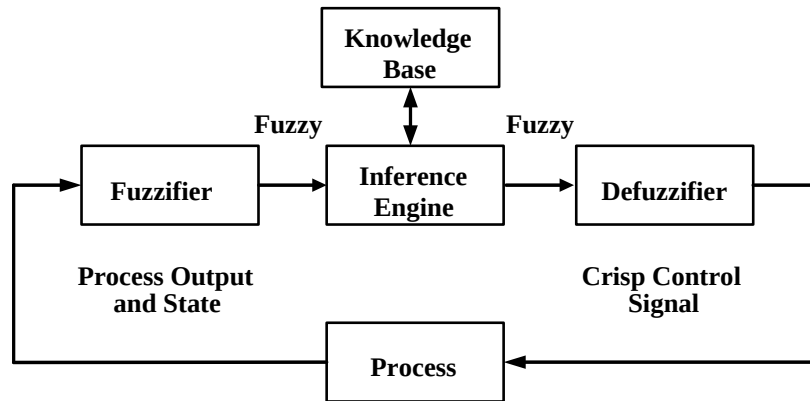


Figure 2.30: Block Diagram of Fuzzy Logic Controller.

2.4.5 ANN ALGORITHM

To resolve the limitations of the P and O and incremental conductance algorithms, a neural network algorithm is employed to predict the MPPs of voltage and current measurements using ambient irradiance and temperature [135]. Moreover, these input parameters can be used to predict duty cycles and achieve possible MPPs [136]. The ANN algorithm is an intelligently regulated technique similar to the FLC [103]. It is one of the popular algorithms and has been employed by the studies in [107, 108, 137]. The ANN algorithm is based on the nervous system and human brain. The training process of neurons (nodes in the network) and the processing units are interconnected. Historical data are used for training through a learning algorithm to deal with specific tasks, and experience is acquired to predict outputs based on input patterns. In the technique, predictions are evaluated by a validation step. A properly trained ANN algorithm provides relatively accurate predictions [138]. The ANN

algorithm has been effectively employed to solve complex problems. The node accepts the input variable, processes it with a transfer function and then passes it to another node. Numerous layers of these nodes have forward connections to other nodes. The layers are categorized as input, output, and hidden, as shown in Figure 2.31. In this figure, each node receives input signals related to a set of weights and produces an output. This output is a function that involves the weighting of input levels. These input levels and bias are added and then processed by a transfer function employed by the network.

In this study, PV modules are considered. They are non-linear in nature and deal with a set of ambient irradiance and temperature variables. They also handle a set of I_{sc} values or a set of V_{oc} values or both as input variables for the node [139, 140]. In contrast, the expected output variables of the algorithm may be duty cycles, current, or voltage levels to continue operating at the MPPs of the solar energy harvesting system [140]. In Figure 2.31, wI_j represents an adaptive weighted signal, which matches j as the node and I as the input signal level; $S1$ indicates the number of nodes. Hence, the expected output current (I_{MAX}) and voltage (V_{MAX}) levels that employ a transfer function, j , in the network's hidden layer can be expressed by Eqs. (2.20) and (2.21), respectively. Figure 2.32 [141] shows a feed-forward multi-layer neural network with an output from one layer of a node that is fed forward to the next layer of nodes and transfer function, $F(y)$. The weights (w_i) are summed up to an activation value of y according to the number of input signals (n). Then, the transfer function converts the sum into an output.

$$I_{MAX}^1 = w_{2_{10}} + w_{2_{11}}z_1 + w_{2_{12}}z_2 + \dots + w_{2_{1S1}} = \sum_{j=0}^{S1} w_{2_{1j}}z_j \quad (2.20)$$

$$V_{MAX}^1 = w_{2_{20}} + w_{2_{21}}z_1 + w_{2_{22}}z_2 + \dots + w_{2_{2S1}} = \sum_{j=0}^{S1} w_{2_{2j}}z_j \quad (2.21)$$

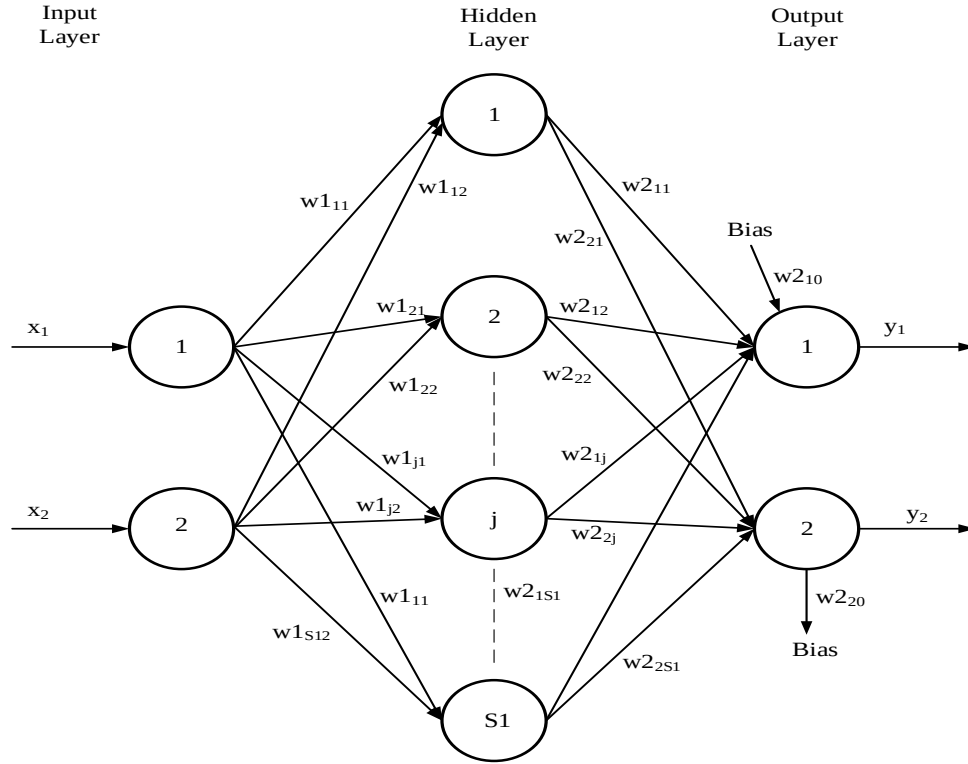


Figure 2.31: Artificial Neural Network Algorithm Connections.

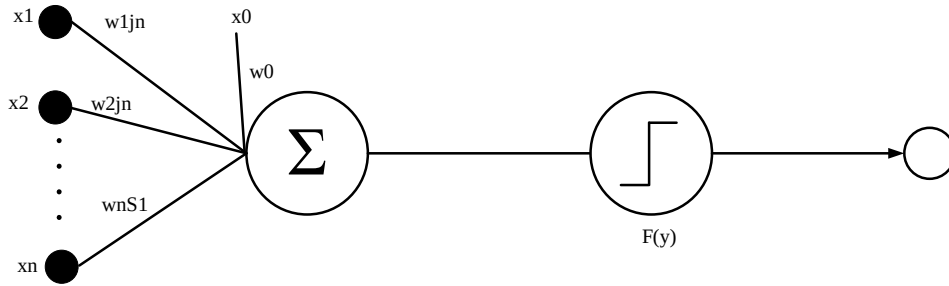


Figure 2.32: Feed-Forward Multi-layer ANN Structure.

The output nodes yield results after the nodes in the hidden layer acquire signal levels from input nodes. The log-sigmoid transfer function in the hidden layer uses the back-propagation neural network for back-propagating the errors. The Levenberg–Marquardt back propagation algorithm is employed for the learning processes and updating the weights for the learning algorithm. This back-propagation method is a trade-off between gradient descent and Gauss–Newton algorithms. It optimally alternates between the two to deliver optimal time and convergence speed with the least possible errors in the fastest time [142]. Suppose that the resulting pattern between the set of ambient irradiance and temperature levels with a set of I_{MAX} and V_{MAX} values of the neural network are stored and trained. In this case, the model can routinely predict the maximum operating points. The ANN algorithm requires suitable historical data to drive its operations, whereas in the FLC control,

adequate knowledge is a prerequisite. The FLC is sensitive and requires attention and strict monitoring [143, 144, 145]. Hence, it is unsuitable for remote deployments, such as remote seismic nodes. The neural network technique has been proven capable of compensating for highly non-linear and uncertain systems as well as exhibiting superiority over other algorithms. The neural network technique provides satisfactory tracking speed, does not produce oscillations near maximum operating points, and has relatively high reliability under varying solar module input levels [146].

The neural network algorithm has been demonstrated capable of handling arithmetic and logic functions [147], reliably learning the relationship between input and output vectors, [148], and performing self-error correlation without external interventions [149]. Most recently, neural network models have been employed to formulate numerous non-linear and solar irradiance estimation applications and have been found to perform well [150]. However, the model must learn and continue to learn the different historical datasets of various PV modules employed [107, 151]. This is because most modules are characterized by different inherent parameters and change with time. Hence, the model requires numerous functions and computational processes to attain its target. Because these cannot be handled by low-power microcontrollers, high-power microcontrollers are necessary, thus increasing cost.

2.4.6 LOOKUP TABLE MPPT TECHNIQUE

The lookup table approach is an indirect technique that uses the functional data of other algorithms and enables processes to run faster [152] as an approximation function. It yields relatively accurate results under varying ambient irradiance and temperature levels [153] and achieves targets with fair accuracy [96]. It is the simplest among the techniques; however, it can reduce the computational cost of math-intensive calculations [154]. The author of [155] used a lookup table to track the MPPs by employing a field-programmable gate array (FPGA) to provide the duty cycle levels. In the FPGA implementation, the processes have relatively high energy consumptions, slower and more complex designs for increasing sizes, and timing delays [156].

In the solar energy harvesting system, the inputs are ambient irradiance and temperature values, and the target outputs are duty cycles. All of these have been transformed, precomputed, and stored in the lookup table. It is a relatively fast method for directly determining the duty cycle across the DC–DC converter. The novelty of this technique lies in utilizing the neural network algorithm to transform the contents of the lookup table

because no known MPPT-based DC–DC converter has implemented it at remote nodes. This study resolves the gap by adopting the neural network technique and employing the previous processes discussed to generate, transform, and use these variables to populate the lookup table. The characteristics of the PV module are identified, and various irradiance measurements for duty cycles are correlated and stored. The table expedites the attainment of targets by precomputing and storing function outputs. Hence, it avoids complex calculations and long processes, replacing them with inexpensive memory and less mathematical computations.

2.5 CONCLUSIONS

This chapter describes the solar cell and PV module parameters and their extraction as well as modeling using MATLAB, PSIM, and Simulink software. Their values conform with the experimental results of the PV-controlled computer system. The PV module is the best energy-harvesting transducer option; its output voltage is a DC signal, and its energy source is relatively abundant. An equally synchronous buck DC–DC converter was developed and demonstrated in the PSIM environment. The converter is capable of analyzing its waveforms at a steady state. It can suitably interface with the hybrid energy storage due to its efficiency and is the key to the formulation of an optimal solar energy harvesting system.

CHAPTER 3 OPTIMIZATION OF SOLAR ENERGY HARVESTING SYSTEM AT REMOTE SEISMIC NODE

3.1 INTRODUCTION

Although MPPT approaches have been employed for several applications in solar energy harvesting systems, the transfer of possible maximum power levels from the PV module across the electrical load and energy storage in solar energy harvesting systems has remained problematic, particularly at remote seismic nodes. These approaches differ in modeling, implementation, popularity, complexity, and most importantly, efficiency [102, 104, 105, 107, 157]. However, these methods either have highly accurate computational processes or relatively low efficiency with simple implementation. Table 3.1 summarizes the approaches, characteristics, and applications.

Table 3.1: Comparison of Various MPPT Algorithms

Type of MPPT Algorithm	PV Module Applicable	Approach in tracking MPP Values [96]	Oscillations at MPP	Buck DC–DC Applicable	Convergence Speed	Implementation Complexity and inclusion of Microcontroller	Iteration or Computing Process	Remarks
Perturb and Observe	Yes	Direct	High	Yes	Slow	Low cost and simple microcontroller required	Periodically [88]	Generates oscillations, inaccurate under rapid input changing, and efficiency reduced
Incremental Conductance	Yes	Direct	Moderate	Yes	Moderate	Costly; complex; simple microcontroller required	Repeatedly [18]	Oscillations are reduced, and realization is complex
Fuzzy Logic Control	Yes	Soft Computing	None	Yes	Fast	Highly complex and requires high-power microcontroller	High Computational Processes [158, 159]	Involves intensive mathematical computations requiring high power microcontroller; not applicable to remote nodes
ANN	Yes	Soft Computing	None	Yes	Fast	Highly complex and requires high-power microcontroller	High Computational Processes [146]	Involves intensive mathematical computations requiring high-

Type of MPPT Algorithm	PV Module Applicable	Approach in tracking MPP Values [96]	Oscillations at MPP	Buck DC–DC Applicable	Convergence Speed	Implementation Complexity and inclusion of Microcontroller	Iteration or Computing Process	Remarks
								power microcontrollers; not applicable to remote nodes
Lookup Table Technique	Yes	Indirect	None	Yes	Fast	Requires simple microcontroller	Neither periodic nor computational process required	Widely used in numerous microcontroller applications with high efficiency; uses inexpensive and simple 8-bit microcontroller; capable of handling proposed approach.

A lookup table for an MPPT-based technique relies on the curve fitting functions of selected PV module parameters, irradiance, and temperature variables as input parameters to predict duty cycles. A novel MPPT technique for solar energy harvesting systems that differs from existing designs is proposed. The technique fills a research gap and logically predicts optimal duty cycles across a synchronous buck DC–DC converter. An LDR and a temperature sensor are utilized to vary according to ambient irradiance and temperature variables, respectively. Moreover, the variables are decoded into digits via an 8-bit microcontroller. A commercial irradiance meter and temperature sensor, which are built-in units in the EESFC computer-controlled PV system, are simultaneously calibrated with the LDR and temperature sensor. Data are created, and the relationship between the proposed and built-in sensors of the computer-controlled photovoltaic system is established. The data inputs are irradiance and temperature variables, and the outputs are duty cycle levels. In contrast, the ANN model transforms the input and output relationship. The neural network model is used to offset the non-linear responses of the LDR. It trains the training dataset through iterations with multiple epochs using a back-propagation algorithm to examine the error function in weight space. The dataset predicted by the neural network model is used to populate the lookup table for interpolation.

The maximum power transfer depends on both source and load impedances [160]. Figure 3.3 represents Thevenin's equivalent circuit of source R_S and load R_L impedances; maximum power is transferred when R_L is equal to R_S .

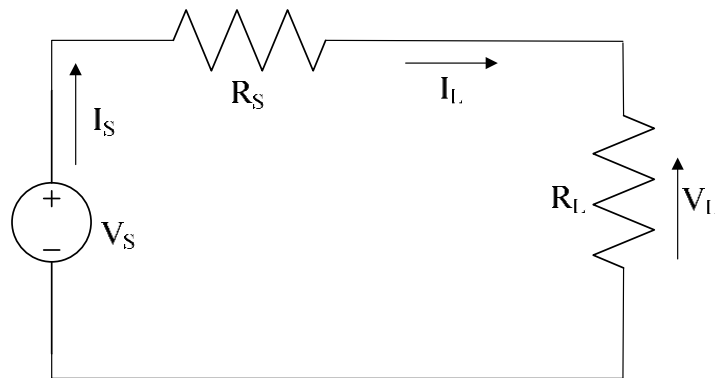


Figure 3.3: Basic Thevenin's Equivalent Circuit and Power Dissipation by Load Impedance.

Voltage Source	=	V_S
Voltage across the Load	=	V_L
Impedance at the Source	=	R_S

Impedance at the Load = R_L
 Load Current = I_L
 By Ohm's Law
 Source Current = I_S

$$I_S = \frac{V_S}{R_L + R_S} \quad (3.1)$$

The power dissipated by load impedance is defined as follows.

$$\begin{aligned} P_L &= I_S^2 * R_L \\ &= \left(\frac{V}{R_S + R_L} \right) * \left(\frac{V}{R_S + R_L} \right) * R_L \\ &= \frac{V^2}{\frac{R_S^2}{(R_L + 2R_S + R_L)}} \end{aligned} \quad (3.2)$$

Differentiation of the denominator of Eq. (3.2) results in the following.

$$\frac{\partial}{\partial R_L} \left(\frac{R_S^2}{R_L + 2R_S + R_L} \right) = - \frac{R_S^2}{R_S^2} + 1$$

To obtain the minimum or maximum value, the first derivative is equated to zero, yielding the following.

$$\frac{R_S^2}{R_L^2} = 1$$

and

$$R_S = \pm R_L \quad (3.3)$$

In the real world, impedance is positive. Hence, Eq. (3.3) is as follows.

$$R_S = R_L \quad (3.4)$$

The foregoing implies that when the ambient energy is harvested by an energy transducer, maximum power is transferred when the impedances of the transducer and power converter are the same. In an energy harvesting system, to extract maximum power, the MPPT algorithm is implemented to match the impedances of the energy transducer and power converter. Figure 3.4 presents the block diagram of the approach where the neural network model generates an accurate dataset for the lookup table.

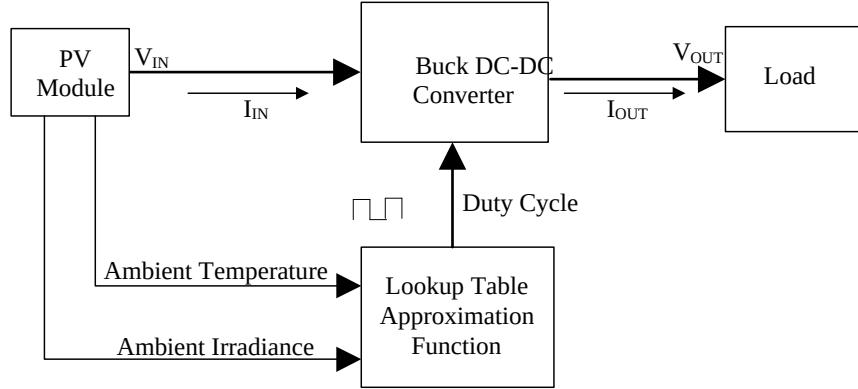


Figure 3.4: Block Diagram of Buck DC–DC Converter controlled by Lookup Table.

3.2 MODELING OF DC–DC CONVERTER IN PSIM

The electrical energy delivered by the conventional DC–DC converter is relatively low and uneconomical due to ambient irradiance and temperature changes as well as the non-linear nature of the energy transducer used. Similar to a solar cell, an energy transducer offers only one maximum power operating point at a time, and this point can be tracked by a controller with the MPPT algorithm. Because the device is a DC–DC converter, the mismatch between the power source and load increases the cost, space, and inefficiency. To overcome this challenge, providing a controller in the form of an MPPT algorithm between the source and load is necessary for matching the impedances. Consequently, maximum power is achieved and transferred by applying a duty cycle to drive the PWM of the DC–DC converter.

3.2.1 CALCULATION OF DUTY CYCLE

The computation of duty cycle levels is based on the assumption that the converter is at a steady state, as shown in Figure 2.21. The integral of the voltage across the inductor, V_L , from zero to the period, T , as well as considering the on and off states, is given by Eq. (3.5); the areas under the on and off states are the same. In contrast, the duty cycle (D) expressed by Eq. (3.7) shows that the output voltage changes linearly with D irrespective of the change in any other element in the buck converter.

$$\int_0^T V_L dt = \int_0^{t_{ON}} V_L dt + \int_{t_{ON}}^T V_L dt = 0 \quad (3.5)$$

$$(V_{IN} - V_O)t_{ON} = V_O(T - t_{on}) \quad (3.6)$$

The duty cycle can be defined as follows.

$$\frac{V_{ON}}{V_{IN}} = \frac{t_{ON}}{T} = D \quad (3.7)$$

3.2.2 CALCULATION OF INDUCTOR VALUE

The inductor is a key element in a buck DC–DC converter. It lowers the input voltage to the desired output and connects directly to the output. It controls, stores, and transfers energy from the source to the load according to the mode of the SW (either on or off). A higher inductance value leads to higher cost and space, requiring a smaller value of the capacitor. In contrast, a smaller inductance value causes the rise and fall of current. In this study, a MOSFET is employed as an SW for the buck converter. Moreover, the values listed in Table 3.2 are utilized to calculate the inductor value that typically in μH expressed by Eq. (3.8).

Table 3.2: Considerations of Buck Converter

Input Voltage, V_{IN}	21.9 V
Output Voltage, V_{OUT}	12 V
Switching Frequency, F_{SW}	10 000 Hz
Output Current, I_O	7.7 A
Load Current, I_{Load}	0.8 A
Inductor Ripple Current, I_R	1.47 A
Output Voltage Ripple, V_R	2.11 V

$$L = \frac{V_{OUT}(V_{IN}-V_{OUT})}{V_{IN}*F_{SW}*I_R} \quad (3.8)$$

$$L = \frac{12 (21.9-12)}{21.9*10000*1.47}$$

$$= 369 \mu H$$

3.2.3 CALCULATION OF CAPACITOR VALUE

In a buck converter, the capacitor and inductor form a low-pass filter, and the corner frequency is computed at a low frequency to minimize switching ripples. Similar to the inductor, the output capacitor, C_{OUT} , typically in μF is expressed by Eq. (3.9) as a key element of the converter; however, it stores its energy in the form of an electric field. It is assumed to produce a considerable output voltage, V_o .

$$C_{OUT} = \frac{1}{8*L*F_{SW}^2*V_R} * V_{OUT} = \frac{1}{8 * 369 * 10^{-6} * 10000^2 * 2.11} = 1.6054 \mu F \quad (3.9)$$

3.2.4 PULSE-WIDTH MODULATION

Figure 3.3 shows a direct-coupled DC–DC buck converter with the PWM designed in the PSIM environment. It consists of a 120-W PV module to energize a load, such as a remote seismic node. It is typically characterized by a 12-V terminal voltage and draws a 0.8-A current. In the PWM, the frequency is fixed, and the voltage output is varied according to the duty cycle level based on the carrier signal. The duty cycle is used across the DC–DC converter for a specific voltage output to be delivered, as shown in Figure 3.3. Due to the fixed frequency, noise levels can be filtered out. Figure 3.3 shows the regulation of the load voltage and battery.

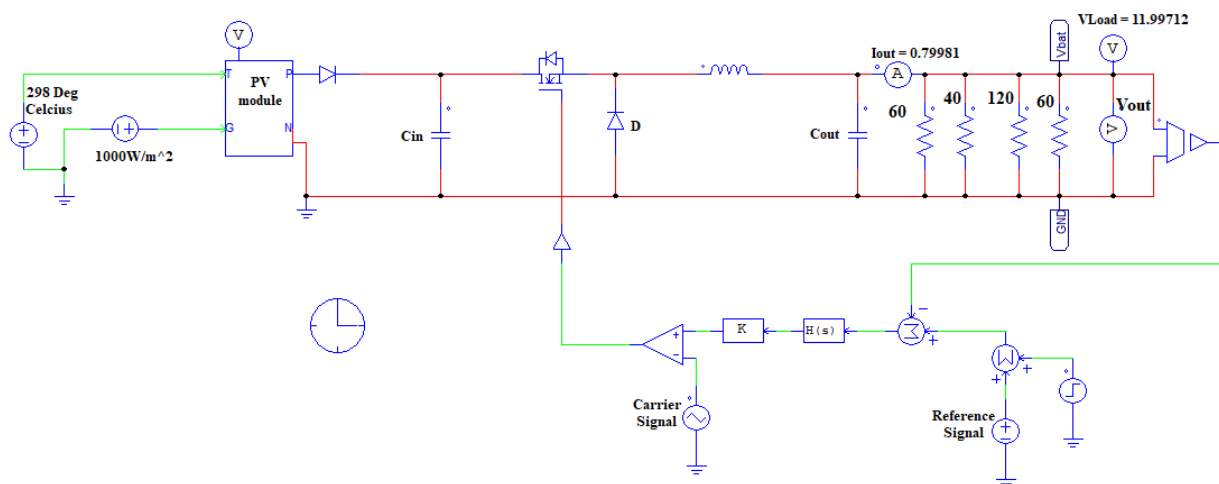


Figure 3.5: Direct Coupling of Buck Converter Design in PSIM to energize Remote Seismic Node.

Figure 3.6 shows the buck DC–DC converter with the P and O MPPT algorithm developed in C programming language in the PSIM environment to derive the possible maximum voltage, V_{MAX} , and current, I_{MAX} , values. It provides optimal duty cycles across the PWM to drive the DC–DC converter to track the relative maximum voltage and current levels from the PV module.

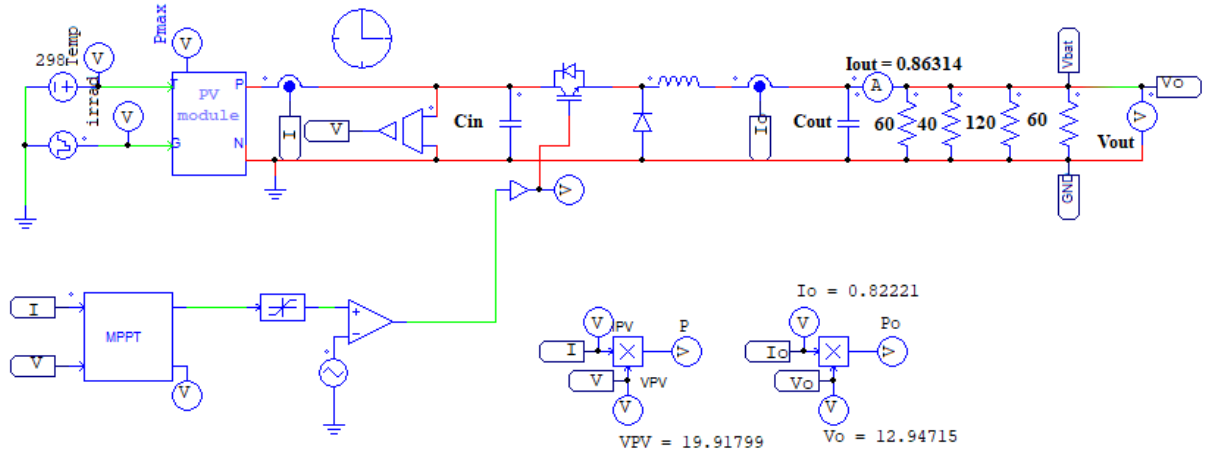


Figure 3.6: Buck Converter with P and O MPPT in PSIM.

3.3 ANN AS MPPT CONTROLLER

In this research, the ANN model is adopted to transform the irregularities exhibited by the inputs of the PV module. Additionally, the relationship between the PV module input and duty cycle levels to be used across the DC–DC converter is linearized and compensated for. Datasets are generated for the input and output levels, which are used to populate the lookup table. The model utilizes a feed-forward neural network of multilayers in nature and the Levenberg–Marquardt back-propagation algorithm to train the layers using ambient irradiance and temperature variations as input data and duty cycle as output. To improve the accuracy of predictions, a log-sigmoid transfer function is applied to the hidden layer of the model. In this study, the neural network consists of two input layers of ambient irradiance and temperature measurements, two hidden layers, one output layer consisting of duty cycle measurements, and 10 neurons for the input and output layers (Figure 3.7).

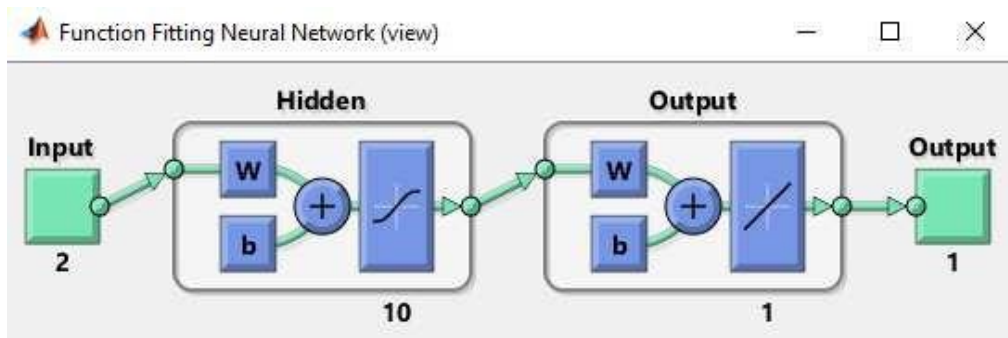


Figure 3.7: ANN Model Training.

The neural network model provides a strong relationship between input and output, enabling the close connection between measured and predicted values.

3.4 LOOKUP TABLE-BASED MPPT MODEL

In this work, a lookup table is interfaced with the LDR to track the possible maximum operating points from the PV module and deliver optimal performance. The precomputed ambient irradiance and temperature observations are simultaneously compared in the lookup table using an algorithm. A selected LDR is calibrated with an irradiance meter attached to the physical parameters in the EESFC computer-controlled PV system to mimic the irradiance meter and react to different irradiance levels. The design yields outputs via an 8-bit microcontroller through an analog input port driven by the lookup table to decode different irradiance values into digits. The lookup table content, consisting of different ambient irradiance and duty cycle levels, is derived from the ANN model. The training data of the neural network model is generated by an experimental unit of EESFC computer-controlled PV system. The lookup table assigns a reference duty cycle to different ambient irradiance levels without high-power computations across the PWM to drive the synchronous buck DC–DC converter.

3.4.1 LDR AS IRRADIANCE METER

Due to the high cost of an irradiance meter to measure ambient irradiance levels and the low funding of seismic node deployment, an LDR is necessary. Moreover, for simplicity, this study adopts a simple LDR sensor and optimizes its constraints to create a new design by establishing a correlation between LDR and V_{LDR} using the regression-based neural network model. The LDR exhibits the change in resistance as a function of ambient irradiance, and resistance decreases with the increase in irradiance. The ambient irradiance levels vary the output levels of the LDR.

Figure 3.8 shows the LDR connection circuit in the Proteus environment that detects irradiance levels. Irradiance measurements and their output levels are obtained and used in populating Table 3.3. The relationship between ambient irradiance hitting the LDR and its output voltage is shown in Figure 3.9, and can be approximated by the expression in Eq. 3.10. The measurements derived, indicating that the voltage across the LDR (V_{LDR}) decreases with the rise in the irradiance level (expressed by Eq. (3.10)) and exhibits non-linearity. The LDR exhibits internal non-linear characteristics, and the function can be represented with a logarithm function to

demonstrate linearity [161]. Figure 3.10 represents the variation between ambient irradiance and output voltage levels of the LDR in logarithmic form. The measurements listed in Table 3.3 are computed and plotted again, taking the form of a linear plot, as expressed by Eq. (3.11), where m represents the slope, and c denotes the y-axis intercept of the line as constants. In contrast, y is an output variable based on the change in x . In the study, a temperature sensor, LM35, is employed to detect ambient temperature levels. It exhibits a linear relationship between temperature and terminal output variables, as expressed by Eq. (3.12). Variable V_{TP} is the voltage output level of the sensor that varies with the difference between the ambient ($T_{Ambient}$) and reference (T_{Ref}) temperature levels; the constant reference voltage, V_{REF} , is the voltage measurement at the reference temperature (in °C). Among the PV module characteristics, β is the coefficient of the V_{OC} of the module depending on the irradiance and temperature levels. It is a factor responsible for the non-linear temperature voltage relationship. Based on Eq. (3.10) and Figures 3.9 and 3.10, the irradiance observations are sensitive to the V_{LDR} measurements.

$$V_{LDR} = \frac{R_{LDR}}{R_{LDR} + 10000} * V_{CC} \quad (3.10)$$

$$y = m * x + c \quad (3.11)$$

$$V_{TP} = \beta * (T_{Ambient} - T_{Ref}) + V_{REF} \quad (3.12)$$

The power, P_O , generated by the solar energy harvesting system is mainly influenced by the parameters given in Eq. (3.13) [162]. The parameters are ambient irradiance, $G_{Ambient}$; PV module size, M_{SIZE} ; and energy conversion rate, E_{RATE} (E_{RATE} depends on the type of DC–DC converter employed), given by Eq. (3.14) [163]. Note that η_{DC-DC} and η_M are the DC–DC converter and PV module efficiencies, respectively.

$$P_O = E_{RATE} * M_{SIZE} * G_{Ambient} \quad (3.13)$$

$$E_{RATE} = \eta_{DC-DC} * \eta_M * (1 - \beta(T_{Ambient} - T_{Ref})) \quad (3.14)$$

Table 3.3: LDR Connection Circuit Measurements

Irradiance (Wm^{-2})	V_{LDR} (V)	Log Irradiance (W/m^2)	Log V_{LDR} (V)
10	3.19	1	0.503791
100	0.98	2	-0.00877
200	0.59	2.30103	-0.22915
300	0.44	2.477121	-0.35655
400	0.35	2.60206	-0.45593
500	0.29	2.69897	-0.5376
600	0.25	2.778151	-0.60206
700	0.22	2.845098	-0.65758
800	0.2	2.90309	-0.69897
900	0.18	2.954243	-0.74473
1000	0.16	3	-0.79588

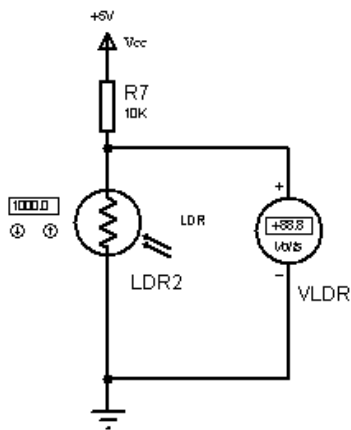


Figure 3.8: LDR Connection Circuit.

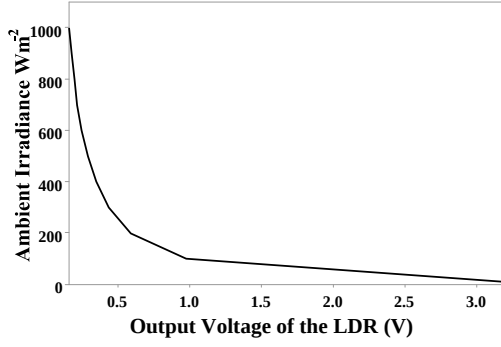


Figure 3.9: Relationship between Irradiance and V_{LDR} .

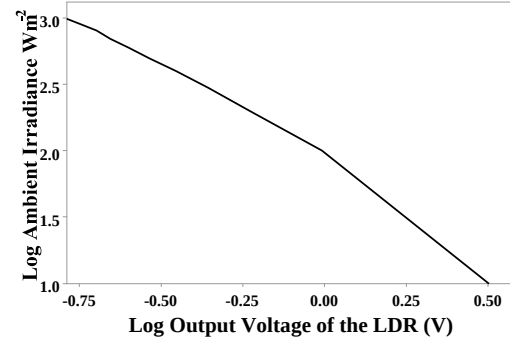


Figure 3.10: Relationship between Log Irradiance and Log V_L .

Based on Table 2.1, the PV module maximum current, I_{MAX} , is attained at 25 °C, the temperature coefficient of I_{SC} is α (0.0023 A/°C), and the V_{OC} coefficient is β (−0.00127 V/°C). Thus, by considering this selected PV module and testing the curve fitting equation versus the real data of the PV module in the experimental setup, Eq. (3.15) can be rewritten as Eq. (3.16).

$$V_{MPP} = \beta(T_{Ambient} - T_{MPP}) + V_{25} \quad (3.15)$$

$$V_{MPP} = -0.00127(T_{Ambient} - 25) + 17.2 \quad (3.16)$$

The principles involved in the generation of current I_{PV} from the solar cell are discussed in Section 2.2.2 with reference to Figure 2.4 and Eq. (2.2). Current I_{PV} is a function of the ambient irradiance ($G_{Ambient}$), reference irradiance (G_{Ref}), ambient temperature ($T_{Ambient}$), and reference temperature (T_{MAX}). Based on Eq. (2.2), I_{PV} can be defined in the relationship among the parameters in Eq. (3.17), where I_{MAX} is the maximum current generated at particular ambient irradiance and temperature. In contrast, $I_{MAX, Ref}$ represents the maximum generated current at the reference temperature (in °C). The I_{SC} temperature coefficient (α) is a factor responsible for the non-linear temperature–current relationship; it is provided by the PV module vendor.

$$I_{MAX} = (\alpha * (T_{Ambient} - T_{MAX}) + I_{max,Ref}) * \frac{G_{Ambient}}{G_{Ref}} \quad (3.17)$$

$$I_{MAX} = (0.0023 * (T_{Ambient} - 25) + 7) * \frac{G_{Ambient}}{1000} \quad (3.18)$$

The relationships of the PV module parameters are given by Eqs. (3.16) and (3.18), where −0.00127 and 0.0023 are the gradients for generating V_{MAX} and I_{MAX} , respectively; their intercepts are 17.2 V and 7 A for V_{MAX} and I_{MAX} , respectively. The mathematical models of this selected PV module are included in the algorithm to predict both I_{MAX} and V_{MAX} and then the duty cycle across the PWM to drive the DC–DC converter.

DATA BY 3.4.2 TRANSFORMED ANN FOR LOOKUP TABLE

A total of 1098 samples of irradiance and temperature levels were obtained as input dataset and duty cycle for the output from the experimental setup of EESFC computer-controlled PV system.

The PV module characteristics are 120 W, 21.9 V (as V_{OC}), and 7.7 A (as I_{SC}). Table 3.4 summarizes the characteristics of an ANN model. The feed-forward neural network (multilayer in nature) and the Levenberg–Marquardt back-propagation algorithm are used to train the layer of the ambient irradiance. A log-sigmoid transfer function is applied to a hidden layer of the model to improve prediction. In this work, the neural network consists of an input layer of ambient irradiance and temperature measurements, two hidden layers, and one duty cycle output layer.

Table 3.4: ANN Model Characteristics

Transfer Function for Hidden Layers	Log-Sigmoid
Training Algorithm	Levenberg–Marquardt Back-propagation
Type of Neural Network	Feed-forward
Performance Index	MSE
Number of Hidden Neurons	10
Number of Samples	1098

In this research, 10 neurons for the input and output layers containing 1098 samples and the command “nftool” are used to execute the neural network algorithm. The model consists of 10 neurons, and a log-sigmoid transfer function is employed; the development of the model is shown in Figure 3.11. The Levenberg–Marquardt back-propagation algorithm is employed to engage the “nntrain” tool for updating the weight and bias values in agreement with the algorithm in the MATLAB environment. This algorithm improves the close link between irradiance and duty cycle levels, as shown in the neural network training in Figure 3.11. The samples are apportioned into 70 %, 15 %, and 15 % for training, validation, and testing, respectively.

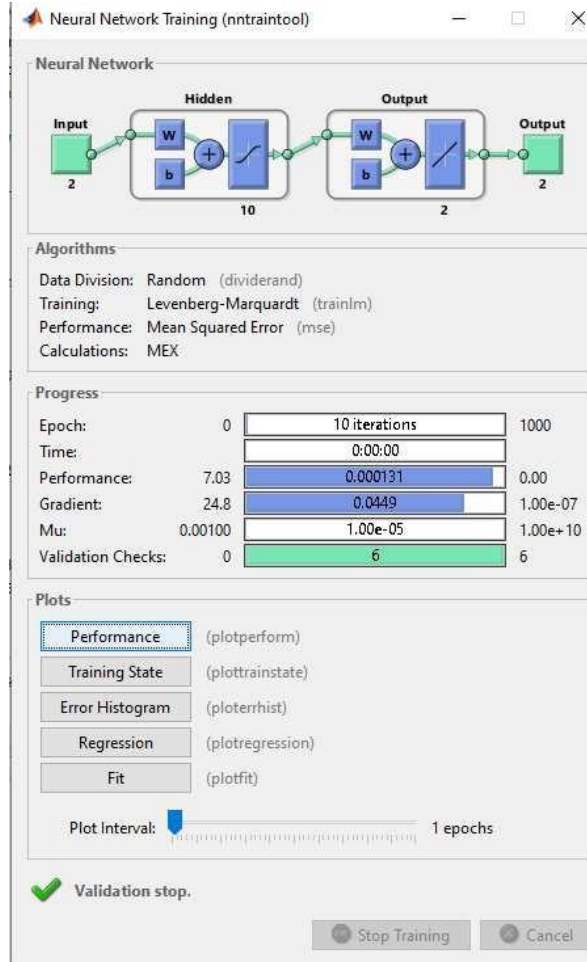


Figure 3.11: Neural Network Training.

The relatively small mean square error (MSE) value justifies the high precision and stable nature of predicting the duty cycle levels as outputs [164]. The root mean square error (RMSE) shows the deviation of measured values from the predicted values; it is the square root of MSE used for determining the accuracy of the model. These two parameters of the neural network training are used to evaluate the results. The neural network algorithm repeatedly performs training until the performance index (given by Eq. (3.19)), which is the squared difference of measured and predicted values, approaches zero.

$$\begin{aligned}
 MSE &= \frac{1}{N} \sum_{i=1}^n (\text{Measured Values} - \text{Predicted Values})^2 \\
 &= \frac{1}{N} \sum_{i=1}^n (x_i - y_i)^2
 \end{aligned} \tag{3.19}$$

n = Number of Iterations

N = Total number of Measured Values

x = *Measured Value*

Y = Predicted Value

The RMSE is the square root of MSE, as given by Eq. (3.20). It determines the deviation between the values predicted by the model and measurements, expressing the fidelity of the regression model. In the regression model technique, the predicted measurements differ from the observed measurements with prediction errors or residuals.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^n (x_i - y_i)^2} \quad (3.20)$$

3.5 CONCLUSIONS

This chapter provides an overview of available MPPT approaches to power a remote seismic node. The drawbacks and advantages were highlighted. The principle of employing the MPPT algorithm was demonstrated in PSIM using the P and O algorithm in the buck DC–DC converter. A gap converter was discovered in the use of the lookup table by interpolation to predict the duty cycles across synchronous DC–DC. The technique is based on the dataset acquired from the experiment and stored in a memory. Then, when queried, a target output is issued. The ANN model was employed to generate transformed data for the lookup table. The modeling of curve fitting equations was also performed to measure the inputs of the lookup table via an 8-bit microcontroller. The use of the lookup table, LDR, and temperature sensor in solar energy harvesting systems without high computational processes and expensive sensors can be easily justified by the low cost of power solution at remote seismic nodes.

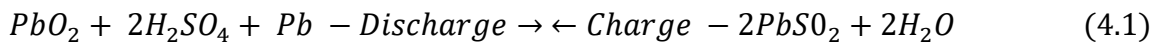
CHAPTER 4 HYBRID ENERGY STORAGE

4.1 INTRODUCTION

In the solar energy source, where ambient irradiance and temperature fluctuations are uncontrollable, the solar energy harvesting system at a remote seismic node requires energy storage for the continuity of its power source. As mentioned, a lead–acid battery, which is usually employed, is problematic and frequently fails because it has a low charging rate, resulting in a shorter lifecycle. In this study, a supercapacitor is combined with the lead–acid battery to facilitate battery charging and satisfy the electrical energy demand at a remote seismic node. In the solar energy harvesting system, various hybrid topologies of lead–acid battery and supercapacitor across loads are employed to optimally extract power from both energy storage types [165, 166, 167]. These topologies can deliver various output power levels during shaded and unshaded periods of ambient irradiance. The energy storage hybrid minimizes the routine cost and increases reliability because the two topologies are complementary.

4.2 LEAD–ACID BATTERY ENERGY STORAGE

A remote seismic node frequently relies on a lead–acid battery to supply continuous power. However, the battery exhibits a relatively short lifecycle and low power density characteristics. As an energy storage system in the solar energy harvesting system, the battery charges to store electrical energy from the DC–DC converter and discharges to deliver electrical energy across a load. The electrochemical charge–discharge processes are expressed by Eq. (4.1); the source voltage (V_{IN}) and output voltage (V_O) relationship is given by Eq. (4.2) [168], where R_{INT} is the internal resistance, and I_O is positive during charging and negative when discharging. The value of R_{INT} depends on the ambient temperature, amperage per hour, and charging and discharging rates of the battery.



$$V_O = V_{IN} \pm I_O * R_{INT} \quad (4.2)$$

The source voltage, V_{IN} , varies with the battery's state of charge (SOC), and the DC–DC converter is set between the PV module and node. It is implemented to ensure that the converter controls the electrical parameters of the PV module and node to achieve a high efficiency rate.

The considerations that determine the output parameters of lead–acid batteries comprise the SOC, terminal voltage, and current, as shown in Figure 4.1 [169]. The type of DC–DC converter controls the terminal voltage.

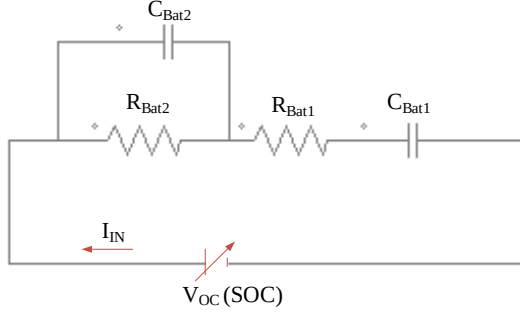


Figure 4.1. Basic RC Battery Model.

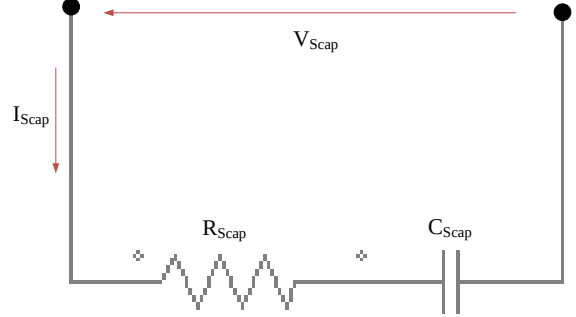


Figure 4.2. Basic RC Supercapacitor Model.

4.3 SUPERCAPACITOR ENERGY STORAGE

A supercapacitor provides benefits to a lead–acid battery in hybrid energy storage, such as improving the charging rate and prolonging the battery lifecycle. The electrical energy, E_{Scap} , stored in a supercapacitor is directly proportional to its capacitance, C and the stored charge Q in coulombs to the terminal voltage V_{Scap} across the supercapacitor is given in Eq. (4.3) [170]. While Eq. (4.4) [171] represents the electrical energy stored in the supercapacitor, E_{Scap} in joules. The terminal voltage, V_{Scap} , in Eq. (4.5) and Figure 4.2 [172] are the basic expressions of the RC supercapacitor. The charging and discharging efficiencies of the supercapacitor rely on the DC–DC converter employed in the solar energy harvesting system. Based on the specifications of the supercapacitor, five cells of 2.7 V and 10 F are connected in series to obtain 13.2 V as the terminal voltage. The output power of the supercapacitor, P_{Scap} , is influenced by its internal elements, particularly the equivalent series resistance (ESR), as expressed by the relationship in Eq. (4.6). Although the ESR limits power, maximum power can be obtained when matched with the load impedance.

$$Q = CV_{Scap} \quad (4.3)$$

$$E_{Scap} = \frac{1}{2} * C * V^2 \quad (4.4)$$

$$V_{Scap} = \sqrt{\frac{2 * E_{SCAP}}{C}} \quad (4.5)$$

$$P_{Scap} = \frac{V_O}{4 * ESR} \quad (4.6)$$

4.4 HYBRID OF LEAD-ACID BATTERY AND SUPERCAPACITOR

The extraction of pulse power shortens the lifecycle of a lead-acid battery and downgrades its terminal voltage [173, 174]. A supercapacitor effectively stores charges, and its negligible internal resistance [175] tends to stabilize the lead-acid battery.

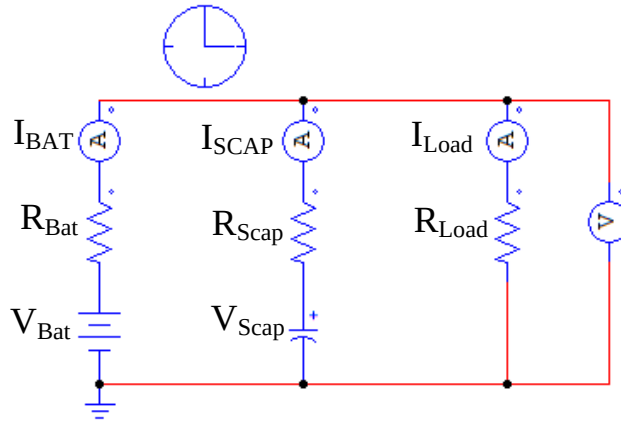


Figure 4.3: Direct Connection of Battery and Supercapacitor Model.

A buck converter tends to deliver more than 90 % energy conversion efficiency [176]. In this study, a synchronous buck DC-DC converter is adopted to control the current flow through the supercapacitor. The goal of the adopted DC-DC topology integrated into the hybrid energy storage of direct connection of the battery and supercapacitor as shown in Figure 4.3. This increases the overall current across the load as indicated in Figure 4.3, as well as improves the lifecycle and the mechanical stress of the battery.

Table 4.1 [177, 178] summarizes the comparison of essential parameters of these energy storage units and their performance. The energy losses are due to the internal resistance of the battery, whereas in the supercapacitor, the ESR is due to the nature of the electrolyte and charge/discharge currents [178]. Overall, the supercapacitor offers effective energy storage for a remote seismic node because of its low ESR, extended lifecycle, and relatively high density.

Table 4.1: Lead-acid Battery and Supercapacitor Parameter Performance

Parameter	Lead-acid Battery	Supercapacitor
Power Density ($\text{Wh}\cdot\text{kg}^{-1}$)	<1000	<10 000
Energy Density ($\text{Wh}\cdot\text{kg}^{-1}$)	10–100	1–10
Lifecycle	<1000	>500 000

Parameter	Lead–acid Battery	Supercapacitor
Charge/Discharge Efficiency (%)	70–85	85–98

With the proposed hybrid energy storage and referring to Table 4.2, a 120-W PV module and the P and O MPPT technique are used to regulate the output voltage levels. The proposed hybrid is simply based on the buffering nature of the supercapacitor to complement the lead–acid battery and optimize the benefits of each energy storage. Based on the energy conservation law, the energy balance depends on the ratio of the available energy from the source to the demand of elements that are ready to accept the available energy. In the case of under-demand (e.g., solar energy as energy source (E_{PV}) and E_{NODE} as node load), Eq. (4.7) holds. The wastage is due to the unexploited energy and ineffective energy conversion. However, in the case of overdemand from E_{PV} , the unexploited energy is consumed. For example, the hybrid energy storage (E_{HYB}) and the balance of energy takes the form of Eq. (4.8).

Table 4.2: Lead–acid Battery and Supercapacitor Parameters

Parameter	Lead–acid Battery	Supercapacitor
Nominal Voltage (V)	12	13
Capacitance (F)	Nil	10
Capacity (Ah)	200	Nil
Number of Cells in Series	6	5

$$E_{PV} = E_{NODE} + E_{UNEXP} + losses \quad (4.7)$$

$$E_{PV} = E_{NODE} + E_{HYB} + losses \quad (4.8)$$

The total current generated by the PV module is I_{PV} and shared to the current node (I_{NODE}), I_{BAT} , and I_{SCAP} . Equations (4.9) and (4.10) mathematically express the processes.

$$I_{PV} = I_{NODE} + I_{BAT} + I_{SCAP} + losses \quad (4.9)$$

$$V_{OC} = V_{BAT} + I_{BAT} * R_{INT} \quad (4.10)$$

$$I_{PV} = \frac{V_O}{R_{NODE}} + \frac{V_O}{R_{INT}} + C * \frac{dV_O}{dt} \quad (4.11)$$

The PV module and buck converter for charging the hybrid energy storage of lead–acid battery and supercapacitor are designed in PSIM, as shown in Figure 4.4. The simulation results of V_{PV} , V_{Load} (voltage across the load), I_{Load} (load current available for the lead–acid battery and

supercapacitor), and V_{Bat} (battery voltage) are shown in Figure 4.4. Figure 4.3 demonstrates the supercapacitor discharging voltage, available battery voltage, and comparison of individual terminal voltage values of the lead–acid battery. Figure 4.4 illustrates the designed circuit in PSIM, connecting the supercapacitor to the terminals of the lead–acid battery as well as the PV module and P and O MPPT integrated into the synchronous buck converter circuit to energize the node. In this study, the supercapacitor serves as buffer to the lead–acid battery, representing the hybrid of the two types of energy storage. This implies that additional electrical energy is available to sustain the load for a long time. Moreover, as shown in Figure 4.4, during that period, the voltage across the supercapacitor decreases, and the rate of decline depends on the capacity of the supercapacitor.

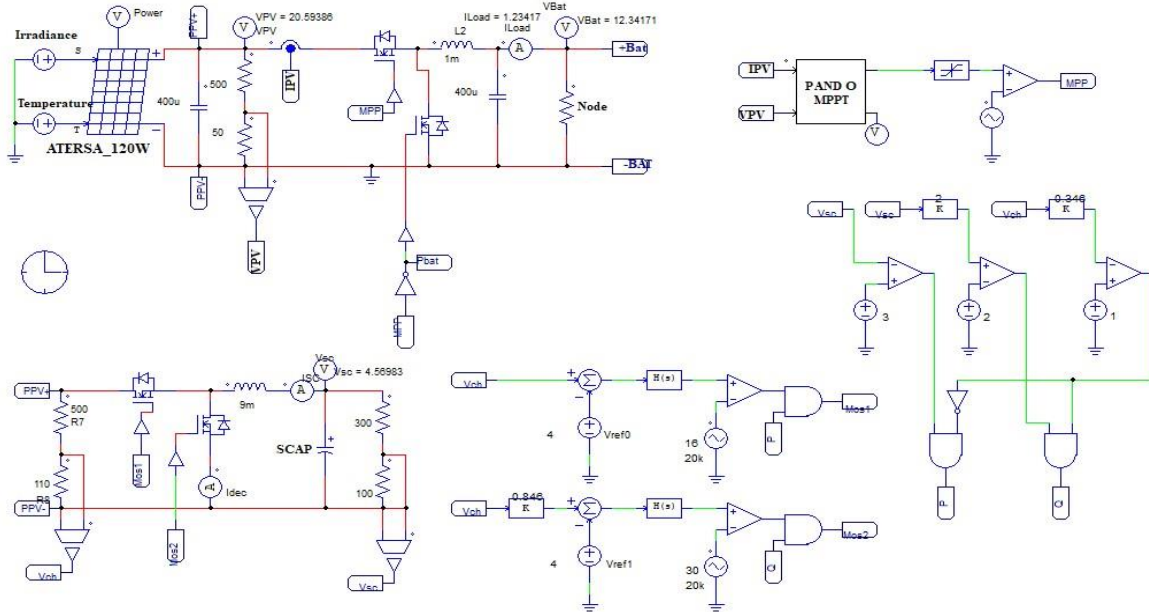


Figure 4.4: PV Module and Buck Converter for charging Hybrid Energy Storage of Lead–acid Battery and Supercapacitor.

4.5 PROPOSED HYBRID ENERGY STORAGE FOR REMOTE SEISMIC NODE

Excess ambient irradiance levels are harvested during the day, to enable sufficient electrical current, which enables continuous and reliable solar energy harvesting system at the remote seismic node. This aims to increase the available current at the load. The I_{PV} of the PV module in Figure 4.4 is exploited, and the possible maximum current is delivered across the lead-acid battery and supercapacitor as given in simulation results of Figure 4.5. Figure 4.5(a) represents current levels I_{Bat} and I_{Scap} delivered to the lead-acid battery and supercapacitor respectively, while Figure 4.5(b) demonstrates as output current against time, with higher current level at the node, by employing the circuit in Figure 4.4.

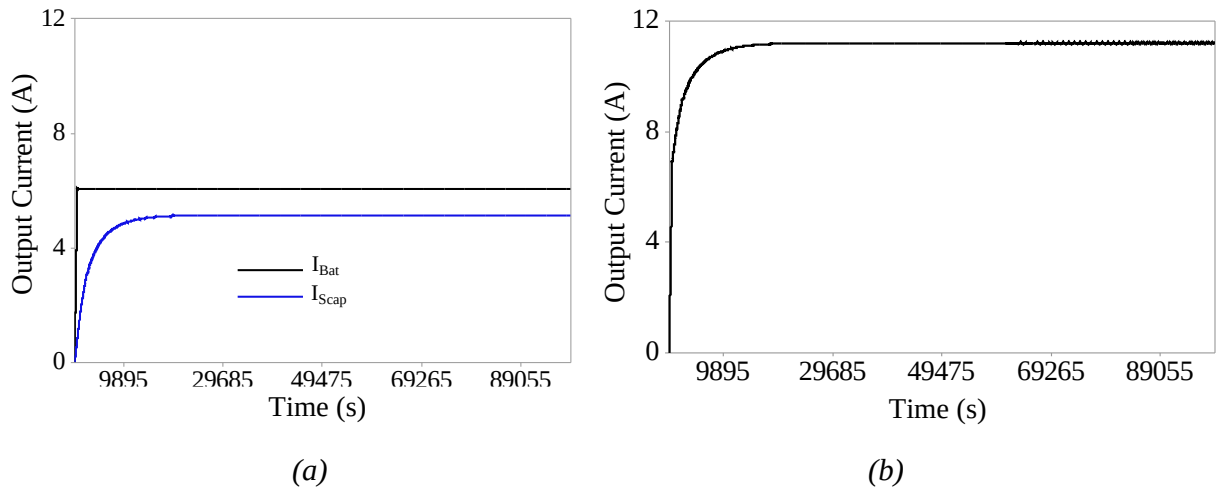


Figure 4.5: Simulated generated Current of (a) I_{Bat} and I_{Scap} (b) Hybrid of Lead-acid Battery and Supercapacitor.

4.6 CONCLUSIONS

This chapter provides an overview of the integration of the energy storage systems for powering the remote seismic node. The benefits of the supercapacitor are exploited, and the limitations of lead-acid battery are reduced to improve its lifecycle and supply continuous current flow to the load. The characteristics of the hybrid lead-acid battery and supercapacitor with synchronous buck DC-DC converter circuit in PSIM environment are designed and described. The hybrid energy storage is the secondary source solution for the remote seismic node. The inadequacies of a single secondary energy source that are inherent in lead-acid batteries render them inadequate. The inclusion of the supercapacitor to the solution enables the rapid replenishment of charges, and the lead-acid battery balances the average energy demand.

CHAPTER 5 RESULTS AND ANALYSIS

5.1 INTRODUCTION

In this chapter, the modeling outcomes of this study are tabulated, their simulations are plotted, and suitable comparisons are presented to observe the degree of consistency. The demonstrations of these models were performed under variable conditions and input parameters in the experimental setup, proposed validation, and MATLAB, Simulink, and PSIM programs. The main model, i.e., the PV module, has non-linear outcomes due to its internal and external parameters. The influences of these parameters are simulated under different approaches using varying irradiance and temperature levels. Moreover, a synchronous buck converter model consisting of MOSFETs, SWs, inductors, and capacitors is developed to deliver the desired voltage levels at the remote seismic node. An optimal solar energy harvesting system is characterized by its relatively maximum efficiency by continuously tracking the MPPs regardless of the PV module and load inputs. This is achieved by employing the MPPT technique to interface with the DC–DC converter to optimally transfer the PV power, $PPV = V_{MAX} * I_{MAX}$, across the remote seismic node and the hybrid energy storage shown in Figure 5.1.

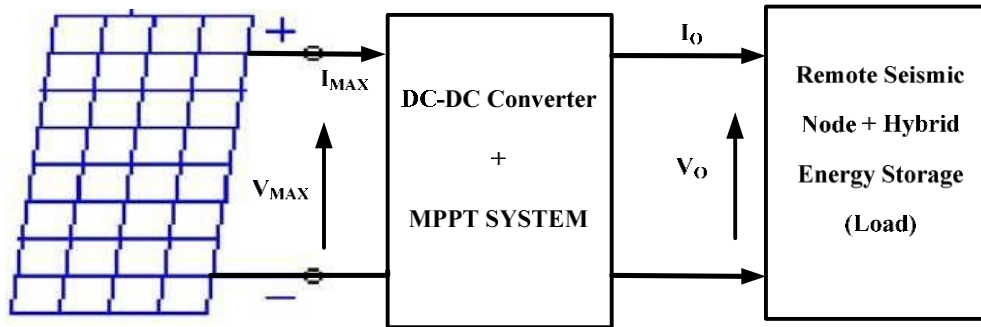


Figure 5.1: Block Diagram of Optimal Solar Energy Harvesting System.

By increasing or decreasing V_{MAX} , the optimal output power, $P_O = V_O * I_O$, and efficiency, η , of the optimal energy harvesting system is expressed by Eq. (5.1). In this study, signals from the PWM controls the converter and are analytically obtained based on Figure 2.25 and using Eq. (5.2) or (3.7). The sum of “SW On” and “SW Off” is the switching period of the MOSFET in Eq. (5.2), and the output voltage, V_O , can be controlled by the converter’s duty cycle levels.

$$\eta = \frac{V_O * I_O}{V_{MAX} * I_{MAX}} \quad (5.1)$$

$$D = \frac{V_O}{V_{MAX}} = \frac{SW \text{ On} + SW \text{ Off}}{SW \text{ Off}} \quad (5.2)$$

In the proposed method, a 120 W PV module is selected and used; its parameters are summarized in Table 2.1. The V_{MAX} values for the PV module are computed according to the flowchart shown in Figure 5.2. The flowchart is derived from the algorithm (coded in C), the code is formulated in Proteus for the microcontroller, and the flash memory of the microcontroller is used for the stored lookup table to feed the PWM of the converter. The PWM generates modulated signals to drive the synchronous buck converter, as shown in Figure 5.3.

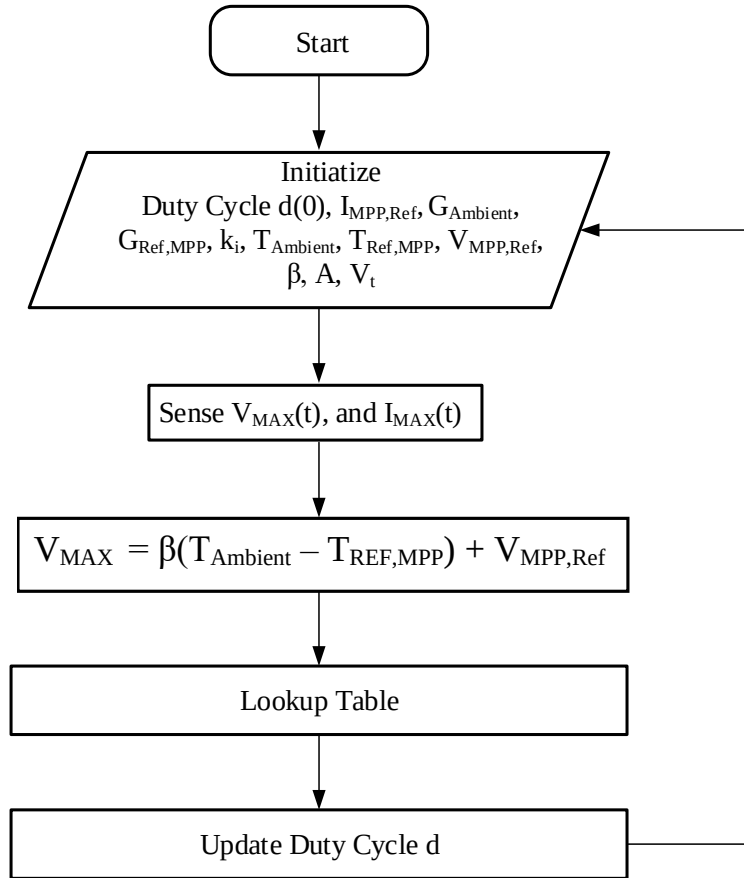


Figure 5.2: Flowchart of the Proposed Method.

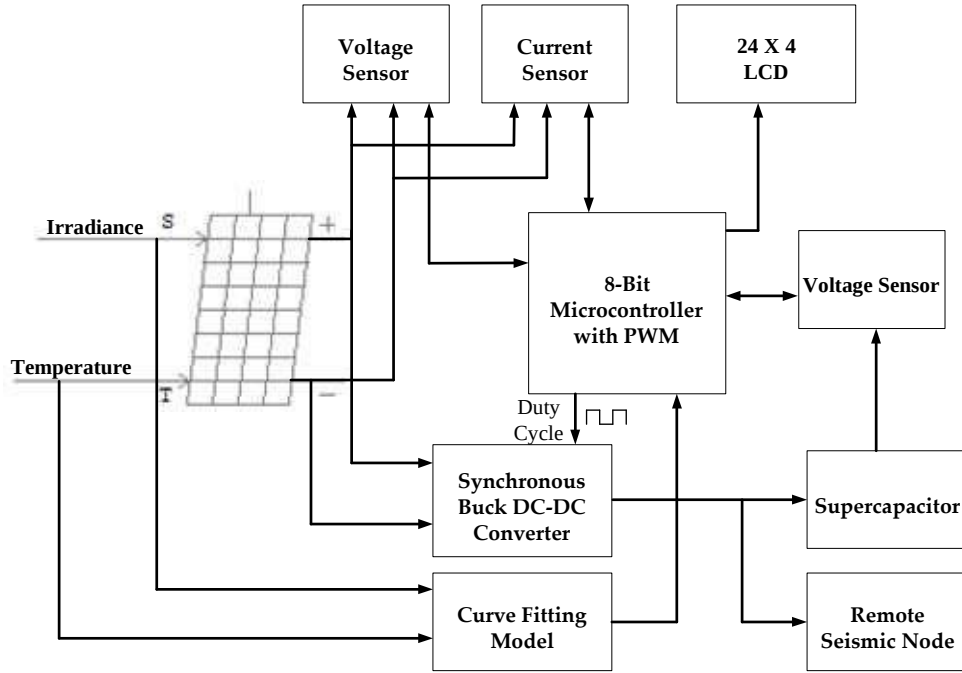


Figure 5.3: Schematic of Proposed System.

An experiment is set up to validate the proposed and PSIM models, as shown in Figure 5.4; the figure shows a computer-controlled PV system. The system power is 120 W and has a solar lamp with different solar irradiance levels ($70.162\text{--}663.048\text{ Wm}^{-2}$ at $25\text{ }^{\circ}\text{C}$). The PV module is characterized by the parameters listed in Table 2.1. The irradiance meter and temperature sensor are interfaced with a desktop computer to observe and acquire data, as shown in Figure 5.4. Current and voltage characteristic curves are also plotted. A built-in interface in the desktop computer is used to vary and control the input parameters and acquire the output variables.

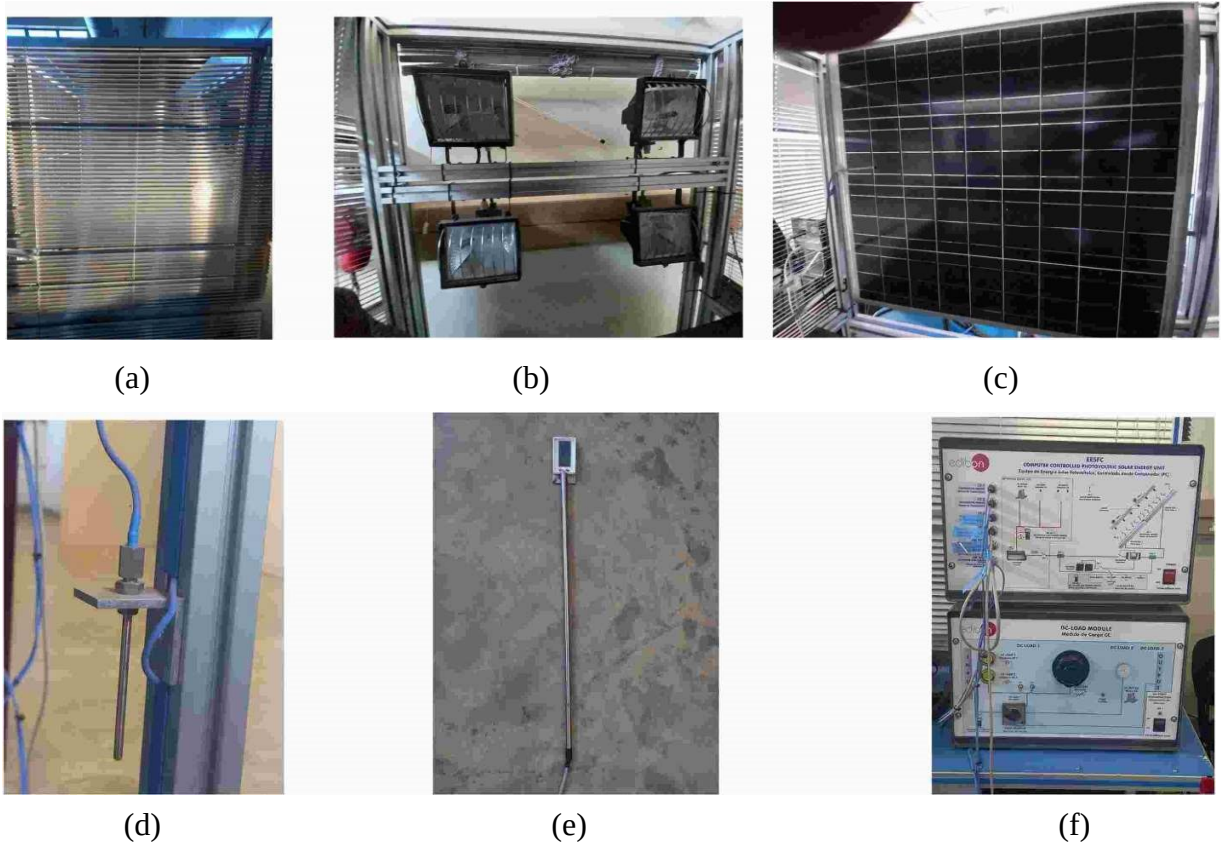


Figure 5.4: Experimental Setup: (a) Processing Cabinet, (b) Solar Lamp, (c) 120-W PV Module, (d) Ambient Temperature Sensor, (e) Irradiance Meter, and (f) DC–DC Converter.

Using the Simulink circuit shown in Figure 2.15, the real four-day ambient irradiance and temperature against hourly measurements at Palapye are simulated and plotted, as shown in Figure 5.5 and Figure 5.6, respectively. These indicate the relationship between the average hourly observations of the ambient irradiance and temperature measurements. The irradiance and temperature measurements, which are the input parameters of the PV module, are 0–630 Wm^{-2} and 18–32.8 $^{\circ}\text{C}$ for 4 days consecutively. Then, the generated current (I_{PV}), terminal voltage (V_{PV}), and generated power (P_{PV}) against hourly measurements of the PV module are simulated and plotted, as shown in Figures 5.7, 5.8, and 5.9, respectively. These are the amount of current, terminal voltage, and power generated by the 120-W PV module, which were observed hourly. The measurements were obtained in Simulink with the highest value of 4.8 A and 630 Wm^{-2} for the generated current and ambient irradiance values, respectively. The generated current has been confirmed to depend on irradiance values. Figure 2.21 clearly shows

that Palapye experiences an ambient irradiance level exceeding 400 Wm^{-2} during one-third of each day, implying that irradiance has sufficient potential.

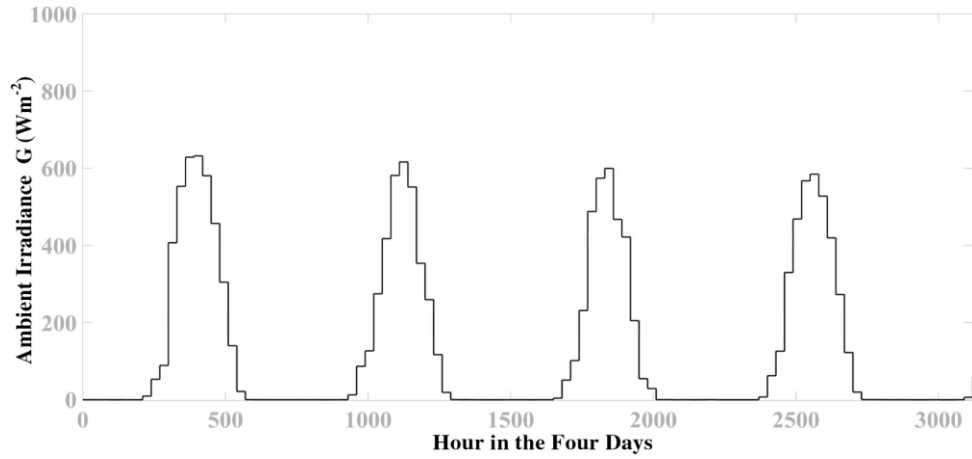


Figure 5.5: Four-day Ambient Irradiance Measurements at Palapye.

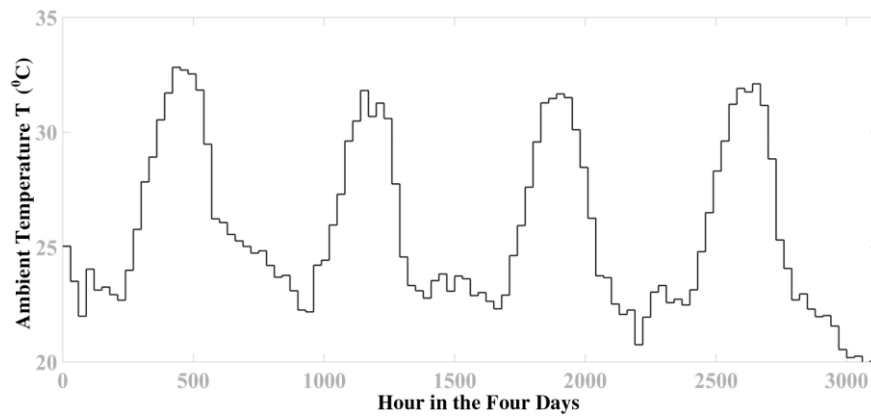


Figure 5.6: Four-day Ambient Temperature Measurements at Palapye.

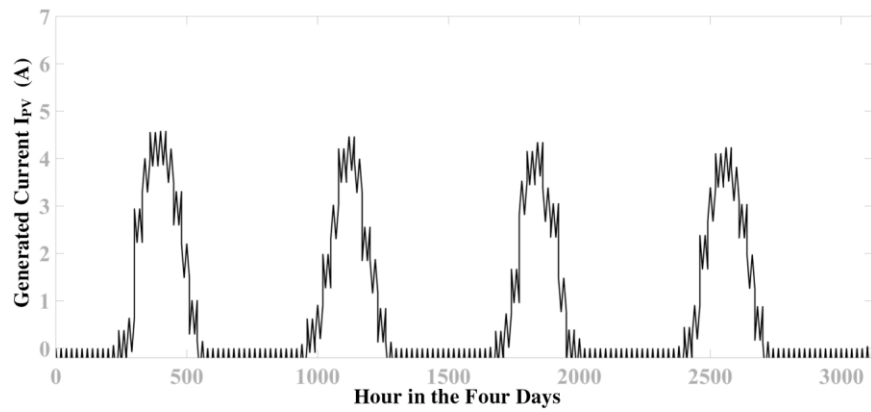


Figure 5.7: Generated Current (I_{PV}) from 120-W PV Module.

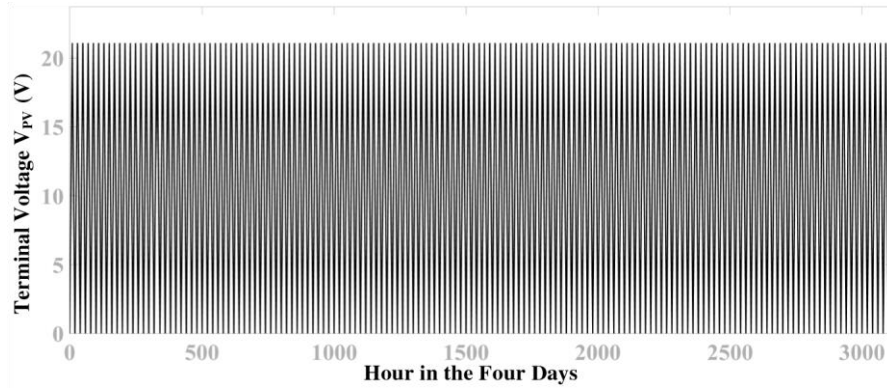


Figure 5.8: Terminal Voltage (V_{PV}) from 120-W PV Module.

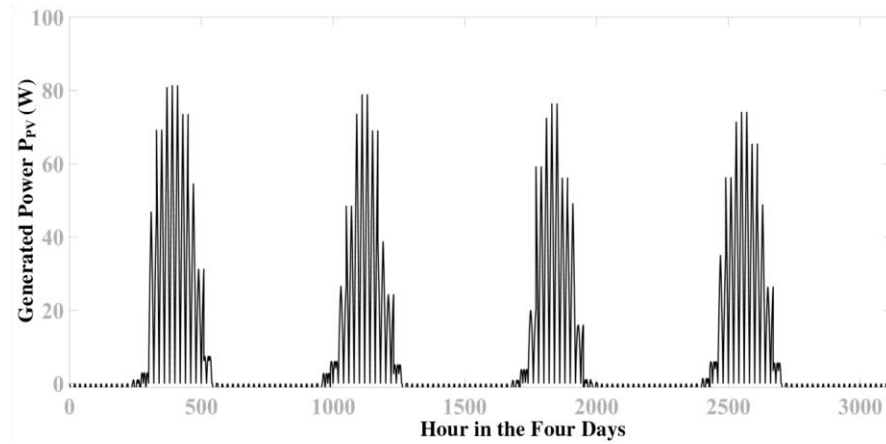


Figure 5.9: Generated Power (P_{PV}) from 120-W PV Module.

5.2 PV MODULE MODELING

The PV module can be modeled mathematically using the fundamental solar cell equations or employing simulation tools (e.g., PSIM), which are inherent with these equations. The I–V and P–V relationships of the developed model can be demonstrated in the PSIM environment. In this study, the relationships among the electrical outputs were implemented using a variable irradiance level in the range $663.048\text{--}70.163\text{ Wm}^{-2}$ at $25\text{ }^{\circ}\text{C}$. With the PV module model characterized by a number of solar cells connected in series, N_s is 36 and an assumed ideality factor (A) of 1.43 were used for the Simulink, PSIM, and proposed approaches. The voltage, current and power measurements of the techniques were acquired. The simulated characteristic behaviors of I–V and P–V are plotted with the Minitab program shown in Figure 5.10. They are in accordance with the behaviors of the PV module's current, voltage, and power curves. To achieve optimal results from the PV module, an MPPT algorithm is included in the solar energy

harvesting system in the Proteus environment via an 8-bit microcontroller to validate the PV module model [179].

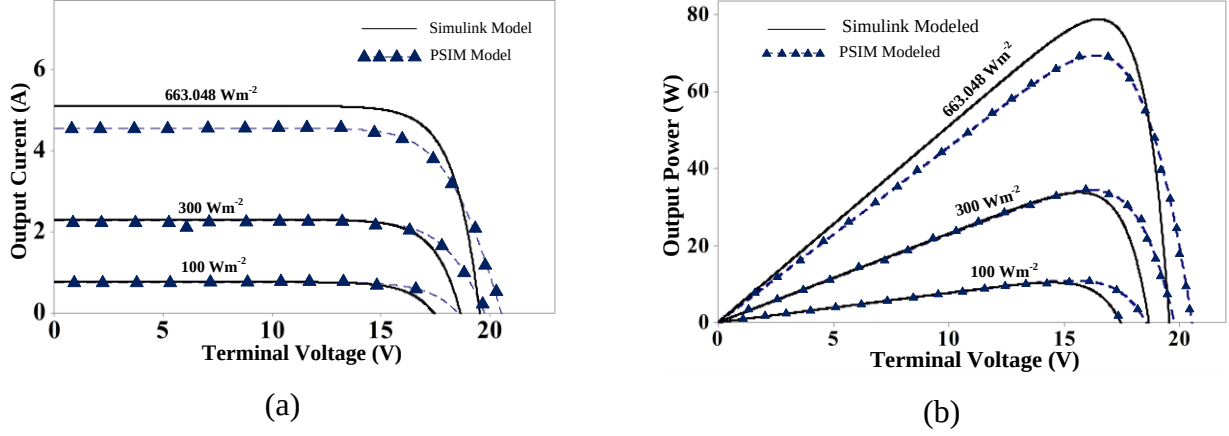
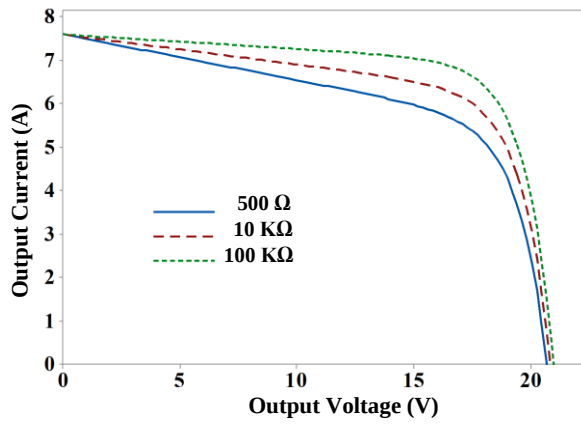


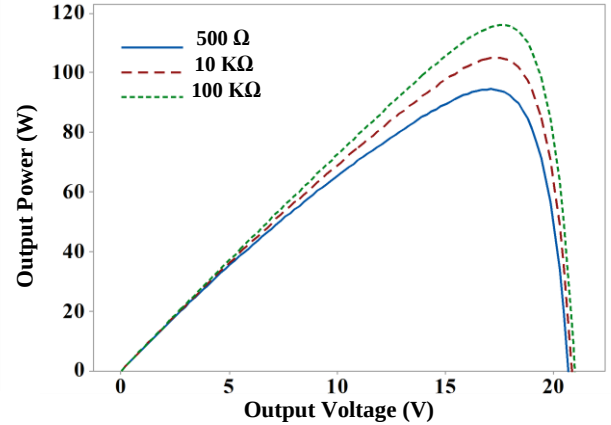
Figure 5.10: Model Curves of Simulink and PSIM (a) I-V (b) P-V.

5.2.1 EFFECTS OF PARASITIC RESISTANCE ON PV MODULE

The 120 W solar module is characterized by two key power losses from the series resistances of R_s and R_{SH} , which are parasitic resistances within the PV module. The increase in R_s and decrease in R_{SH} lead to further losses. In practical terms, R_{SH} causes parallel leakage current and can be estimated using Eq. (2.9), which is the inverse slope of the curve shown in Figure 2.7. This implies that different shunt resistance values create different I-V and P-V curves due to manufacturing defects. In Figure 5.11, the variation in R_{SH} values influences the I-V and P-V curves. The I_{SC} value remains virtually constant, the V_{OC} values slightly change, and the V_{MAX} values are considerably affected. The increase in R_{SH} values affects the I-V and P-V areas, which equally tend to increase the PV module's V_{MAX} and efficiency levels. This implies that an infinite R_{SH} value is the best option for optimal energy conversion. Figure 5.12 shows the variations in the relatively low R_s values (from 0.001 and 1 Ω). The increase in R_s values decreased the I-V and P-V curves, leading to reductions in the MPP values. The I_{SC} values slightly varied, and V_{OC} values are fixed. The V_{MAX} and I_{MAX} values are clearly affected as demonstrated by the I-V and P-V plots shown in Figure 5.12; this indicates that the MPPs are considerably influenced by the series resistance levels of the PV module. Based on Eqs. (2.3) and (2.7), the series resistance modifies the saturation current (I_{SAT}) levels of a solar cell. This current can sufficiently characterize the I-V curves of the PV module, adversely affecting the generated power and efficiency.

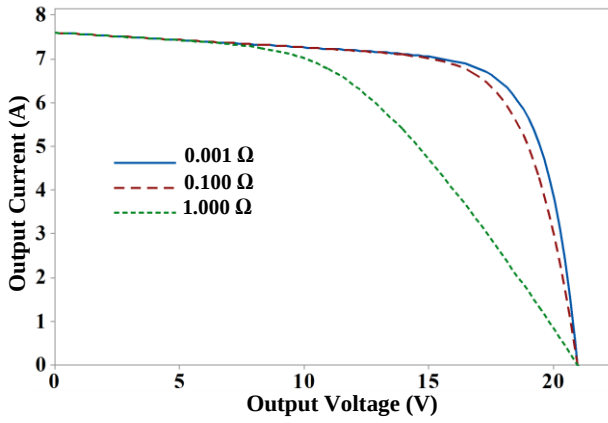


(a)

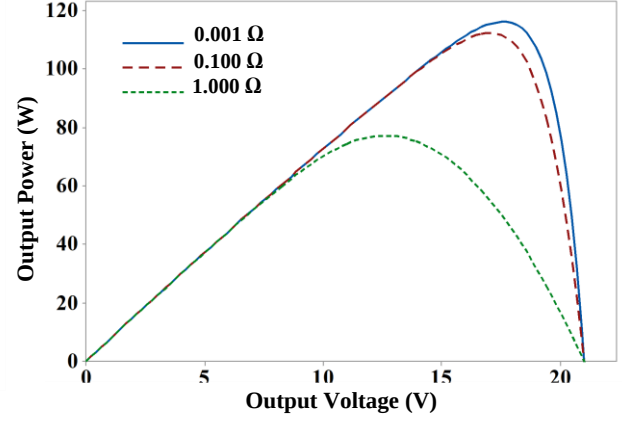


(b)

Figure 5.11: Variation in R_{SH} of Solar Cell on (a) I-V Curve (b) P-V Curve.



(a)



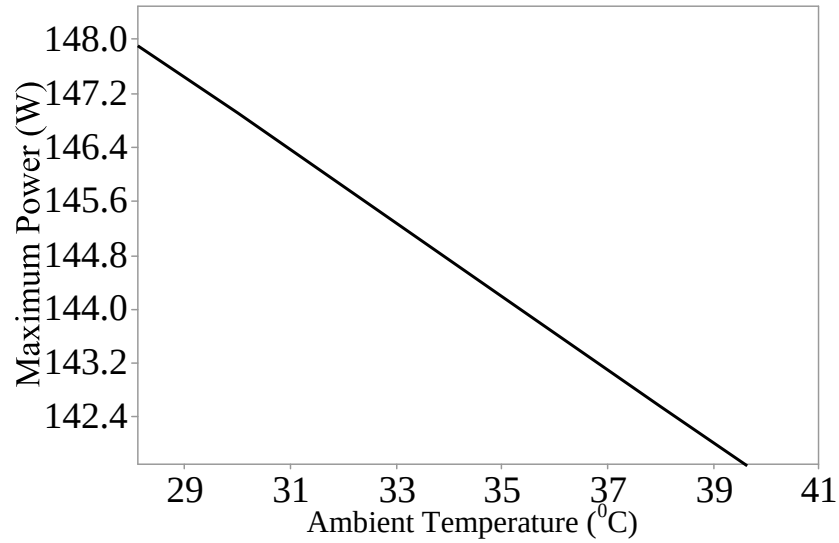
(b)

Figure 5.12: Variation in R_s of Solar Cell on (a) I-V Curve (b) P-V Curve.

Table 5.1 summarizes the extent of impact of R_{SH} and R_s on V_{OC} measurements as the ambient temperature increases. The table lists the following values of the PV module: $R_{SH} = 36\ 000\ \Omega$, $R_s = 0.288\ \Omega$, $V_{OC} = 21.9\ V$, and $I_{SC} = 7.7\ A$. Distinct behaviors of the basic parameters of the solar cell with changes in the ambient temperature are observed. The I_D value relatively increases, and V_{PV} decreases. In contrast, the I_{PV} and I_{SH} measurements are relatively unaffected when the ambient temperature increases with a constant irradiance of $1000\ Wm^{-2}$. Most importantly, Figure 5.13 shows that the increment in ambient temperature linearly reduces the MPP levels.

Table 5.1: Impact of Temperature Measurements on Solar Module Parameters

Ambient Temperature (°C)	I_D (A)	I_{SH} (A)	V_{PV} (V)	I_{PV} (A)
28	6.8400×10^{-3}	6.1789×10^{-4}	19.4550	7.6060
30	1.1640×10^{-2}	6.1772×10^{-4}	19.3010	7.6116
35	2.3640×10^{-2}	5.6158×10^{-4}	18.9130	7.6236
38	3.0840×10^{-2}	5.5500×10^{-4}	18.6830	7.6308
40	3.5640×10^{-2}	5.5077×10^{-4}	18.52930	7.6350

*Figure 5.13: MPPs and Increasing Ambient Temperature Levels*

5.3 EVALUATION OF PROPOSED LOOKUP TABLE MPPT TECHNIQUE WITH OTHER MODELS

The integration of the proposed MPPT algorithm into the synchronous buck converter in the solar energy harvesting system at the remote seismic node is necessary to deliver optimal and continuous electrical power.

By avoiding the mismatch in impedance between the PV module and load, an optimal duty cycle is applied across the PWM of the converter. Optimal energy conversion occurs, and the MPP, V_{MAX} , and I_{MAX} levels are continuously tracked regardless of the input parameters of the PV module, as shown in Figure 5.14. In this figure (considering the left-hand side of the area of V_{MAX} and I_{MAX}), the output current increases with the output voltage and power.

By considering the circuits in Figures 3.3 and 3.4 as non-MPPT and MPPT (based on the P and O algorithm) buck converters, respectively, the irradiance levels obtained are 500, 1000, 800, 900, 600, and 200 Wm^{-2} at 25 °C. The irradiance levels at 12 points from 0 to 0.06 s are used as inputs across the piecewise linear ramp in the PSIM simulation environment. The Figures 5.15 and 5.16 reveal the V_{MAX} and P_{MAX} measurements of the PV module against time in seconds. Where the comparison of the Figures 5.15 and 5.16 shows that the MPPT algorithm influenced the converter by increasing the electrical power by more than 21 %, thus outperforming the non-MPPT converter. The optimal increases in the V_{MAX} and I_{MAX} outputs improve the efficiency of the solar energy harvesting system. However, the current and power decrease, and the voltage increases on the right-hand side. Therefore, the MPPT algorithm is continuously required for the energy harvesting system to track the MPPs.

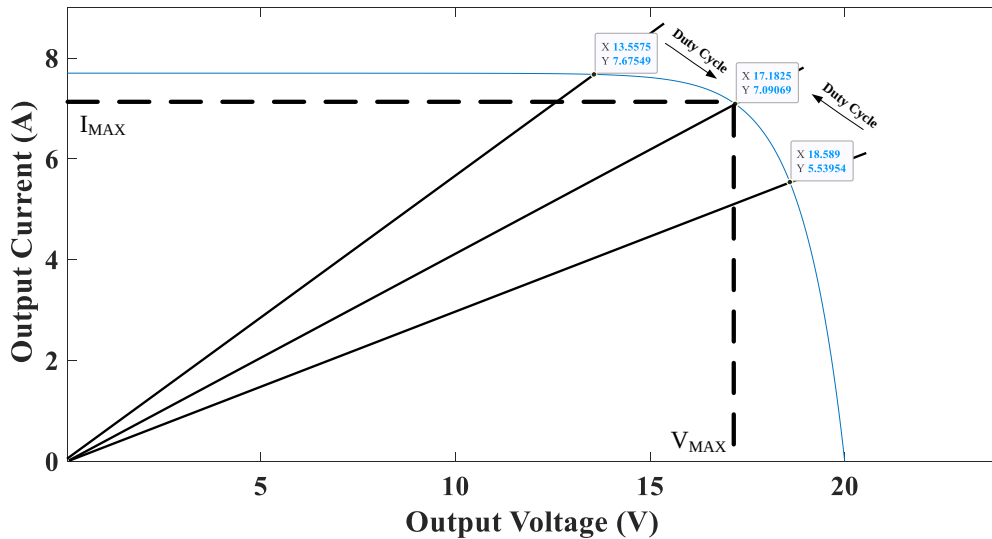


Figure 5.14: Current and Voltage Plots showing MPPs.

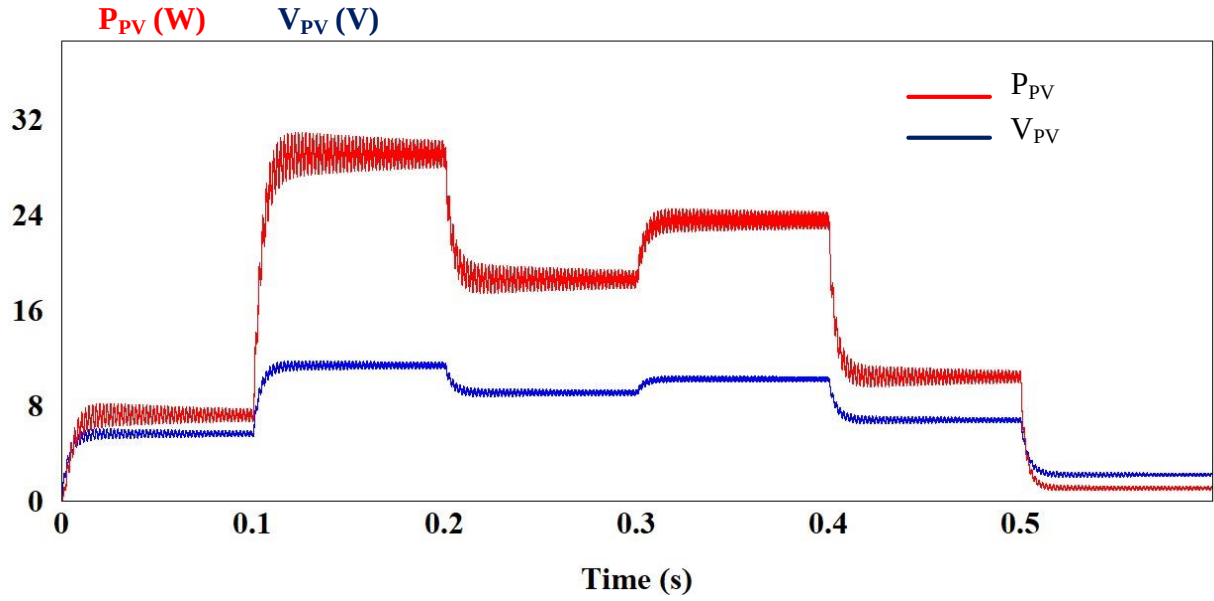


Figure 5.15: V_{MAX} and P_{MAX} levels delivered by Non-MPPT Buck Converter.

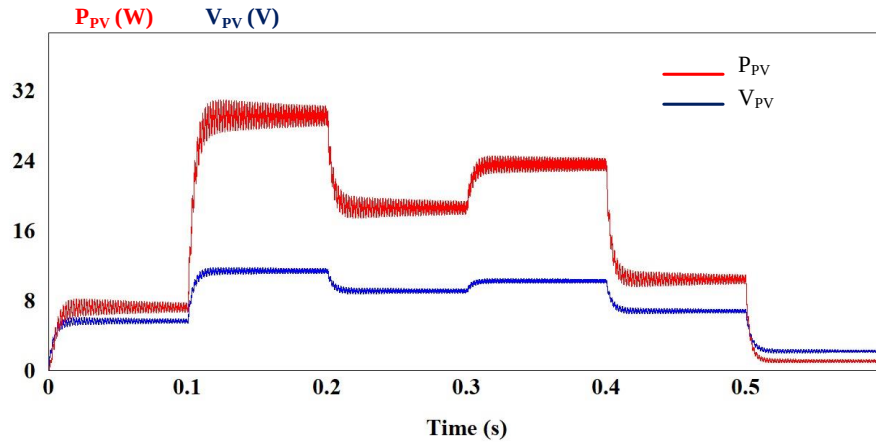


Figure 5.16: V_{MAX} and P_{MAX} levels delivered by P and O based MPPT Buck Converter.

In the solar energy harvesting system, the selected parameters of the PV module to be determined under the standard testing condition are the V_{OC} , I_{SC} , V_{MAX} , and I_{MAX} measurements. The measurement results of the selected PV module obtained from the models developed in PSIM, experimental setup, and proposed study method are summarized in Table 5.2. This table lists the percentage of V_{OC} and I_{SC} measurements implemented in the proposed method that deviate from the ideal model simulated in the PSIM program. Table 5.3 is populated by V_{MAX} and I_{MAX} measurements after the implementation of optimization techniques, showing their deviations (in percent) from the ideal model implemented in the PSIM program. The comparison of models in the Simulink and PSIM environments results in similar trends, with virtually the same V_{OC} and

Isc measurements; the slight variations observed are due to the limitations of the approaches. The deviations in the results (in %) of the proposed method listed in Table 5.2 are caused by neglecting some minor parameters in the PV module.

Table 5.2: V_{OC} and I_{SC} Measurements

Irradiance (Wm^{-2})	PSIM V_{OC} (V)	Experimental V_{OC} (V)	Proposed Model V_{OC} (V)	PSIM I_{SC} (A)	Experimental I_{SC} (A)	Proposed Model I_{SC} (A)
663.048	20.642	17.76	21.115 (2.292 %)	5.105	4.620	5.055 (0.981 %)
659.641	20.642	17.74	21.115 (2.291 %)	5.079	4.5964	5.029 (0.991 %)
652.563	20.629	17.74	21.114 (2.354 %)	5.025	4.547	4.974 (1.012 %)
635.487	20.591	17.71	21.114 (2.539 %)	4.893	4.428	4.842 (1.029 %)
610.708	20.553	17.66	21.113 (2.722 %)	4.702	4.255	4.652 (1.066 %)
574.243	20.490	17.52	21.111 (3.029 %)	4.422	4.001	4.371 (1.151 %)
512.632	20.362	17.46	21.107 (3.659 %)	3.947	3.572	3.897 (1.275 %)
425.966	20.146	17.23	21.101 (4.742 %)	3.280	2.968	3.229 (1.544 %)
281.354	19.689	16.76	21.089 (7.108 %)	2.166	1.960	2.116 (2.316 %)
70.162	18.151	15.1	21.046 (15.946 %)	0.540	0.489	0.490 (9.324 %)

The influence of ambient irradiance levels on the PV module and the comparison of variations in V_{OC} and I_{SC} under the experimental setup, proposed method, and PSIM are shown in Figure

5.17. By implementing the proposed model, the I_{SC} measurements are found to proportionally increase with irradiance, as shown in Figure 5.17(a). In Figure 5.17(b), the proposed model's V_{OC} measurements slightly increase with the irradiance compared with those of the other approaches; the plots virtually have similar trends. Thus, the proposed method is validated and verified.

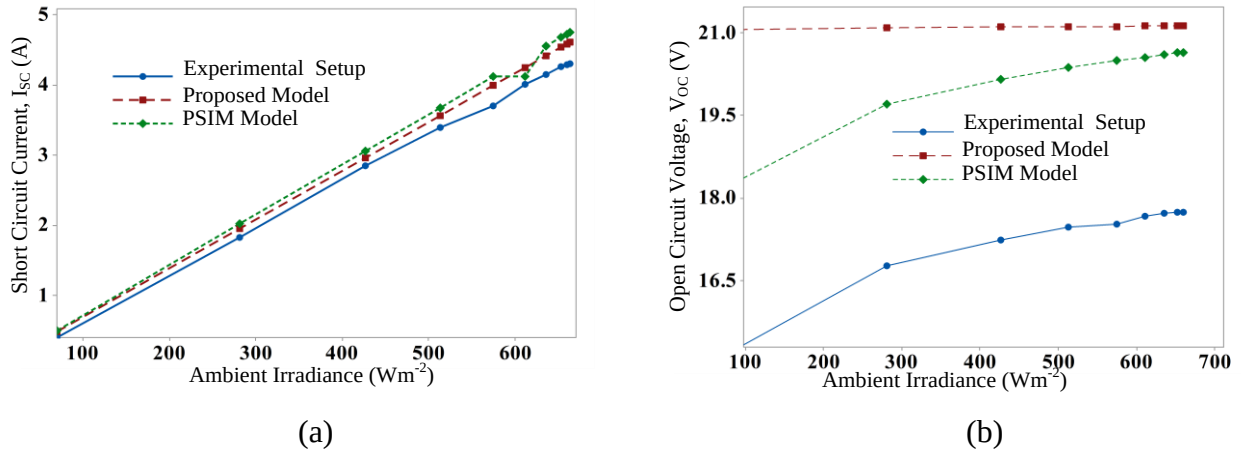


Figure 5.17: Comparison of I_{SC} Measurements of PV Module under Experiment Setup, Proposed Method and PSIM with varying Irradiance: (a) I_{SC} Measurements and (b) V_{OC} Measurements.

The terminal voltage (V_{PV}) generated by the PV module is in the V_{MAX} region of the module, as expressed by Eq. (5.3). The Figure 5.18 indicates the variations of V_{PV} and I_{PV} measurements of the PV module against time in seconds. Figure 5.18(a) shows the variation between V_{PV} and V_{MAX} . Similarly, the I_{PV} and I_{MAX} values are the measurements given by Eq. (5.4) and shown in Figure 5.18(b) for the selected PV module. In these equations, ΔV and ΔI are the differences and small increments or decrements of the measured output voltage and current levels of the PV module, respectively. The V_{MAX} and I_{MAX} values are the output measurements of the optimal solar energy harvesting system and are functions of V_{PV} and I_{PV} of the PV module. In turn, V_{PV} and I_{PV} depend on module's characteristics and electrical conditioning system.

$$V_{PV} = V_{MAX} \pm \Delta V \quad (5.3)$$

$$I_{PV} = I_{MAX} \pm \Delta I \quad (5.4)$$

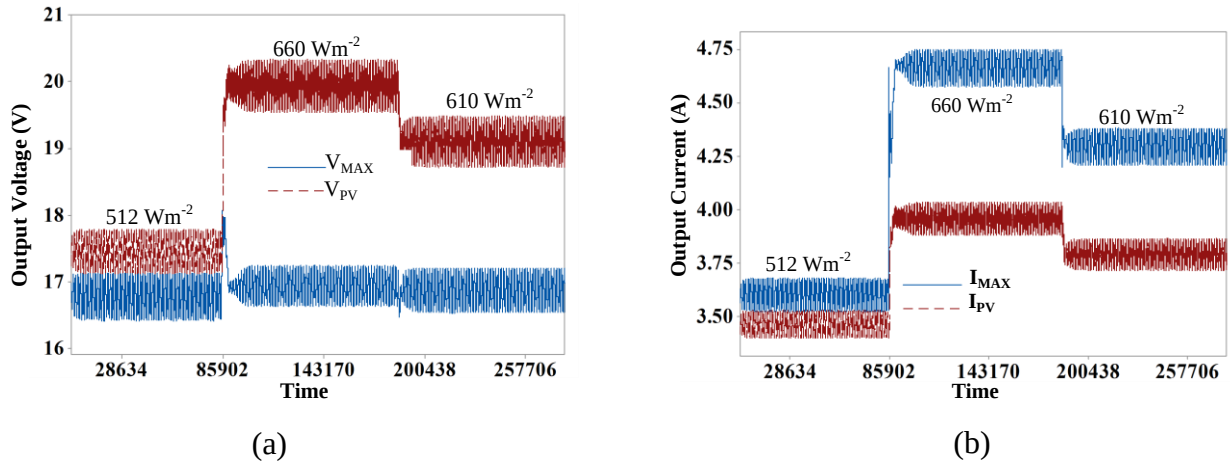


Figure 5.18: Variations in Irradiance Levels across PV Module using MPPT Algorithm: (a) V_{PV} and V_{MAX} Measurements (b) I_{PV} and I_{MAX} Measurements.

Table 5.3 lists the MPPT output levels under varying irradiance, and Figure 5.19 shows the affected values of duty cycle, V_{MAX} , I_{MAX} , and P_{MAX} . As the ambient irradiance varies during the day, the MPPs change, as indicated in Figure 5.19 and Table 5.3. The table indicates that in the use of the three approaches, the I_{MAX} measurements against time in seconds of the considered PV module are between 4.60 and 1.83 A. Figure 5.19(a) indicates the duty cycle observations assigned by the MPPT algorithm against time in seconds. The duty cycle values increase as the irradiance levels decrease, as shown in Figure 5.19(a); they are observed to fall between 0.730 and 0.695. The change in duty cycle in the modeling using the MPPT algorithm is achieved by matching the PV module impedance and load in the solar energy harvesting system to deliver optimal V_{MAX} and I_{MAX} measurements. Figure 5.19 shows the V_{MAX} , I_{MAX} , and P_{MAX} values, which increase with irradiance levels. Figure 5.19(b) indicates the MPPT output levels obtained by the MPPT algorithm against time in seconds. Where irradiance decreased from 663.048 to 70.163 Wm^{-2} , the observed P_{MAX} values are 60 (520), 80 (660), and 70 Wm^{-2} (610 Wm^{-2}), as shown in Figure 5.19(b). Table 5.3 lists the differences between the proposed method and ideal model developed in the PSIM program. The minimum and maximum deviation errors are 0.591 % and 4.804 %, respectively. Thus, the processes have been evaluated and verified; they are found to agree well with the PV module characteristics with varying irradiance levels and fixed temperature.

Table 5.3: V_{MAX} and I_{MAX} Measurements

Irradiance (Wm^{-2})	PSIM V_{MAX} (V)	Experimental V_{MAX} (V)	Proposed Model V_{MAX} (V)	PSIM I_{MAX} (A)	Experimental Setup I_{MAX} (A)	Proposed Model I_{MAX} (A)
663.048	18.067	15.69	17.215 (4.715 %)	4.751	4.301	4.608 (3.015 %)
659.641	18.067	15.63	17.200 (4.804 %)	4.727	4.294	4.584 (3.02 %)
652.563	18.067	15.59	17.200 (4.801 %)	4.677	4.255	4.535 (3.038 %)
635.487	18.067	15.51	17.200 (4.801 %)	4.556	4.156	4.416 (3.067 %)
610.708	18.000	15.36	17.200 (4.447 %)	4.118	4.016	4.244 (3.061 %)
574.243	17.999	15.27	17.200 (4.442 %)	4.118	3.700	3.990 (3.093 %)
512.632	17.870	15.03	17.199 (3.753 %)	3.680	3.392	3.562 (3.193 %)
425.966	17.800	14.53	17.199 (3.375 %)	3.059	2.851	2.960 (3.229 %)
281.354	17.500	14.66	17.198 (1.721 %)	2.021	1.830	1.955 (3.254 %)
70.163	17.300	13.21	17.197 (0.591 %)	0.502	0.400	0.487 (2.873 %)

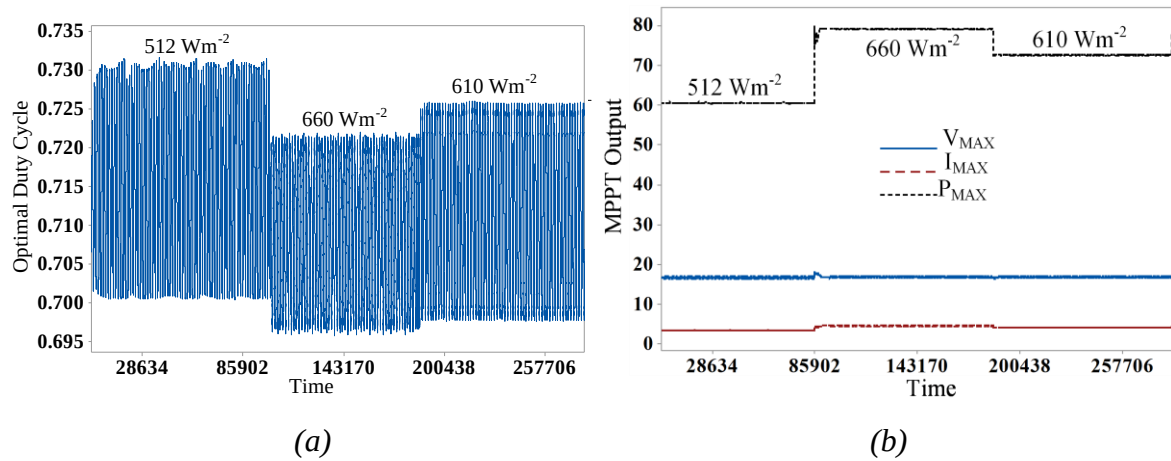


Figure 5.19: Variations in Irradiance across PV Module using MPPT Algorithm: (a) Duty Cycle Variations; (b) V_{MAX} , I_{MAX} and P_{MAX} Variations.

5.3.1 SYNCHRONOUS BUCK CONVERTER MODELING

In this research, the modeling of the synchronous buck converter circuit shown in Figure 5.20 is developed in PSIM to demonstrate its simulation and evaluation. This also aided in confirming the converter's behavior under the 12-V load voltage across the remote seismic node and the hybrid energy storage of the lead–acid battery and supercapacitor. Figure 5.21 represents plot of the output current levels at the inductor and that of the load current delivered by the synchronous buck converter against time in seconds. While Figure 5.22 indicates output voltage levels across both the inductor and capacitor of the converter versus time in seconds. The simulated plot shown in Figure 5.21 describes the time that elapses for the converter to converge to the desired output voltage. The transient response of the inductor is the converter's peak-to-peak ripple current (I_R), and the load current (I_{Load}) is the average value of I_R . As mentioned, Eq. (3.8) indicates that the optimal continuous current operation of the converter requires lower inductor values, and the reduced capacitor value lowers the load voltage. The value of the switching frequency (F_{SW}) affects the inductor current, the capacitor voltage, and the voltage across the load of a solar energy harvesting system. A high F_{SW} value reduces the sizes of the inductor and capacitor, where power loss increases. The lower inductor value increases the current and voltage ripples across the load. The power source requirements at a remote seismic node must be characterized by the optimized continuous current mode of the inductor and the reduced ripples across the load voltage. Typically, a seismic node is a resistive load of approximately 10 Ω . Moreover, this type

of load causes more losses at lower switching frequencies [180]. Based on calculations, the minimum values of the inductor and output capacitor are 369 μH and 1.6054 μF , respectively. In this study, slightly larger inductor and capacitor values were used to satisfy the condition of the remote seismic node, limit the peak-to-peak ripples, and reduce the power loss. An optimal fixed F_{sw} value of 10 kHz is selected, and a 1.23-A load current is delivered, as shown in Figure 5.21. Figure 5.22 shows the simulated output of the inductor voltage shifting from +10 V to -10 V in the form of pulse time instants. The output capacitor maintained the required output voltage of approximately 12 V across the load. Figures 5.21 and 5.22 show the voltage and time in second plots of the proposed DC–DC converter, demonstrating the converter’s ability to regulate the output voltage in the simulations of the transient and steady states that settles within 10 ms.

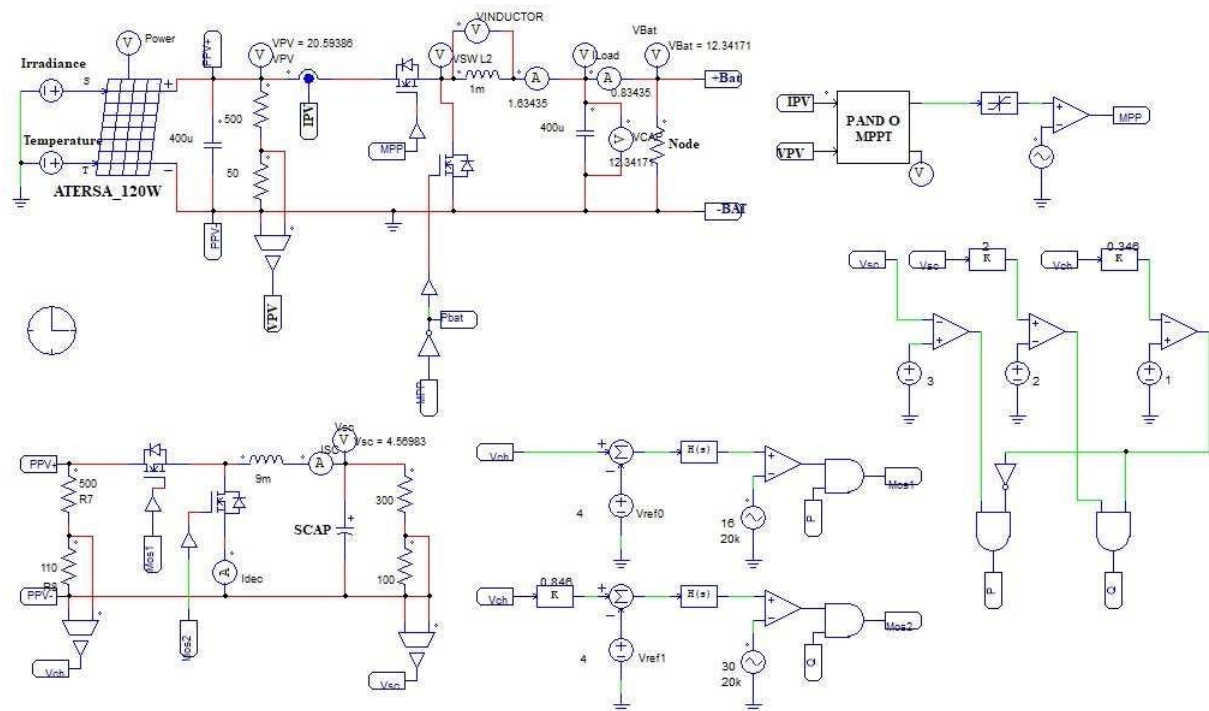


Figure 5.20: Synchronous Buck Converter for Hybrid Energy Storage at Remote Seismic Node .

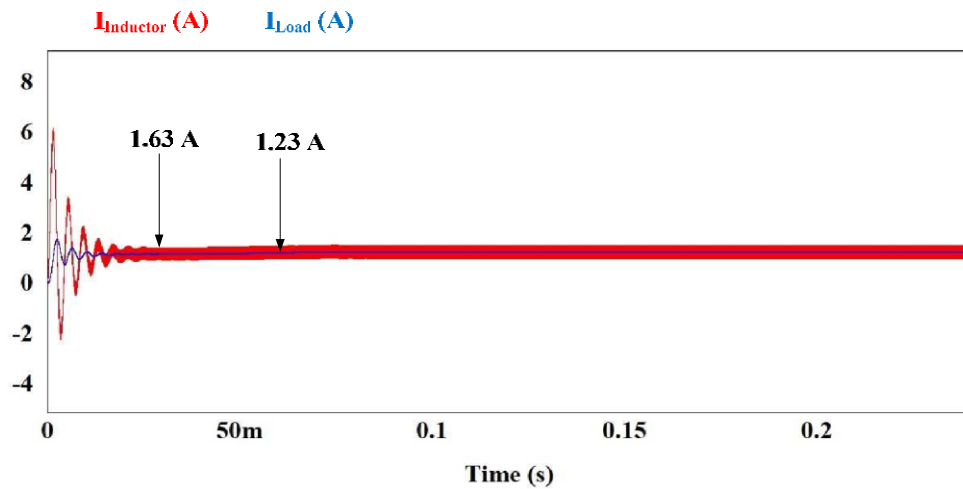


Figure 5.21: Simulated Inductor and Load Current Waveforms.

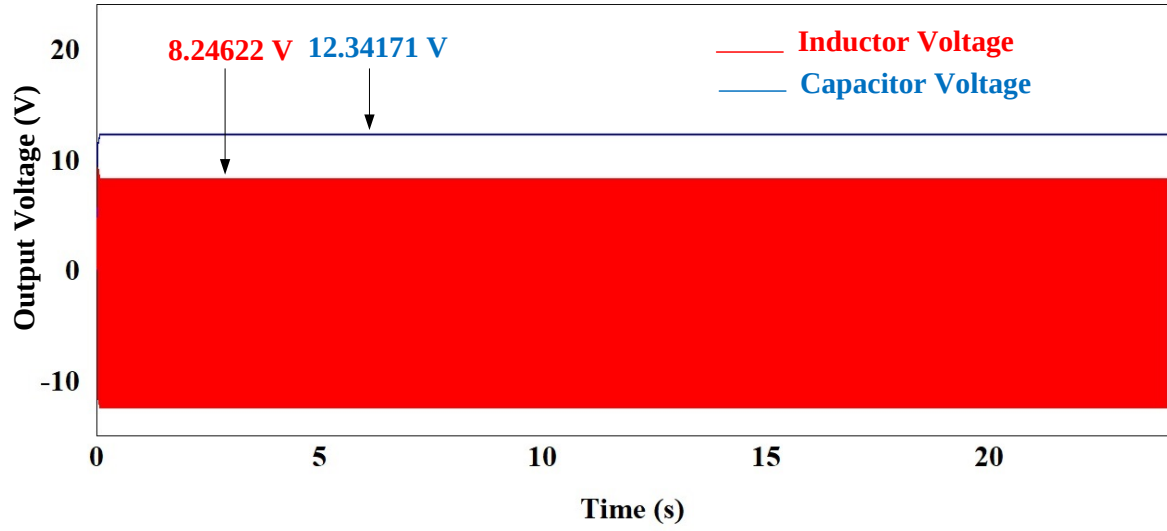


Figure 5.22: Simulated Inductor and Capacitor Voltage Waveforms.

5.3.2 LDR AS IRRADIANCE METER

In this study, the LDR is adopted as an irradiance meter to detect ambient irradiance, which serves as one of the inputs of the proposed lookup table. The calibration of the LDR was achieved by comparing it with a commercial irradiance meter installed with the EESFC computer-controlled PV system. Its resistance levels vary with those of irradiance and terminal voltage responses, which are non-linear in nature. In this work, the logarithmic function of the terminal voltage and neural network algorithm are implemented to compensate for the non-linear responses expressed by the curve fitting equations, i.e., Eqs. (3.10)–(3.14). The measurements acquired from the input parameters of $10\text{--}1000\text{ Wm}^{-2}$ and output measurements of V_{LDR} are presented in Figures 5.23 and 5.24. These correlate the ambient irradiance levels and the terminal voltage values of V_{LDR} ; Table 5.4 lists the relationship between the variations in the irradiance and V_{LDR} levels.

Table 5.4: LDR Connection Circuit Measurements

Irradiance (W/m^2)	V_{LDR} (V)	Log Irradiance (W/m^2)	Log V_{LDR} (V)
10	3.19	1	0.503791
100	0.98	2	-0.00877
200	0.59	2.30103	-0.22915
300	0.44	2.477121	-0.35655
400	0.35	2.60206	-0.45593
500	0.29	2.69897	-0.5376
600	0.25	2.778151	-0.60206
700	0.22	2.845098	-0.65758
800	0.2	2.90309	-0.69897
900	0.18	2.954243	-0.74473
1000	0.16	3	-0.79588

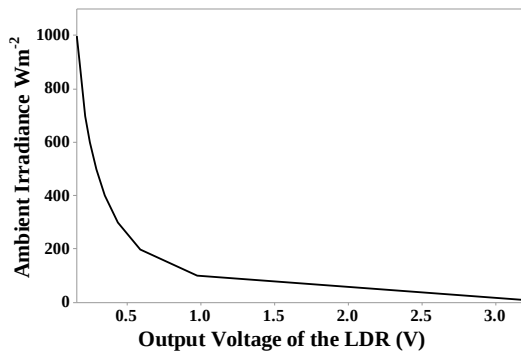


Figure 5.23: Relationship between Irradiance and Terminal Voltage V_{LDR} .

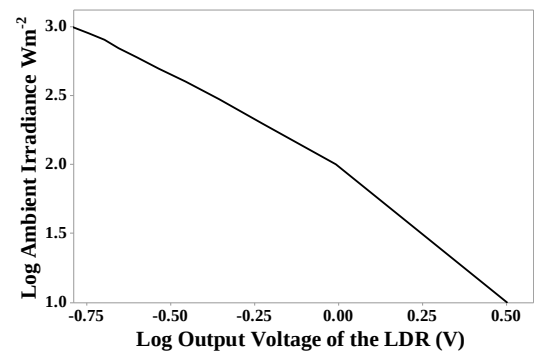


Figure 5.24: Relationship between Log Irradiance and Log Terminal Voltage V_{LDR} .

5.3.3 TRANSFORMED DATA BY ANN MODEL

The ANN model is employed to transform the 2038 samples (acquired from the computer-controlled PV solar energy unit) of irradiance and temperature levels as input and the duty cycle

as output dataset. The V_{oc} and I_{sc} values of the PV module are 21.9 V and 7.7 A, respectively; the other characteristics obtained by the ANN model are summarized in Table 3.4. By varying the irradiance and temperature, 10 hidden neurons in the neural network model and Levenberg–Marquardt learning algorithm are observed to be optimal options. In the samples, 70 %, 15 %, and 15 % are for training, validation, and testing, respectively. Figure 5.25 examines the training algorithm, where MSE is plotted against 188 epochs. Throughout the training, the best performance of model weights and biases in terms of MSE was 1.9634×10^{-7} at 188 epochs and a learning rate of 0.01, as shown in Figure 5.25. Figure 5.26 reveals the comparison of neural network outputs and the training targets. It presents the best regression for training, test, validation, and overall performance data. The summary of the neural network model populates Table 5.5, revealing that the model has learned to predict data based on the trained set; it performs well on the test and validation data. While the data of Table 5.6 compares the MSE and RMSE, obtained based on Eq. (3.19) and Eq. (3.20), which demonstrate the error analysis and the performance of the model,

Table 5.5: Overall Results of Neural Network Model

Neural Network Model	Values
Best Validation Performance	1.9634×10^{-7}
MU	1×10^{-09} at Epoch 188
Gradient	8.2804×10^{-8} at Epoch 188
Training	0.99924
Validation	0.99925
Test	0.99888
Overall Regression, R	0.9992

Table 5.6: MSE and RMSE Results of Neural Network Model

	Samples	MSE	RMSE
Training	1426	1.55428×10^{-7}	1.24671×10^{-3}
Validation	306	1.96343×10^{-7}	4.43106×10^{-4}
Testing	306	1.79201×10^{-7}	4.23321×10^{-4}

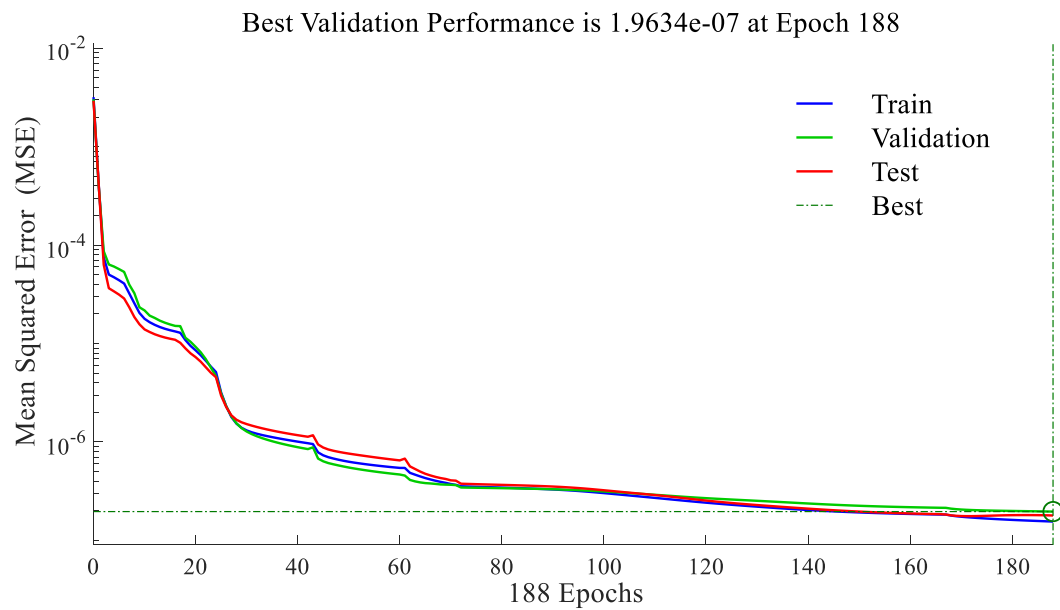


Figure 5.25: Neural Network Performance Training.

The overall regression correlation coefficient, R , is 0.9992. This shows that the observations in the correlation between the output and target levels closely match that between the targets and outputs, as shown in Figure 5.26.

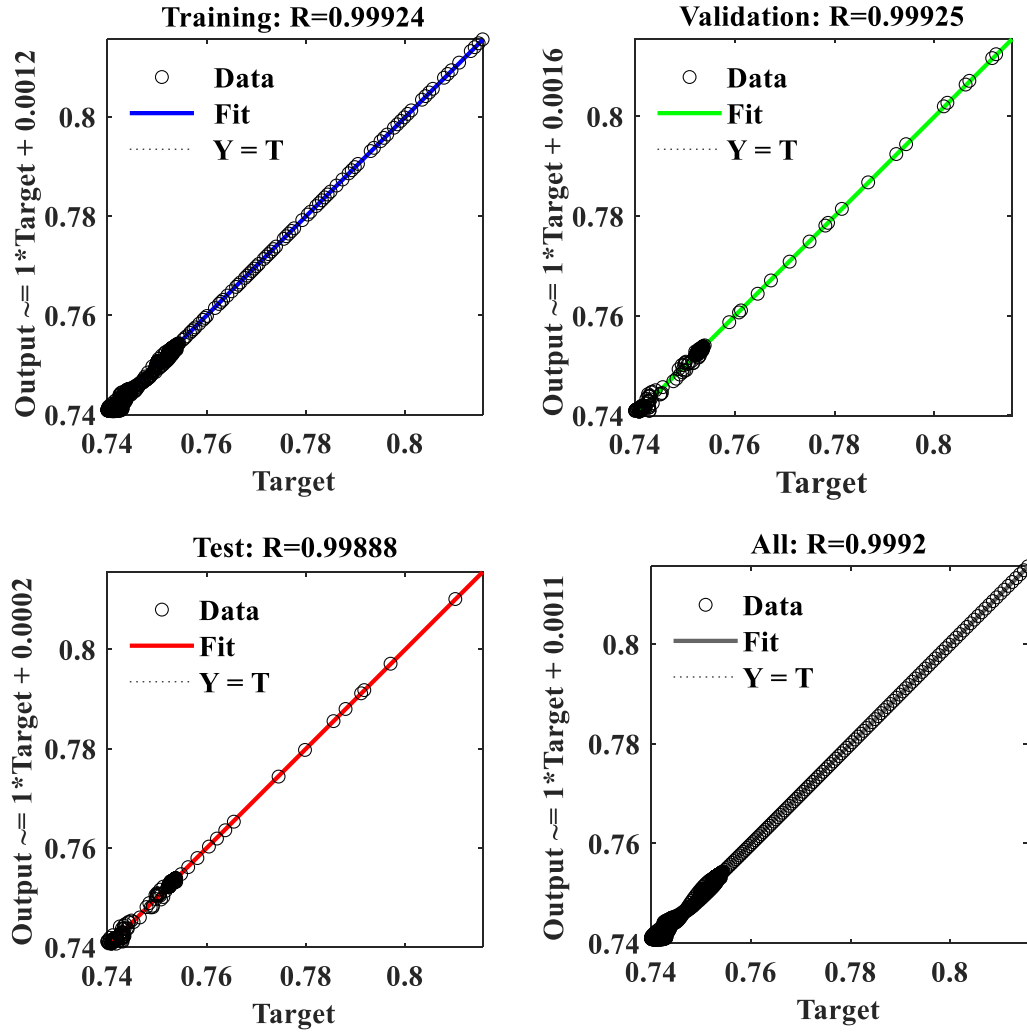
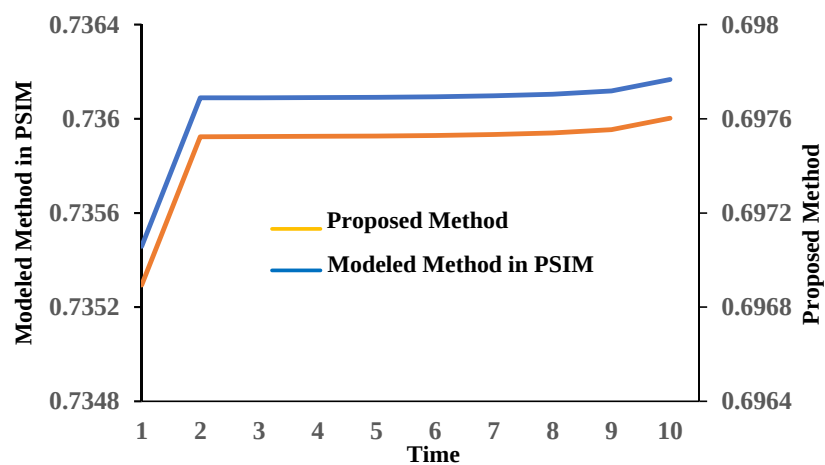


Figure 5.26: Regression Plots Performance Analysis.

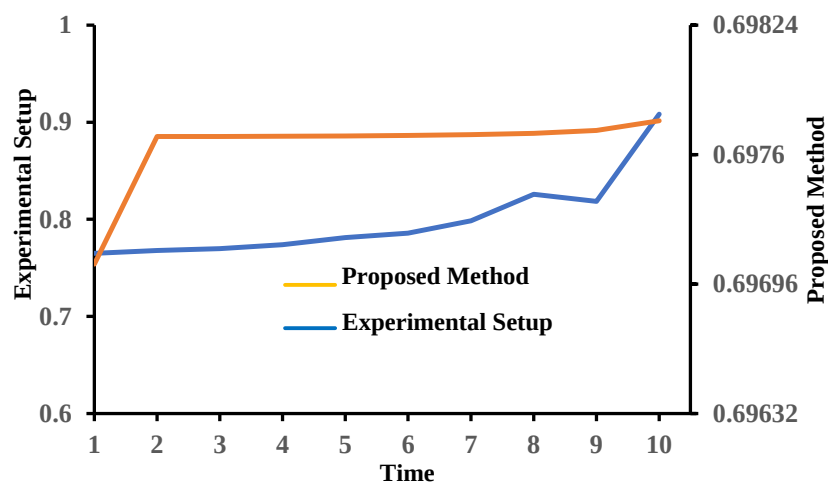
5.3.4 EVALUATION LOOKUP TABLE-BASED MPP TRACKING

In the proposed method, the memory samples are in the form of a lookup table function consisting of a set of irradiance and temperature levels as input data and duty cycle levels as outputs. These samples are from the subdomain of the function, and results are accessed by interpolation. The lookup table is preloaded into the flash memory of a selected 8-bit microcontroller in the Proteus environment to assign an optimal duty cycle across the PWM of the DC–DC converter. The experimental setup and developed P and O MPPT synchronous buck converter in PSIM shown in Figures 5.4 and 5.20, respectively, are implemented to observe the optimal duty cycle measurements for comparison with the proposed method. Figure 5.27 compares the duty cycle observations of MPPT algorithm in PSIM, experimental setup and the

proposed method versus time in seconds. The comparison between the modeled method in PSIM and proposed method is shown by the plots in Figure 5.27(a). The comparison between the experimental setup and proposed method is shown in Figure 5.27(b). The Proteus environment is employed to implement the proposed method due to its capabilities of selecting the microcontroller, using the lookup table, utilizing the C language code, and running practical tests. Moreover, it has printed circuit board layout modules and an integrated schematic. In contrast, the PSIM and Simulink environments lack the foregoing capabilities. They also have limitations in running practical tests and microcontrollers.



(a)



(b)

Figure 5.27: Comparison of Computed Duty Cycle Levels using (a) Model in PSIM and Proposed Method and (b) Experimental Setup and Proposed Method.

5.4 HARDWARE IMPLEMENTATION OF PROPOSED METHOD

The synchronous buck converter circuit shown in Figure 5.28 delivers a 12-V load voltage, and Figure 5.29 represents the overall proposed circuit in the Proteus environment. The circuit shown in the latter figure is a novel optimal energy harvesting system consisting of the 8-bit microcontroller, LDR, temperature sensor, and synchronous buck converter.

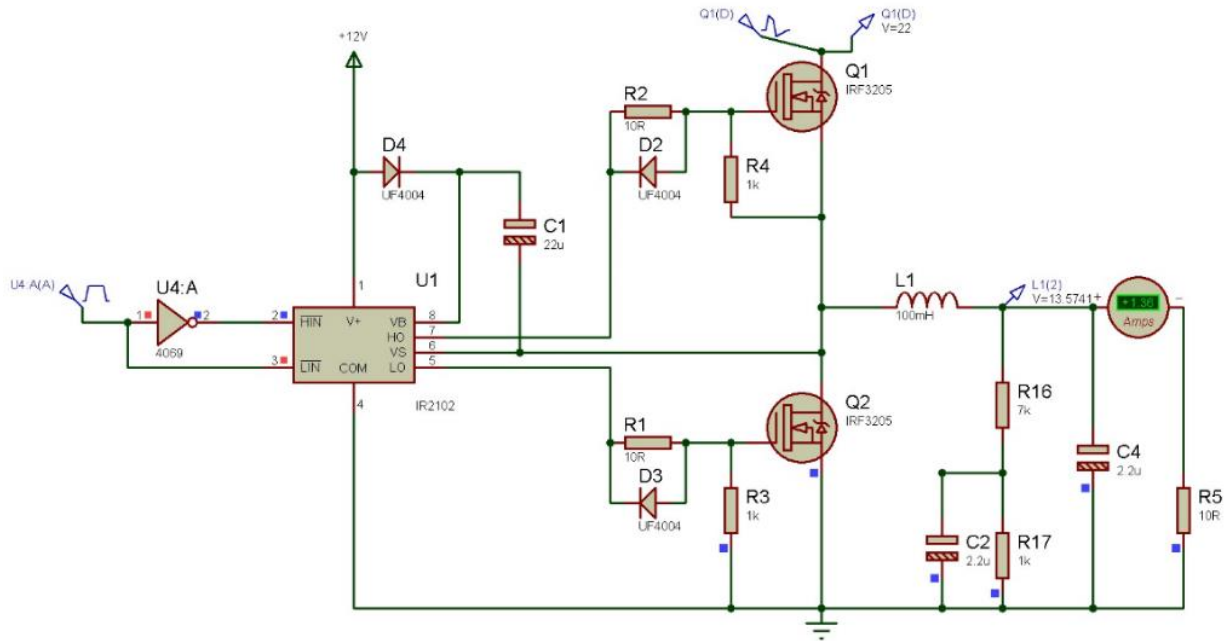


Figure 5.28: Proposed Synchronous Buck DC-DC Converter Circuit in Proteus.

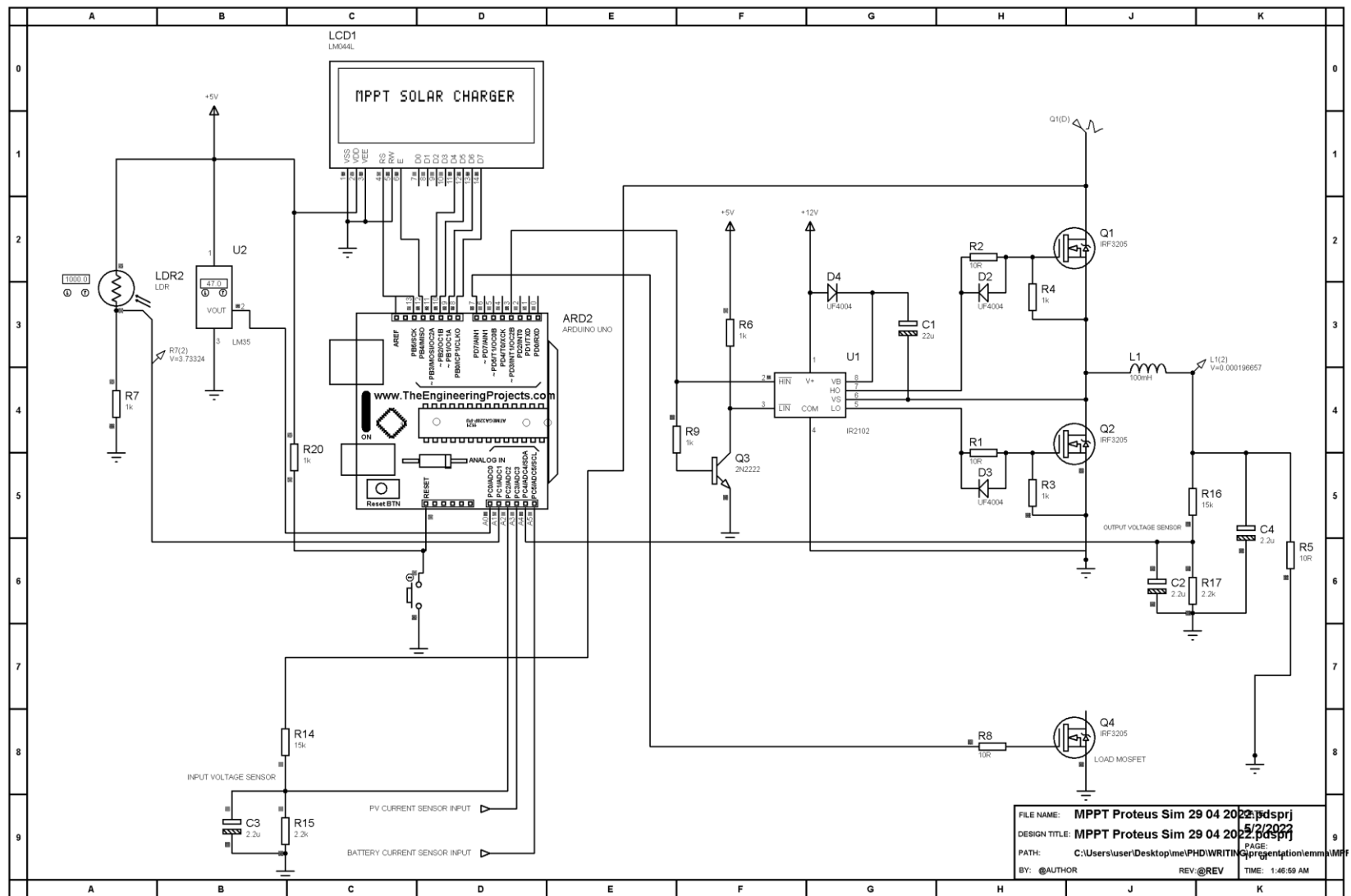


Figure 5.29: Overall Proposed Circuit in Proteus.

5.5 THE HARDWARE DESIGN

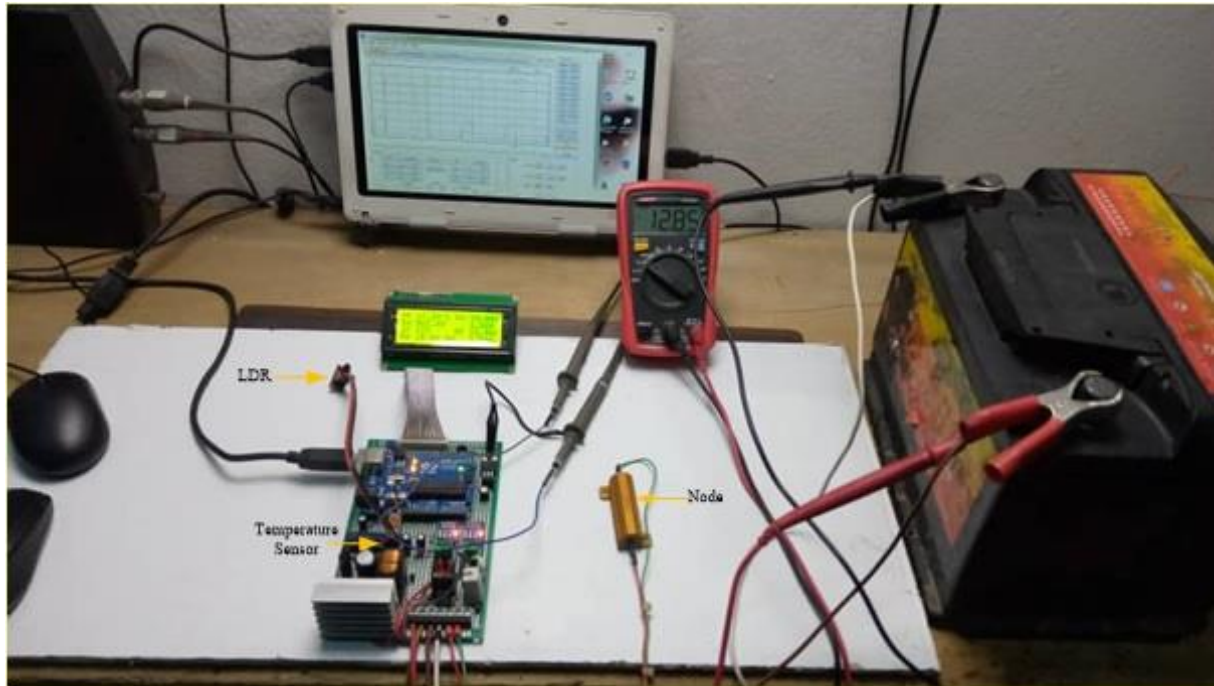


Figure 5.30: Test Platform Overview of the Proposed Circuit

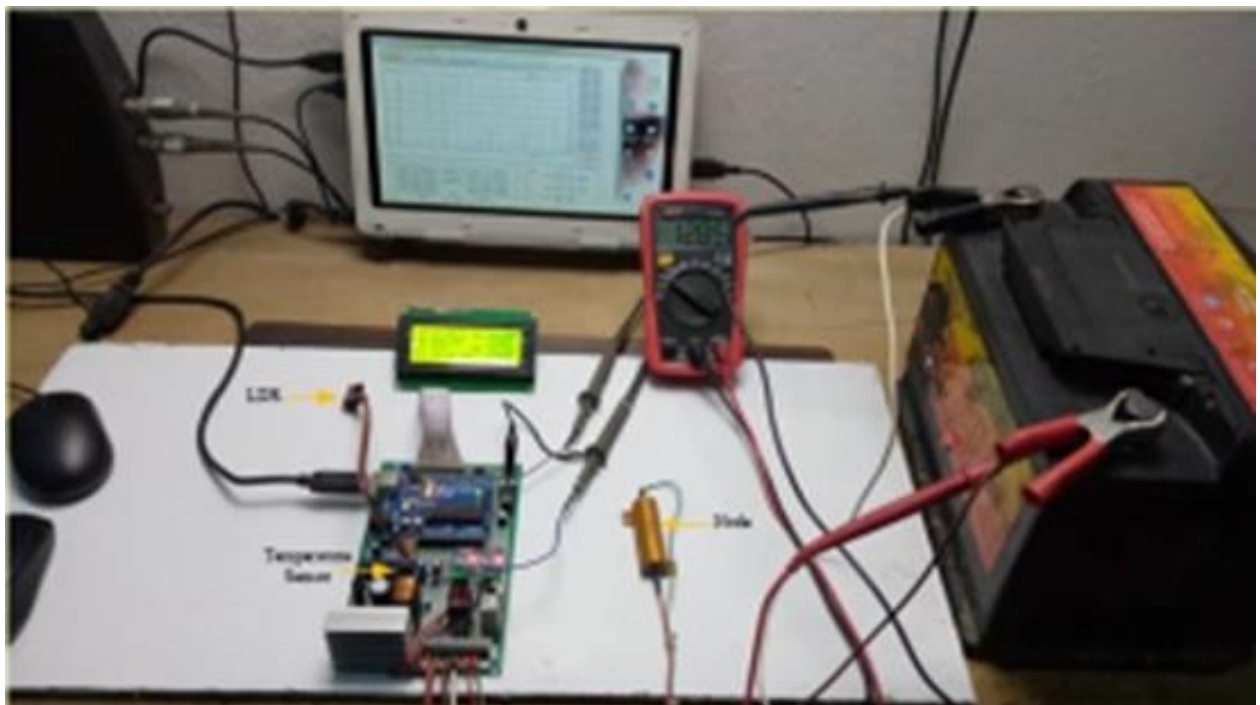


Figure 5.31: Monitors for Proposed Method

5.6 CONCLUSIONS

The PV module is an energy transducer with a relatively low efficiency rating. A technique for optimizing its energy conversion is required to supply and maintain continuous and long-term power sources at a load, such as the remote seismic node. This chapter presents the results of the PV module in the solar energy harvesting system modeled in the MATLAB, Simulink, and PSIM environments. The novel method, which utilizes curve fitting equations with LDR and a lookup table as an MPPT technique to predict the duty cycle, is presented. The experimental setup and model in PSIM are compared. The results of the synchronous buck converter are also presented and discussed to demonstrate the reasons of including the MPPT algorithm into the solar energy harvesting system.

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

This research aims to develop and improve the solar energy harvesting systems at remote seismic nodes by optimally converting energy from the PV module to the node. Low complexity and cost are the MPPT technique requirements to improve energy conversion. This enables the creation of a continuous and long-term seismic database, subsequently allowing the monitoring of the earth's subsurface and the prediction of the seismicity of an area. However, the solar energy harvesting system at remote seismic nodes has frequently failed, and the assembly of long-term seismic databases has been difficult to achieve. Consequently, this has hindered the continuous monitoring of the earth's subsurface and possibility of predicting earthquakes. The proposed approach relies on a less complicated curve fitting model, a lookup table function, an ANN model, and an LDR to achieve an optimal solar energy harvesting system for the node. In contrast, other power solutions are simple circuits with high oscillations and power losses at the MPP or highly complex circuits capable of making relatively accurate decisions.

The study started by extracting the parameters and constraints of a PV module and then developing models using MATLAB, Simulink, and PSIM. The model results are found to agree with established laws and the experimental setup. The MPPT techniques are reviewed. The P and O MPPT and incremental conductance algorithms are direct duty cycle control approaches in a DC–DC converter. In contrast, the FLC and ANN MPPT algorithms are soft computing and intelligent approaches. The methods are discussed based on their merits and inadequacies. The proposed approach adopts curve fitting equations and an LDR to detect variations in ambient irradiance and temperature sensors for ambient temperature changes. An approximation function in a three-dimensional lookup table is interfaced with the LDR to predict duty cycles across the DC–DC converter to track the MPP. The lookup table is populated with the data transformed by a neural network model, which stores irradiance and temperature variables as inputs and corresponding duty cycle levels as outputs; the V_{MAX} and I_{MAX} levels at the MPP are tracked. By interpolating the values in the lookup table, duty cycles are delivered across the DC–DC converter to achieve relatively accurate MPP tracking and higher energy conversion. In this research work, real ambient irradiance and temperature data were acquired at Palapye and simulated in MATLAB to understand and use the data in the modeling of the PV module

and synchronous buck converter. The proposed MPPT based on the lookup table operates as an approximation function and is employed to track MPPs without using voltage and current sensors to reduce power losses and oscillations. The results were evaluated and compared with the experimental setup and MPPT based on the P and O algorithm in PSIM. The behaviors of the lead– acid battery and supercapacitor as well as the hybrid of the two energy storage types were discussed, and the integration of the hybrid energy storage, synchronous buck DC–DC, and PV module was implemented in PSIM. The overall circuit of the novel optimal energy harvesting system consisting of a low-cost 8-bit microcontroller, an LDR, a temperature sensor, a curve fitting model, a synchronous buck converter, and a hybrid of lead–acid battery and supercapacitor was developed in the Proteus environment.

Suitable simulations and tabulations have been implemented for evaluating and comparing the proposed technique with the experimental setup and models in PSIM. The results reveal that the MPPT approach proposed in the thesis agrees with other approaches previously reported in literature, with the deviations falling between 0.591 % and 4.801 % at several observed measurements. The proposed technique is characterized by relative simplicity and faster convergence rate compared with other models. The novel approach is low-cost and reduces computational processes and execution time; hence, its utilization at remote seismic nodes is appropriate.

6.2 NOVELTY OF THE RESEARCH

The novelty of this research lies in the neural network algorithm to transform the contents of the lookup table to deliver no known MPPT-based DC-DC converter at remote seismic nodes. This approach resolves the gap by adopting the neural network technique and employing the previous processes discussed to generate, transform, and use these variables to populate the lookup table. Employing curve fitting equations to extract parameters of a PV module, and lookup table, and an 8-bit microcontroller to deliver optimal solar energy harvesting system. Synchronous buck DC-DC converter via a shunt connection across lead-acid battery and supercapacitor to develop an optimal hybrid solar energy harvesting system at the remote seismic node.

6.3 RECOMMENDATIONS

The possibilities and future prospects of the approaches considered in optimizing the constraints of solar energy harvesting system can be explored because continuous research on improving inaccurate models is a key scope of future work. In this study, research contributions and outputs have been presented, and advantages as well as disadvantages have been identified, forming the bases for future research. The recommendations of this work can be summarized as follows.

6.3.1 PV MODELING

The previous PV modeling and approaches adopted in this study use the fundamental equations to formulate several models; accordingly, extended studies have been implemented. However, areas for improving and optimizing solar cell models remain. These include the use of more than one diode or other semiconductors for better solar energy extraction and demonstration cell parameters. Moreover, approaches for improving the optimal PV output levels using either the tracking rotation or MPPT algorithm are available for further improvement and optimization.

6.3.2 SYNCHRONOUS DC–DC BUCK CONVERTER

In this study, the freewheeling diode is replaced by a low-side MOSFET of the buck converter to improve efficiency by allowing the negative current of the SW to flow through the inductor and provide more electrical energy for the load. A shunt connection integrated into the converter is adopted to optimally feed the hybrid of the lead–acid battery and supercapacitor. The recommendation for future research is to develop a synchronous buck converter with more enhanced feedback control circuits to optimally improve the stability of the converter and the terminal voltage. The converter can be developed to intelligently manage the charging and discharging of the hybrid energy storage.

6.3.3 LOOKUP TABLE-BASED MPPT

In this study, high-level C language is adopted for writing the code, rendering the algorithm easier to develop and modify for the 8-bit microcontroller for decoding and utilizing the lookup table based MPPT. A more user-friendly high-level language that can offer more functionalities and is easier to run with microcontrollers. The output data from the non-linear solar cell and its input irregularities are transformed by the ANN model in this work. To appropriately select a more effective set of transformations or activation functions, the prediction of the lookup table

approximation function must be improved. Moreover, the interpolation of the lookup table may be enhanced if continuous cache memory and runtime computation are available.

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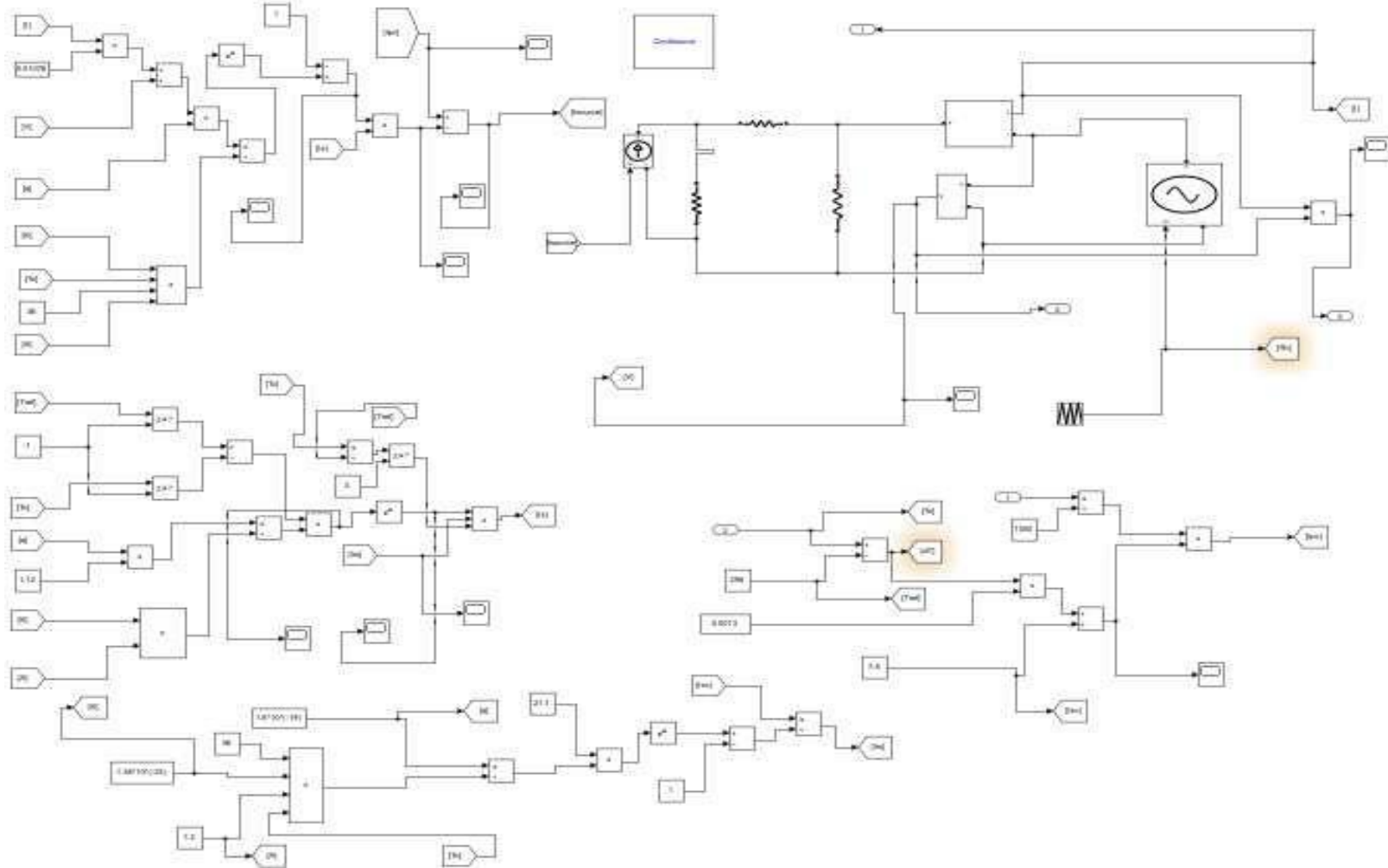
APPENDICES

APPENDIX A: MATLAB Code for simulating Solar Cell at different irradiance and temperature of plots shown in Figure 2.13 and Figure 2.14.

```
clc; clear
all;
K=1.38065e-23;      %Boltzmann's Constant
q=1.602e-19;        %charge of electron
Isc=2.5;             %short circuit current
Voc =0.7;            %open circuit voltage
Kv=-0.123;           %Temperature voltage constant
Ki=0.0032;           %Temperature current constant
Ns=1;                %No. of series connected cells
T=25+273;            %Ambient temperature
Tn=25+273;           %Nominal temperature
Gn=1000;              %Nominal Irradiance
a=1.2;               %diode ideality constant
Eg=1.12;             %Band gap of silicon at 25 degree Celsius
G=500;               %Ambient Irradiance
Rs=0.01076; Rsh=2000;
Vt=Ns*(K*Tn/q);

Ion=Isc/((exp(Voc/(a*Vt)))-1)
Io=Ion*((Tn/T)^3)*exp(((q*Eg/(a*K))*((1/Tn)-(1/T))));
Ipn=Isc;
Ipv=(Ipv+Ki*(T-Tn))*(G/Gn)
Vt=Ns*(K*T/q);
I=zeros(330,1)
I*1;
I(1,1)=0;
V=0:0.0145:0.8;
I=Ipv-Io*exp((V+Io*Rs)/(a*Vt))-((V+Io*Rs)/Rsh)
PO=V.*I;      figure(1)      plot (V,I);
axis([0 0.8 0 1.5]);        xlabel('Voltage in
Volts');      ylabel('Current in Amps');
hold on;      figure(2)      plot (V,PO);
axis ([0 0.8 0 1.5]);        xlabel('Voltage in
Volts');      ylabel('Power in Watts');
hold on;      figure(3)      plot (I,PO);
axis ([0 1.5 0 1.5]);        xlabel('Current in
Amps');      ylabel('Power in Watts')      hold
on
```

APPENDIX B: Simulink modeling blocks of PV Module model shown in Figure 2.15 for four days, input plots of four days Figure 5.5 and Figure 5.6, while Figure 5.7, Figure 5.8 and Figure 5.9 represent the output plots.



APPENDIX C: MATLAB code of Training of Artificial Neural Network shown to deliver Figure 3.5, Figure 3.9 as well as *Figure 5.25 and Figure 5.26*

```
function [y1] = myNeuralNetworkFunction(x1)
%MYNEURALNETWORKFUNCTION neural network simulation function. %
% Auto-generated by MATLAB, 11-Oct-2021 10:01:10. %
% [y1] = myNeuralNetworkFunction(x1) takes these arguments:
%   x = Qx2 matrix, input #1 % and returns:
%   y = Qx1 matrix, output #1 %
% where Q is the number of samples.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [3.273852;25.17];
x1_step1.gain = [0.00318106756843909;1.19047619047619]; x1_step1.ymin
= -1;
% Layer 1 b1 = [-3.2333381616124956537;-
5.5521203174815303427;0.28459702898295569096;6.0449238753458338635;-
0.43745636233015700034;-1.0216619496248402488;-
1.2910920426372307634;3.4644625175862024946;2.6098702252453742645;9.987508211
2984276961];
IW1_1 = [6.4648776233736215957 -1.5626273998872595161;16.676611976707729212
2.7946371134174974316;-4.4953707285911770342
5.8543915639355530445;18.10257445326068293 2.9376611222723680861;-
4.0302854029747274822 6.9598781284241768574;-4.8074815119067233482
2.7472568265153958222;-5.3817800747096358194 -
2.853069612506847097;2.1227028493162207745
3.7135593027042439473;1.7947699630890343592
0.27025260372071602255;7.1418075240802210146 4.5063889726200851982];

% Layer 2
b2 = -4.8628357693547323848;
IW2_1 = [0.91649738711656436596 -2.4138934766419515299 5.6524588375224036341
2.2316119772982223601 -4.7456149657944193265 3.571833000598365615 -
2.8898499417774639042 -0.50317259811058545615 5.9370251424553952546
0.66582613177596816634];

% Output 1 y1_step1.ymin = -1;
y1_step1.gain = 26.4541963758153;
y1_step1.xoffset = 0.739973170138921;

% ===== SIMULATION =====

% Dimensions
Q = size(x1,1); % samples

% Input 1 x1
= x1';
```

```

xp1 = mapminmax_apply(x1,x1_step1);

% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*xp1);

% Layer 2
a2 = repmat(b2,1,Q) + LW2_1*a1;

% Output 1
y1 = mapminmax_reverse(a2,y1_step1);
y1 = y1'; end

% ===== MODULE FUNCTIONS =====

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings) y =
bsxfun(@minus,x,settings.xoffset); y =
bsxfun(@times,y,settings.gain); y =
bsxfun(@plus,y,settings.ymin); end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~) a = 2
./ (1 + exp(-2*n)) - 1; end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings) x =
bsxfun(@minus,y,settings.ymin); x =
bsxfun(@rdivide,x,settings.gain); x =
bsxfun(@plus,x,settings.xoffset); end

```

APPENDIX D: The code in C language embedded in 8-bit Microcontroller

```

#include<LiquidCrystal.h>
LiquidCrystal lcd(8,9,10,11,12,13);

int temp=0; int
inso=0; float
sum =0; float
sum2 =0; float
sum3 =0; float
sum4 =0; float
sum5 =0; float
sum6 =0;

```

```

float temperature =0;
float irradiance =0; float
pvVoltage =0; float
battVoltage =0; float
pvCurrent =0; float
battCurrent =0;
float pv_Max_Current =0; //irradiance dependent maximum output current of PV panel
float pv_MP_Voltage =0; //Maximum power point voltage of PV panel at 1000W/m2


//Inputs
#define tempSensor A0
#define insoSensor A1
#define solar_voltage_in A2 #define
solar_current_in A3
#define battery_voltage_in A4
#define battery_current_in A5


//Outputs
#define PWM_out 3 #define
load_enable 7
uint8_t degree[8] = {0x03, 0x03, 0x00, 0x00, 0x00, 0x00, 0x00, 0x00}; // Degree character


//Constants
#define bulk_voltage_max 14.5
#define bulk_voltage_min 13
#define absorption_voltage 14.7
#define float_voltage_max 13
#define battery_min_voltage 10.5
// #define solar_min_voltage 19
#define solar_MP_current 2.0
#define charging_current 2.0
#define absorption_max_current 2.0
#define absorption_min_current 0.1
#define float_voltage_min 13.2
#define float_voltage 13.4
#define float_max_current 0.12
#define LCD_refresh_rate 1000


//Modes
byte BULK = 0; //Give values to each charging mode
byte ABSORPTION = 1;
byte FLOAT = 2;

byte mode = 0; //We start with mode 0 BULK

```

```

//Variables float bat_voltage =
0; float bat_current = 0; int
pwm_value = 0; float
solar_voltage = 0; float
solar_current = 0; float
solar_power = 0; String
load_status = "OFF"; int
duty_cycle = 0; unsigned int
before_millis = 0; unsigned int
now_millis = 0;
String mode_str = "BULK";

//----- void
setup()
{
pinMode(solar_voltage_in,INPUT);    //Set pins as inputs
pinMode(solar_current_in,INPUT); pinMode(battery_voltage_in,INPUT);
pinMode(battery_current_in,INPUT);

pinMode(PWM_out,OUTPUT);           //Set pins as OUTPUTS
digitalWrite(PWM_out,LOW);         //Set PWM to LOW so MOSFET is off
pinMode(load_enable,OUTPUT);
digitalWrite(load_enable,LOW);     //Start with the relay turned off

//TCCR2B = TCCR2B & B11111000 | B00000001; // for PWM frequency of 31372.55 Hz
//TCCR0B = TCCR0B & B11111000 | B00000010; // for PWM frequency of 7812.50 Hz

lcd.begin(20,4);
lcd.createChar(1, degree);
lcd.setCursor(0,0);
lcd.print("          ");
lcd.setCursor(0,1);
lcd.print(" MPPT SOLAR CHARGER "); delay(2000);
lcd.clear();
}

//----- void
loop()
{
//solar_voltage = get_solar_voltage(15);
//bat_voltage = get_battery_voltage(15);
//solar_current = get_solar_current(15);
solar_power = bat_voltage * solar_current;
duty_cycle = map(pwm_value,0,255,0,100);

```

```

/*-----Display Result-----*/

for(int j = 0; j < 10; j++) // loop through and display 10 number of times
{
    for(int i = 0; i < 10; i++) // loop through reading raw adc values 10 number of times
    {
        temp=analogRead(tempSensor); // read temperature input pin
        sum += temp; // store sum for averaging
        inso=analogRead(insoSensor); // read irradiance input pin
        sum2 += inso; // store sum for averaging
        pvVoltage=analogRead(solar_voltage_in); // read PV voltage input pin
        sum3 += pvVoltage; // store sum for averaging
        battVoltage=analogRead(battery_voltage_in); // read batt voltage input pin
        sum4 += battVoltage; // store sum for averaging
        pvCurrent=analogRead(solar_current_in); // read PV current input pin
        sum5 += pvCurrent; // store sum for averaging
        battCurrent=analogRead(battery_current_in); // read batt current input pin
        sum6 += battCurrent; // store sum for averaging
        delayMicroseconds(10);

    }

    sum=sum/10; // divide sum by 10 to get average
    sum2=sum2/10; // divide sum by 10 to get average sum3=sum3/10;
    // divide sum by 10 to get average sum4=sum4/10; // divide sum by
    10 to get average sum5=(sum5/10); // divide sum by 10 to get
    average sum6=(sum6/10); // divide sum by 10 to get average

    temperature=sum*(5/1023.0)*100; irradiance=(sum2*(5/1023.0))-
    1.75; irradiance=irradiance/3.1*1000;
    pvVoltage=sum3*(5/1023.0)*7.2; battVoltage=sum4*(5/1023.0)*7.2;
    pvCurrent=(sum5*(5/1023.0)*3.28)-1.78;
    battCurrent=(sum6*(5/1023.0)*3.28)-1.78;

    // pv_Max_Current = (0.0023*(temperature-47)+7.0)*irradiance/1000;
    pv_Max_Current = (0.0023*(temperature-47)+solar_MP_current)*irradiance/1000;
    pv_MP_Voltage = (-0.1272*(temperature-47))+ 17.2;

    ///////////////////////////////////FLOAT////////////////////////////////////
    /////////////////////////////////// if(mode
    == FLOAT){

```

```

    if(bat_voltage < float_voltage_min){
mode = BULK;
    mode_str = "BULK";
    }

    else{
        if(solar_current > float_max_current){ //If we exceed max current value, we change mode
mode = BULK;    mode_str = "BULK";
        }//End if >

        else{
            if(bat_voltage > float_voltage){
pwm_value--;
                pwm_value = constrain(pwm_value,0,254);
            }

            else {
                pwm_value++;
                pwm_value = constrain(pwm_value,0,254);
            }
        }//End else > float_max_current

        analogWrite(PWM_out,pwm_value);
    }
} //END of mode == FLOAT


//Bulk/Absorption
else{
    if(bat_voltage < bulk_voltage_min){
mode = BULK;
        mode_str = "BULK";
    }

    else if(bat_voltage > bulk_voltage_max){
mode_str = "ABSORPTION";
        mode = ABSORPTION;
    }

    ////////////////////////////////////BULK////////////////////////////////////
    ////////////////////////////////////
    if(mode == BULK){ //if(battVoltage > 14){
        if(pvCurrent > pv_Max_Current){ //Maximum power current tracking
pwm_value--;
            pwm_value = constrain(pwm_value,0,250);
        }
    }

```

```

/* else{
    if(pvVoltage < pv_MP_Voltage){      //Maximum power voltage tracking
pwm_value--;
        pwm_value = constrain(pwm_value,0,254);
    }
*/
    else {
        pwm_value++;
        pwm_value = constrain(pwm_value,0,250);
    }
    analogWrite(PWM_out,pwm_value);
}      //End of mode == BULK

//////////////////////////////////ABSORPTION//////////////////////////////////
//////////////////////////////////
if(mode == ABSORPTION){    if(pvCurrent > absorption_max_current){  //If we exceed max current
value, we reduce duty cycle    pwm_value--;
        pwm_value = constrain(pwm_value,0,254);
    }//End if > absorption_max_current

    else{
        if(bat_voltage > absorption_voltage){
pwm_value++;
            pwm_value = constrain(pwm_value,0,254);
        }

        else {
            pwm_value--;
            pwm_value = constrain(pwm_value,0,254);
        }

        if(solar_current < absorption_min_current){
mode = FLOAT;
            mode_str = "FLOAT";
        }
    }//End else > absorption_max_current

    analogWrite(PWM_out,pwm_value);  }//
End of mode == absorption_max_current

} //END of else mode == FLOAT

```

```

    if(battVoltage < battery_min_voltage){
digitalWrite(load_enable,LOW);
    load_status = "OFF";
    }
    else {
digitalWrite(load_enable,HIGH);
    load_status = "ON";
    }

```

```

    if(j == 0){    lcd.clear();
lcd.setCursor(0,0);
lcd.print("TP");
lcd.setCursor(3,0);
lcd.print(temperature);
lcd.write(1);
lcd.print("C");
lcd.setCursor(0,1);
lcd.print("IN");
lcd.setCursor(3,1);
lcd.print(irradiance);
lcd.setCursor(0,2);
lcd.print("DT");
lcd.setCursor(3,2);
lcd.print(duty_cycle);
lcd.setCursor(0,3);
lcd.print("LD");
lcd.setCursor(3,3);
    lcd.print(load_status);

```

```

    lcd.setCursor(11,0);
lcd.print("PV ");
lcd.setCursor(14,0);
lcd.print(pvVoltage);
lcd.print("V");
lcd.setCursor(11,1);
lcd.setCursor(14,1);
lcd.print(pvCurrent);
lcd.print("A");
lcd.setCursor(11,2);
lcd.print("HYB ");
lcd.setCursor(14,2);
lcd.print(battVoltage);
lcd.print("V");
lcd.setCursor(11,3);

```

```
    lcd.setCursor(14,3);  
    lcd.print(battCurrent);  
    lcd.print("A");  
  }  
}  
}
```