Simulation Study of Lithium-Ion Battery Charging and Discharging with MPPT Flyback Converter Approaches

Abstract:

Renewable sources of energy cannot adequately integrate to the electrical grid without an effective methodology for controlling the conversion of electrical power from renewables into stored energy in a battery. In this thesis, a computer model has been developed using the computer-programming language 'Java' which evaluates the effect of various types of flyback converters on the charging and discharging of lithium batteries within a solar photovoltaic energy network that utilizes maximum power point tracking The primary focus of this thesis is to establish how the isolated flyback converter interacts with the “PV” system and “Li” battery using various “MPPT” algorithms under differing operating and environmental parameters. As part of this study, a complete mathematical model for a “PV” array was created to determine how changes to irradiance and temperature would impact the “PV” array performance. Additionally, a “Li” battery model that captures the complex nonlinear behavior for charge and discharge, the way the “SOC” changes, and the voltage behavior was also constructed to ensure accurate representation of Lithium-ion battery performance. We also created a model of the isolated flyback dc-dc converter to transfer energy from the “PV” source to the battery in a manner that maximizes charge and discharging efficiencies and that keeps battery-safe operation as a top priority. Multiple “MPPT” algorithms were used, including “Perturb & Observe” and “Incremental Conductance methods”, to find and extract the maximum available power from the array at all times. To dynamically select the optimum climatic and machine operating conditions, we also developed an intelligent “MPPT” selection mechanism combining all of the above algorithms.

The “MPPT” generators produce control signals for the flyback converter that can vary the duty cycle to maintain the proper voltage and current for charging a battery. Utilizing the simulator allows users to track important battery information while the battery is being charged and discharged as well as determine battery operation profiles during the charging and discharging process. Furthermore, the "MPPT" efficiency of the simulator produces a large database of test data from users.

The results from this study provide evidence that the MPPT-controlled flyback converter will allow one to extract a higher percentage of available energy, maintain a safer operating condition for lithium-ion batteries. This study illustrates how environmental factors and MPPT algorithms can affect the efficiency of lithium-ion battery charging and how these factors may contribute to decreasing the effective lives of lithium-ion batteries. The findings from this study will be beneficial for the design and optimization of photovoltaic charging systems that are used in conjunction with lithium-ion batteries in renewable energy applications.

Keywords: *Lithium-ion battery, MPPT algorithms, Flyback converter, Photovoltaic system, Battery charging and discharging, State of charge, Renewable energy systems, DC–DC converter, Solar energy, Power management.*

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Chapter 1

Introduction

The “Lithium-ion batteries” are becoming more and more mutual in both energy storage and electric vehicle markets. Temperature has an enormous effect on performance and safety for Lithium-ion Batteries and therefore, developing the correct thermal management systems is vital to extending “lithium ion battery’s” Life, by limiting the exposure of LIB's to additional heat and keeping them safe during operation [1-12].

Research is still being done to develop and test new methods of cooling for “Lithium-ion Battery Systems” because better cooling systems will allow for increased performance of “Lithium Ion batteries” in general. By providing more uniform temperatures across the Lithium-ion Battery cell it will also provide greater safety and longevity [3- 7].

In determining a specific battery type's performance, estimating how long that particular battery will last, and designing any battery management system for that battery type, being able to accurately predict battery voltage, battery efficiency and battery lifespan are important metrics in developing an effective battery model. Developing a battery model requires you to find the best possible solution to tradeoff between speed of calculations and accuracy of results. Understanding the effects of the charging/discharging cycles on the internal stresses to the battery's chemistry over a period of period helps further recognize how those stresses lead to battery deprivation. [4- 6].

The way a battery is charged will have a large impact on its life expectancy and operating efficiency. Previously, batteries were charged with a standard constant current; however, there is a shift to using multiple stages of charging with optimized methods to increase charging speeds and reduce degradation of the battery over the course of its lifetime. The goal of these charging strategies is to achieve fast-charging while maintaining the longevity of the battery. [2 - 7].

A reliable way to estimate a battery's state parameters allows optimal. The machine learning and optimized neural network method used in combination has proven to be beneficial for providing more accurate estimates of a battery state because it captures the nonlinear behaviour of the battery over time as a result of the changes in the environment [8 - 13]

Furthermore, choosing the right indicators of battery health is key for accurately monitoring the health of a battery and diagnosing problems with the battery. Using a data-driven approach that takes into consideration historical charging data allows for increased accuracy when estimating SoH and provides the opportunity to utilize more adaptive control methods through the implementation of modern BMSs (Battery Management Systems). [5-10]

The presence of imbalance between cells in battery packs limits usable capacity and increases the rate of degradation. Applying active balancing systems and intelligent balancing control methods allows the uniformity of operation, maximum utilization of all energy from the entire battery pack, and increased reliability for the whole system due to more accurate estimates of SOC. [11- 14].

For having a reliable and effective maintenance plan in the long term, the facility to recognize useful life of “lithium ion batteries” is very important. The combination of sophisticated deep learning and hybrid signal-processing technologies has been shown to accurately identify degradation patterns of the batteries and result in more effective proactive management of the batteries, thus prolonging their operational lifetimes. [9 - 15].

1.1 Motivation

The increasing usage of Renewable Energy Sources worldwide has created a dramatic expansion in the development and deployment of Renewable Energy Systems, most notably through the use of “Solar Photovoltaic” technology, across all three major market sectors such as Residential, Commercial, and Industrial. Meanwhile, due to the growing concern over climate change and greenhouse gas emissions, the “Electric Vehicle” market is growing exponentially. “Lithium-Ion batteries” accepted form of both Electric Vehicles and RESs.

However, the combination of solar photovoltaic technology with lithium-ion battery storage systems creates many challenges for App Developers. Solar irradiance and ambient temperature continually change during the day; consequently, the output power of PV arrays can likewise fluctuate with the changes in solar irradiance. To harvest the maximum amount of energy, the algorithms necessary to guarantee that the PV array operates at maximum efficiency despite variations in environmental conditions. In addition, improper charging and discharging of batteries can ultimately result in either voltage stress or low efficiency and premature capacity fade, as well as possible serious safety concerns, such as dangerous thermal runaway.

This research was initiated in order to develop a theoretical model as well as a simulation platform that combines photovoltaic arrays with lithium-ion batteries and flyback DC-DC converters using advanced “maximum power point tracking” techniques. The purpose of this combination is to improve energy production from renewable sources while at the same time providing safety for lithium-ion battery systems and increasing the overall type of renewable energy storage efficiency required for “electric vehicle” charging stations, as well as off-grid applications.

1.2 Problem Statement

There are various issues associated with using PV-battery systems despite the fact that they are well documented and used today.

- The “maximum power point tracking” methods are not able to accurately follow the maximum power point when there is a very rapid change in measures of the sunlight being received at that time (such as solar irradiance) and the temperature of both the solar panel and connected batteries; as a result, the overall amount of energy harvested is less than what is possible.
- Depending on the charging profile being used and the suddenness of the load being placed on a battery, a lithium-ion battery may be placed under stress through voltage spikes, excessive current, or thermal stress, resulting in reduced lifespan.
- Some systems today do not incorporate intelligent controls or dynamic control strategies that allow the dynamic selection of the most appropriate MPPT algorithm depending on changing operating conditions; this lack of dynamic selection will limit the overall system performance.
- Energy transfer from the PV to the battery, and from the battery to the load will often be inefficient, resulting in wasted energy, without taking steps to incorporate appropriate controller usage.

To address these challenges, a simulation framework is developed in this research that will incorporate PV modelling, battery characterization, and advanced MPPT algorithm controls that are integrated with flyback converter control. The purpose of the simulation framework will be to allow for the most efficient energy transfer from PV to battery and from battery to load, while at the same time maintaining the health and safety of the battery throughout operation.

1.3. Objectives:

The main goals of this project are given below:

- To create models and simulations using mathematics for both photovoltaic arrays and lithium-ion batteries. Additionally, we will develop models and simulations for the different environmental conditions affecting photovoltaic arrays and batteries using Flyback DC to DC converters, as well as lithium-ion batteries' temperature and humidity ranges, etc.
- To implement multiple “maximum power point tracking algorithms” including “Perturb & Observe” and “Incremental Conductance algorithms”, and develop a hybrid intelligent MPPT selection strategy to determine which “maximum power point tracking” algorithm will work best with the dynamic operation of an array and battery system.
- Generate the control signals for the Flyback converter used for transferring energy from the photovoltaic array to the battery based on the MPPT output to provide stable battery charging process

- Simulate battery cycles, as well as analyze the battery's State of Charge, voltage, current, and temperature to assess performance of the system.
- Assessing the impact of irradiance, temperature, and MPPT algorithm choices on the efficiencies of the batteries, charging dynamics, and overall energy harvesting capabilities. To the extent that we can obtain the real battery data sets, we will validate the simulation framework.

1.4. Contributions:

The following contributions are solved by this thesis work:

- **Comprehensive Sub-Modeling of an Integrated System:** Integrated "PV" Arrays with Lithium-Ion Batteries and Isolated Flyback Converters will be modeled completely using varying environmental conditions in running a simulation.
- **Combined Hybrid MPPT Approaches**: Will Implement Multiple MPPT Algorithms Together and will use the Hybrid Selection Method to determine which algorithm(s) Will Be Selected to Maximize Energy Collection.
- **Secure and Effective Battery Management**: A Control Structure has been developed so that the batteries are charged/discharged based on either voltage and/or current and to minimize the stress on maximize useable life
- **Presentation Assessment Framework:** Comprehensive analysis of the working performance of "PV" battery systems will help assess the effectiveness of the converter; that is, what percentage of the energy through the converter is converted into operational energy. In addition, performance evaluation also provides a baseline for the

- SOC values or, battery's State Of Charge values, energy losses via the PV battery system and the thermal performance of a PV battery system.
- **Authorization based on Simulation**: Simulation results can also be used to validate the proposed simulation method, and will provide up-to-date knowledge on how to utilize a PV battery system to optimally support Renewable Energy resources and the growth of Electric Vehicle Infrastructure.
- The proposed study's primary goals are to address these identified issues by advancing the way that efficient and safe PV battery systems are designed, thereby supporting the enablement of renewable energy solutions and the development of Electric Vehicle infrastructure.

1.5 Thesis Organization

The outstanding thesis is structured as follows:

- **Chapter 1** illustrates the overview of the concepts, aim and objective, contributions problem statement and the flow of the thesis.
- **Chapter 2** briefly illustrated the essential background concepts and technologies related to our work including lithium-ion battery, charging and discharging techniques, flyback convertor, MPPT technique and algorithm, fuzzy logic control and conventional controllers
- **Chapter 3** presents an extensive review of state of art including current directions in DAI in terms of AI workflow, distributions paradigms, supporting infrastructure, management techniques, and various applications.
- **Chapter 4** illustrates thesis research methodology including the steps and approaches we went through to produce this work. Then it introduces the proposed framework for charging and discharging in lithium – ion battery.

- **Chapter 5** explains the charging technique without the MPPT, MPPT based control, MPPT algorithm, design of the fuzzy logic controllers such as inputs, membership functions, rule base, integration of fuzzy MPPT with flyback convertor and control flow diagram is illustrated in this chapter.
- **Chapter 6** briefly explains the controlling strategy of the system. The working principles of MPPT and fuzzy logic controller, simulation environment, outcomes that are obtained without the MPPT or conventional MPPT, charging performance are demonstrated in this chapter.
- **Chapter 7** concludes the thesis and discusses the future directions of thesis area. Fig. 1.1 illustrated the flow or organization of the thesis.

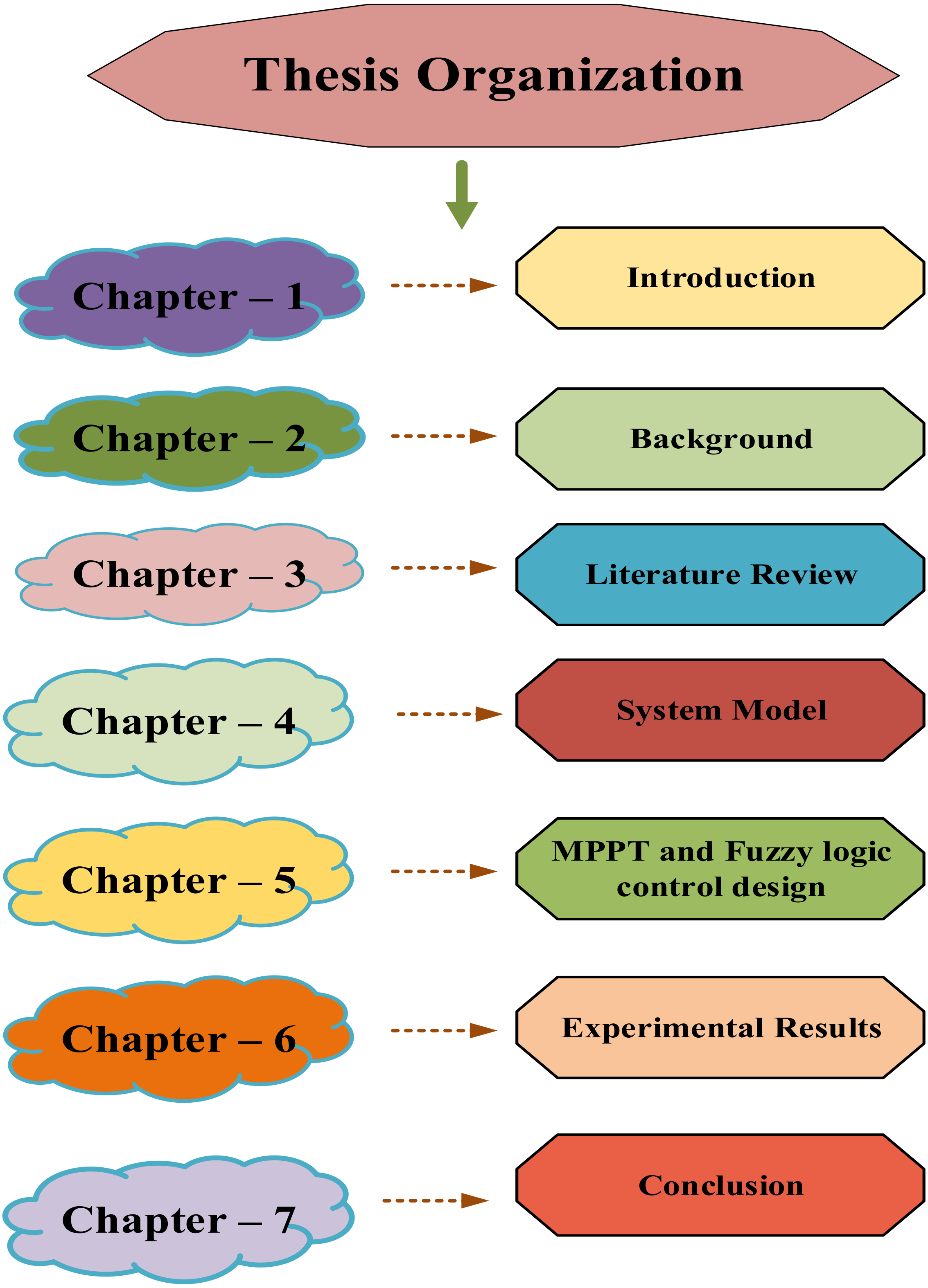

Fig 1. 1 Thesis Organization

Chapter 2

Background

An increasing interest in utilizing clean energies such as wind and solar along with improved technologies to capture, store, and distribute that energy has resulted in rapid development within both lithium ion battery and development of advanced power electronics. The long cycle life, and low self-discharge characteristics of “Li-ion” batteries have resulted in widespread use across many industries, including portable electronics and electric vehicles. However, in order to achieve optimal levels of performance and longevity from these batteries, very accurate, reliable and safe methods for controlling both battery charging and discharging will be needed. In addition, intelligent methods of power conversion and maximum power point tracking (MPPT) will be required when Li-ion battery systems are connected to a renewable power generation source, such as a solar PV system.

The objective of this chapter is to cover some fundamental concepts and prior research associated with the charging and discharging of Li-ion batteries, DC-DC converters, and control techniques based on MPPT, which will provide a foundation for the simulation study outlined in the rest of this paper.

2.1 Lithium-Ion Battery

"Lithium-ion (Li-ion) batteries" are rechargeable power sources that store energy through a liquid or gel electrolyte, offering high energy density, light weight, and long life, making them ultimate for portable electronics, electric vehicles, and grid storage. It is the leading form of energy storage technology levels of energy density, efficiency, long cycle. However, there are many degradation mechanisms that result in a reduced life expectancy for lithium-ion batteries, including but not limited to capacity fading, lithium plating, and thermal stresses on the battery. [16]. They work by inserting (intercalating) lithium ions into the porous structures of graphite anodes and other cathode materials during charging, releasing them during discharge, a process that allows for repeated recharging without significant loss of capacity. Fig. 2.1 shows the structure of the Lithium – Ion Battery.

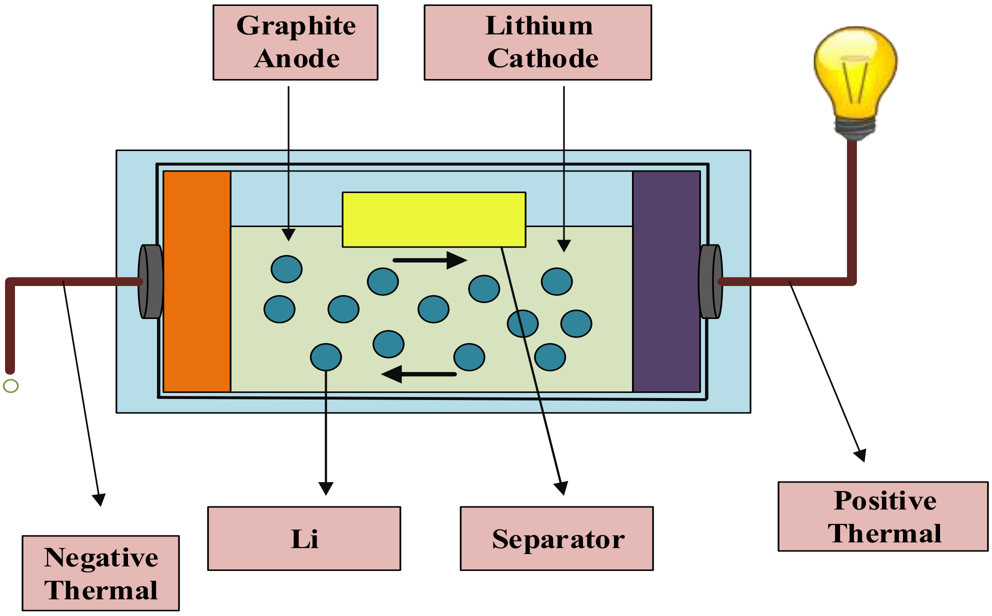

Fig 2. 1 Lithium- Ion Battery

2.1.1 Components of Lithium-Ion Battery

The primary component of the lithium-ion battery is listed below:

- **Anode:** When charged, a lithium heavy battery stores Lithium Ions on the Anode. The Anode is usually made of graphite and will release the Lithium Ions back to the cathode when discharged.
- **Cathode:** or positive electrode, discharges the Lithium Ions and is generally made of Lithium Metal Oxide, LCO, LMO, or NMC, when a battery is discharging.
- **Electrolyte:** The Electrolyte in a lithium-ion battery is a liquid or polymer with dissolved Lithium Salts in it that allow for the Lithium Ions to travel or move throughout the battery between electrodes.
- **Separator**: The Separator is a thin and porous barrier. This physically separates the anode and cathode, preventing short-circuiting, but allows ions to pass through.
- **Current Collectors:** The metal Current Collectors consist the Current Collectors conduct electrons to the external circuit for energy needs.

The components that are presented in the lithium-ion battery is illustrated in Fig. 2.2

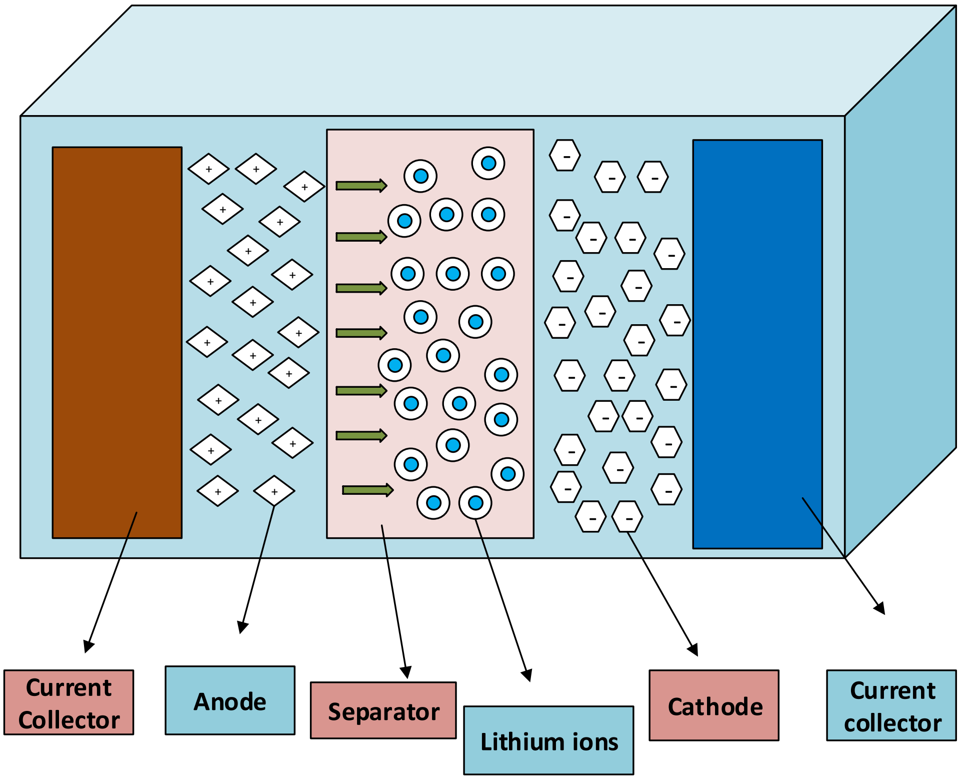

Fig 2. 2 Components of Lithium-ion battery

2.2 Battery Charging

Lithium-ion batteries are charged through a two-step Constant Current - Constant Voltage process. First, in this process the battery maintains a steady current until the battery voltage reaches a limit typically around 4.2 volts. After this point has been reached, the battery will hold the voltage constant as the current gradually decreases to prevent any possible overcharging and maximize the battery's capacity. Lithium-ion batteries tend to have a longer lifespan when they are charged with less than full capacity and are subjected to limited ranges of temperature extremes. The integration of electric vehicles into power systems will create complicated issues when it comes to the control of electric vehicle charging and discharging. To provision battery, enhance energy utilization and decrease the electric grid, coordinated electric vehicle charging strategies are important. [17]. Lithium-ion batteries save power by the movement of lithium ions inside the battery from the positive electrode to the negative electrode.

Charging phase of the lithium battery is illustrated below:

- **Constant Current Phase**: A constant power charges the battery, increasing its voltage.
- **Constant Voltage (CV) Phase**: Once the battery reaches its upper voltage limit (around 4.2V), the charger holds this voltage constant, and the current gradually decreases.
- **Dissolution of the Charge**: Charging stops when the current drops to a very low level (e.g., 0.05C), indicating full saturation, but this can be slow, so some chargers stop at typically at the percentage of 80.

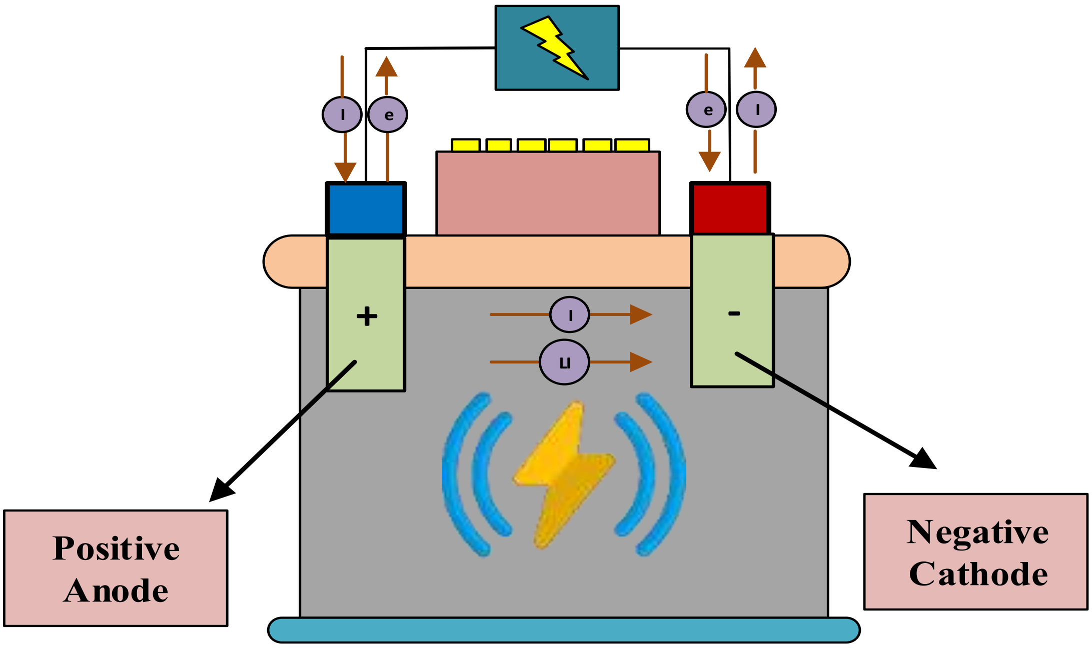

Fig 2. 3 Battery Charging

2.2.1 Battery Charging Modes

Li-Ion (Lithium-ion) batteries must follow a carefully-defined charge procedure. Charging Li-Ion batteries requires a well-defined multi-stage charging method to guarantee safe and reliable operation, due to their susceptibility to excessive voltage, while lead-acid batteries may use an unregulated charger.

The battery charging modes of lithium ion battery is classified into three categories which as follows.

- Charging with constant power
- Continuous charging of power
- Charge quickly or boost

2.2.1.1. Charging with constant power

The level of charge on a battery today is about 10%. Constant Current Charging supplies current to a battery at a set voltage and will cut the charger off once that battery has reached the maximum volt level. One disadvantage of using Constant Current Charge (CCV) technique is the possibility of overheating resulting in battery failure sooner than would have otherwise been expected.

2.2.1.2. Continuous Charging of power

A charger will provide full current up into a battery until reaching the specified voltage, at which point the current will be reduced to a narrow range. A battery can be left attached to the charger until it is required to charge and will keep charged at its float voltage, There's a constant trickle charge provided for a battery due to its normal self-discharge. Although this method of charging takes more time to complete, it's the only method of charging a battery (to ensure maximum life) until used, when the battery reaches its maximum balanced discharge voltage (point).

2.2.1.3. Charge quickly or boost

The combination of these two methods above allows a battery charger to charge the battery quickly (high current), while preventing overcharging, as the total current is limited to a predetermined amount until the battery reaches a high enough voltage (present voltage). As the battery nears its full charge, the amount of current supplied decreases gradually. This approach works well for lithium ion and like-type batteries, and it also minimizes the possibility for overcharging due to a high-current condition.

2.3 Battery Discharging

The release of chemical energy stored in a battery to create electrical energy is referred to as 'discharging.' The term 'discharging' refers as a result series of process between two electrodes which causes a flow of electrons from one terminal to another terminal through a circuit. Essentially, discharging a battery means using the energy previously stored in the battery in the form of electrical power to supply current to a load until the battery has either been fully discharged or completely recharged. Fig. 2.4 represents the discharging process of lithium-ion battery.

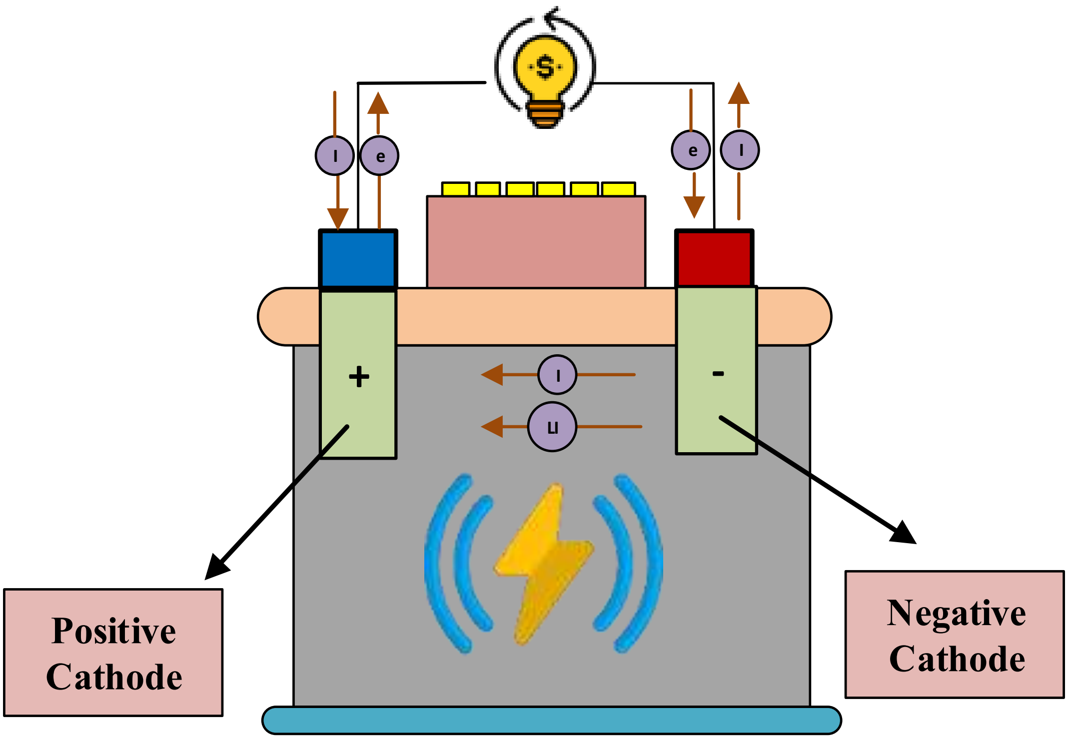

Fig 2. 4 Battery Discharging

The discharging process is mentioned below:

- **Anode:** Negative electrodes are made of graphite, where lithium atoms lose their electrons and create lithium (Li+) ions.

- **Electrocycle and Separator:** Using a porous separator, Li+ ions can move the liquid electrolyte. Meanwhile, the anode will send electrons through circuit wires connected to an external device (this powers that external device) and finally to the cathode.

- **Exterior Circuit**: Electrons flow from the anode into the external load (the device being powered) until they reach the cathode.

- **Cathode**: Li+ ions and electrons recombine at the cathode within the active material's structure, thereby completing the current flow and creating electricity from an electron/nanotechnology perspective.

2.4 DC-DC Convertor

DC-DC converters convert direct current (DC) voltage levels from one voltage source into a different voltage, either up (boost) or down (buck). DC-DC converters utilize electronic switches, inductors, capacitors, and transistors to efficiently transfer power from input voltage sources to output voltage sources. By utilizing these switching devices, DC-DC converters create a very reliable and controlled volt/Amps value for the end-user electronics (including smart phones, laptops, tablets, and electric vehicles). Unlike inefficient linear voltage regulators, DC-DC converters provide regulated outputs with very little disturbances to other parts of the entire electric system. Power electronics are circuits that allow for the controlled conversion of one level of Direct Current (DC) to another level of DC with the use of Power Switching Devices to store and release Energy through Inductor and Capacitor(s), providing stable power delivery. Power electronics are used in Electric Vehicles, Solar Power Systems, and various Portable Devices to regulate voltage and control power. Power electronics have Greater Efficiency than Linears.

2.4.1 Types of DC-DC Convertor:

DC-DC convertors are normally classified in to isolated and non-isolated convertors. An isolated converter is a type of power supply that uses a transformer to physically and electrically separate its input from its output. Because there is no direct path for current between the two parts of an isolated converter, it eliminates the risk of ground loops and electrical shock, as well as allows independent grounding for both the input and output. These characteristics of isolated converters make them essential for ensuring the safety of medical, industrial and consumer electronics. Since the energy is transferred by electromagnetic induction rather than conduction, this method also provides better noise immunity by decoupling the input and output circuits.

DC-to-DC converter is very important in the conditioning of electrical power between energy sources and loads, there are many types of converters available, all with unique design characteristics to enhance the efficiency of conversion, reduce losses and allow for multi-directional power flow. Advances in the design of DC-to-DC converters have had a significant impact on the reliability and efficiency of renewable energy systems and of the infrastructure used for charging electric vehicles. [22]

The definition of a non-isolated DC - DC converter is a DC - DC power converter that shares a common electrical ground and does not have galvanic separation (good grounding) between the input and output terminals. A non-isolated DC - DC converter has a direct electrical connection (the same Circuit) between its output and input, which enables it to have a simpler design, smaller size, and High efficiency. This makes non-isolated DC - DC converters very Cost effective for many applications such as point of load regulation when there is not a large voltage safety concern. Fig. 2.4 shows the types of isolated and non-isolated DC-DC convertor.

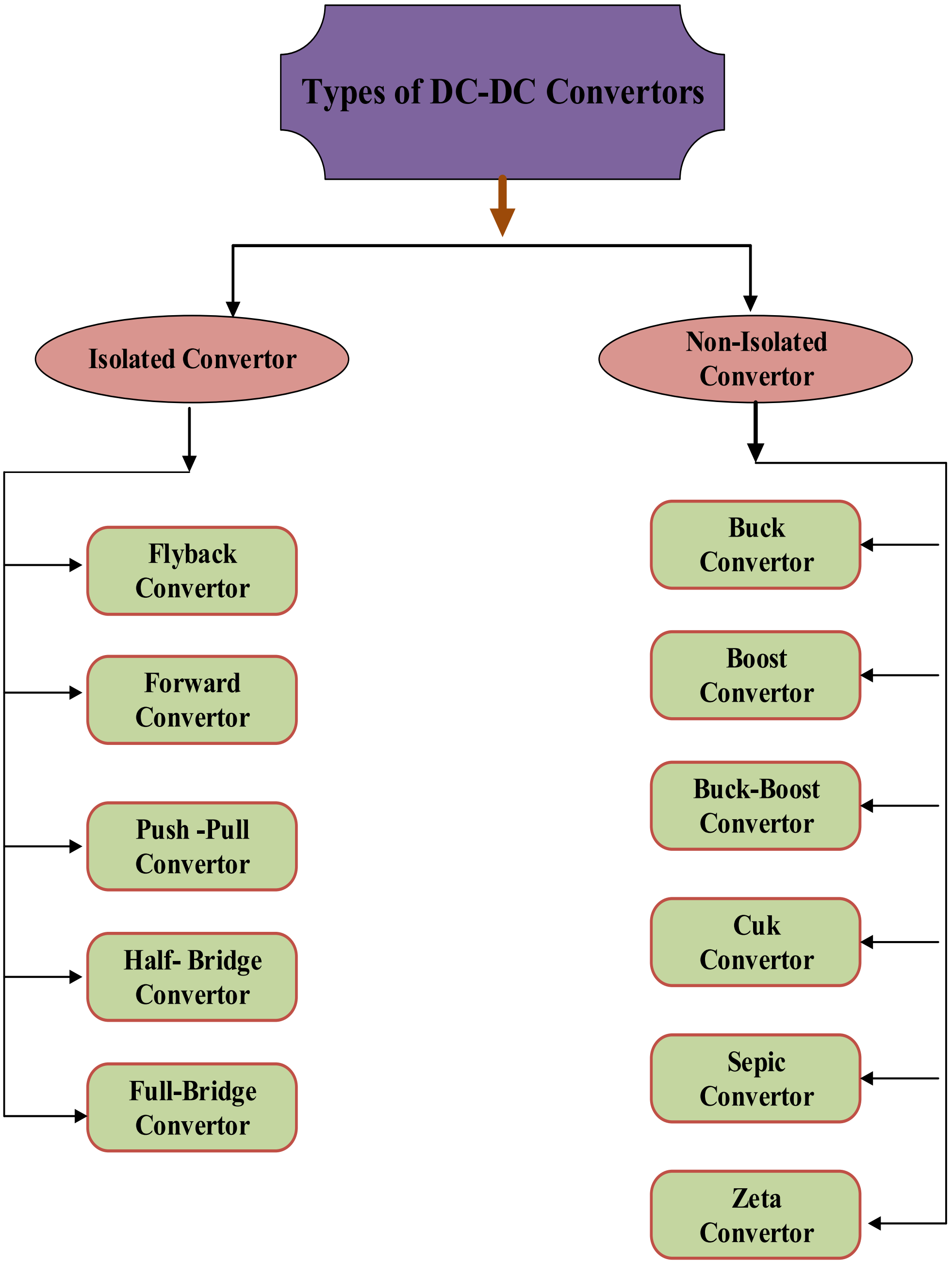

Fig 2. 5 Types of DC-DC Convertor

Fig. 2.5 represents the types of "DC-DC Convertor". The DC-DC convertor is classified into isolated and non-isolated convertor.

2.4.2. Isolated convertors:

An isolated converter is a power electronic converter that provides a separation of the electrical connection between the source and the load; the input has no electrical connection to the output. Instead, the source is load through a transformer or some other form of magnetic coupling.

2.4.3. Key points of isolated convertors:

- **Galvanic Isolation**: The input and output circuits will be separated in order to avoid any source-to-load direct current flowing and to increase safety and improve resistance to electrical faulting.

- **Voltage Level Conversion**: The transformer allows for an increase or reduction of the input voltage depending on application requirements.

- **Applications:** The isolated converter used in a variety of applications such as power supplies, battery chargers, and DC-DC converters and are also commonly found in “renewable energy systems” such as solar PV battery systems.

2.4.4. Examples:

Examples of isolated convertors are such as flyback convertor, forward convertor, pull-push convertor, half-bridge convertor, full-bridge convertor.

2.4.5. Non-Isolated Convertors:

A Non-isolated power electronic converter is a way to convert energy from one form to another: a converter's input and output are physically connected without passing through a transformer that providess galvanic isolation.

2.4.6. Important Attributes of Non-Isolated Convertors:

- **None Galvanic isolation**: Because there is no galvanic isolation between the input and output of a non-isolated converter, both must share the same level of safety, protection, etc., when they connect to each other through a common electrical path.

- **Voltage conversion**: A Non-Isolated Power Converter can only convert voltage, but it does not provide a means of stepping up or down the voltage independently using a transformer. Instead, the adjustment of the AC voltage is accomplished using a method known as duty-cycle control.

- **Usage:** Non-isolated DC to DC convertors include Buck, Boost and Buck-Boost workings used in battery operated devices, DC motors and other small electronic devices.

2.5 Fly back Convertor

A flyback converter is a type of isolated DC-to-DC yellow (or isolated AC-to-DC) converter which uses the magnetic coupling of magnetically coupled inductors (flyback transformer) to store energy whilst the switch is in the on state and then transfer that energy to the load when the switch is off. This differs from all other types of transformers in that flybacks transfer energy through the magnetic coupling of inductor coils instantaneously rather than storing energy and then transferring it later as with all standard transformers. The term "MTTP flyback" specifically means a flyback which uses an MTPP (Maximum Power Point Tracking) controller (the most common use of a MTPP controller is in solar PV applications) which continually adjusts the duty cycle of the flyback so that optimally operates at maximum power output, independent of changes in temperature or solar irradiance/angle of incidence. Fig. 2.5 illustrated the block diagram of the flyback convertor.

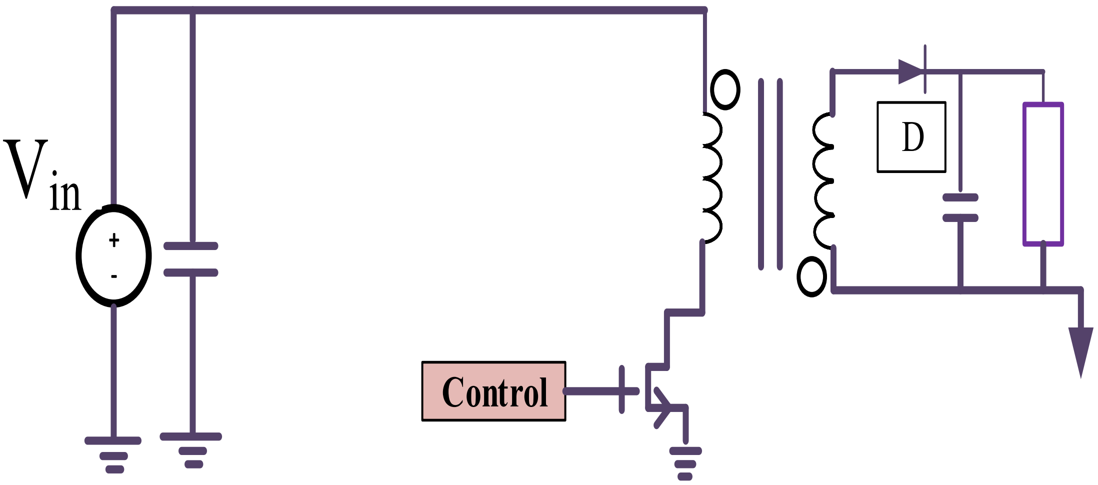

Fig 2. 6 Flyback Convertor

The core intelligence of the flyback converter is the MPPT Algorithm, which consists of various algorithms (e.g., P&O or Incremental Conductance) that enable the flyback converter to sense voltage/current being produced by the PV and calculate the power produced by the panel.[19]

Another common technique to improve overall system efficiency is to use multiple flyback stages operating in parallel – a technique known as Interleaving.

2.5.1 Working principles of flyback Convertor

Flyback converters work by storing energy during the ON-state of a switch in the magnetic field of a transformer and releasing that energy to the output during the OFF-state of the switch. This allows for galvanic isolation. As current flows through the primary coil of the transformer when the switch is ON, energy is stored in the transformer. When the switch is turned OFF, the stored energy flows back through a diode to charge the output capacitor and supply power to the load. Flyback converters also operate like buck-boost converters but use a transformer to couple inductance.

2.5.1.1. ON Phase (Recharge/Charge Mode - Energy Storage)

- The control circuitry, which is part of the Maximum Power Point Tracking (MPPT) System, will energize the primary switch. Energizing the primary switch connects the primary winding of the transformer across the input DC supply (e.g., output from solar panel(s)). The primary current will flow through the primary winding and create a magnetic field in the transformer core. The energy transferred from the input supply is stored in the air gap of the core of the transformer.
- Because of the winding polarity of the transformer (indicated by the dots shown in the schematics), the induced voltage in the secondary winding is negative (reverse bias); as a result, the output signal diode will prevent any current from flowing to the load. The load will be powered solely by the output capacitor for the duration of this cycle.

2.5.1.2. OFF Phase (Transfer Mode - Energy Transfer)

- The control circuit now switches off the Primary Switch. The magnetic field generated in the transformer is now collapsed, thus reversing the polarity of the voltage across both the primary and secondary windings.
- Now that only the secondary diode is being forward-biased, all of the stored energy in the transformer can now transfer to the secondary side, where it can be used to supply the load(s) and recharge the output capacitor.

2.6 MPPT Technique

“Maximum power point tracking” is a technique used to maximize output from solar panels. A Flyback converter configured to perform MPPT function derives its method of extractions from a particular kind of DC to DC converter. Flybacks also have several advantages such as voltage boost, galvanic isolation and increased packing density for solar power systems (especially for lower power levels, i.e. 100-150 Watts), enabling improved efficiency in solar power systems under a much wider range of conditions than with standard methods. The comparison of flyback topologies versus other traditional MPPT methods should not be understood as a challenge between technology competitors. Instead the comparison of flyback topology to other MPPT technologies illustrates how flyback topologies promote and enable MPPT capabilities, especially for connecting solar energy systems to the power grid. The basic principles underlying both types of flybacks are the same; however, the MPPT algorithm is able to continuously adjust the operation of the switch by changing its duration of "on" or "off" operation.

MPPT or Maximum Power Point Tracking is an electronic device (or powering up device) that is used on photovoltaic systems & other sources where the output power fluctuates to get as much out as possible by continually searching for the best combination of voltage & current. It is a more stable, efficient way of using solar panels to harness solar energy than was previously possible using other growth technologies that didn't use an algorithmic approach with a charge controller/inverter. An MPPT allows a designer to design a charge controller that will optimize the efficiency of the charging process & the overall energy capture from solar panels. Fig. 2.7 illustrated the

Working of MPPT controller.

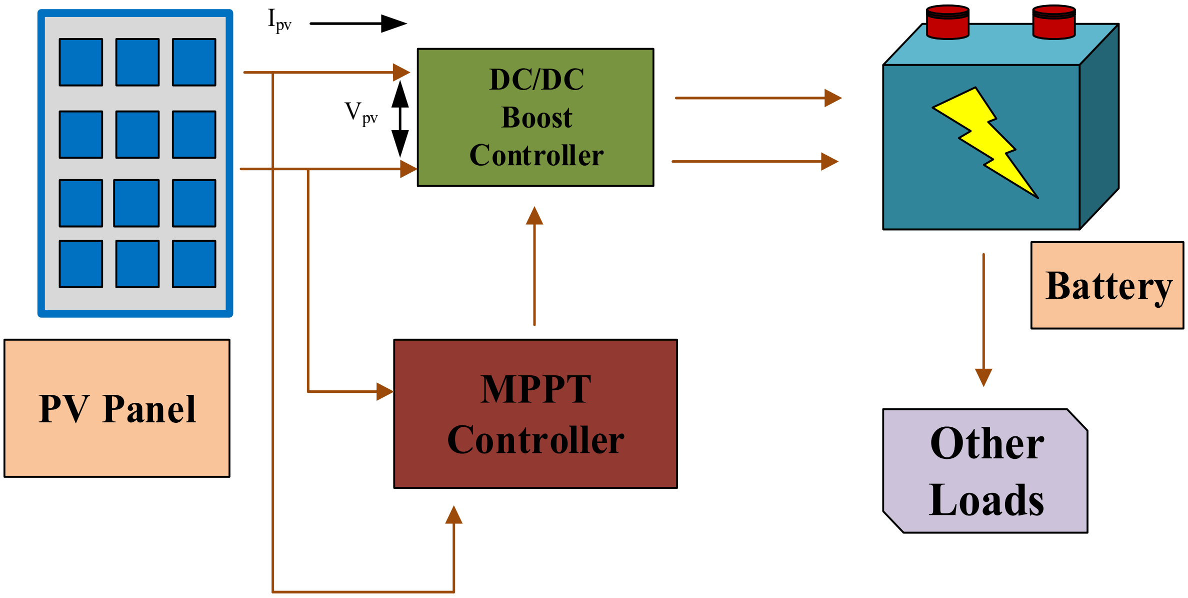

Fig 2. 7 MPPT Controller

2.6.1 Core perception of MPPT technique

The working principles of MPPT are given below:

- **Diverse Rules:** The output and efficiency of solar photovoltaic modules depend on the environment and conditions under which they are operating at any given time.
- **Detecting the Sweet Spot**: The maximum power point tracking (MPPT) function in solar charge controllers continuously monitors the voltage (V) and current (I) of the solar module(s) to calculate the product, or power (Power = V x I).
- **Flexibility:** By dynamically adjusting the load to the battery bank or the power

grid continually throughout the day, MPPT allows the battery charger (or power grid) to operate at the V/I combination that is maximising the power delivered from the solar modules - known as the maximum power point (MPP).

- **Best Precision:** Consequently, more energy is collected with MPPT compared to conventional controllers, such as positive/negative (PWM), particularly during morning/evening/dusk hours or during cloudy weather days.

2.6.2 Advantages of MPPT Technique

MTTP technique offers a lot of advantaged which are listed below:

- **Higher Energy Yield:** MPPT adjusts the voltage and current of the solar panel(s) to always deliver the maximum possible power output, which increases the total energy produced.

- **Improved Efficiency**: MPPT makes sure the solar panel(s) are operating at their best point which increases the amount of energy that can be used regardless of the conditions when producing energy.

- **Better Performance during Poor Conditions**: MPPT will produce more energy in low-light, cloudy, or partially shaded scenarios compared to other systems.

- **Faster & Healthier Battery Charging**: Excess voltage is converted to additional current by the MPPT. Thus, batteries are charged faster and more effectively, but MPPT will also prevent over-charging or deep discharging batteries, which increases the life of the battery.

- **System Flexibility**: For larger PV systems, MPPT provides more options for configuring the solar panel(s) and allows for the most efficiency from the system by accounting for the different orientations and shading patterns.

- **Cost Reduction**: By increasing energy output and extending the life of the battery, the overall operational costs of the system are reduced. Even with a higher initial investment for the MPPT, the long-term ROI will be better.

- **Increased Consistency**: By quickly adjusting to rapid fluctuations in sunlight, MPPT provides a more stable and consistent power supply.

2.6.3 MPPT Algorithm:

“Maximum Power Point Tracking” algorithm steps are determined by the technique being applied. The “Perturb and Observe” is usually one of the most popular methods in MPPT operations. To determine where maximum power can be obtained, this algorithm changes the operating voltage of a solar panel at short intervals and measures the corresponding power output to identify the point of maximum output. The steps involved in MPPT algorithm are below mentioned:

Step 1

Initiating: Initial conditions such as disabled watchdog timers and maximum current limits have been established in order to enable maximum search range.

Step 2:

Extent: Measuring the PV Panel's Voltage/Current are completed in this stage.

Step 3:

Examine: Calculating the Current Power Output by using the formula P=V*I

Step 4:

Comparison: Comparing the Current Power Output to the Prior Cycle's Power Output and the Current Panel's Voltage to Prior Cycle's Voltage.

Step 5

Transportation: If the power increases, then the algorithm persists with the previous voltage adjustment (increase) and therefore continues to raise the positive voltage bias. If the power decreases, then the algorithm will switch direction on the previous step (decrease) and will subsequently reduce the positive voltage bias.

Step 6

Repetition: These steps will be performed in a continuous manner (i.e. every sampling time interval) until the Maximum Power Point (MPP) is reached. After reaching the MPP, the algorithm will adjust itself to establish an Oscillator about this MPP.

Step 7:

Termination: When the MPP is achieved, the algorithm will indicate that the system is functioning optimally through energy-efficient operation and will therefore exhibit periodic fluctuations about the highest output of available electricalenergy.

2.7 Fuzzy Logic Control

Fuzzy Logic Control is a kind of intelligent control that replicates how humans think through fuzzy sets and use of "if-then" rules. The fuzzy logic method can effectively handle both vague inputs and uncertainties through transforming qualitative knowledge into efficient and continuous control. Because of this versatility, FLC has been particularly favorable for applications where human-like decision-making is desirable such as in appliances, automotive systems and industrial processes.

Fuzzy logic control is an intellectual method that don’t require an accurate framework of the system to control, as its name implies, it is especially useful with non-linear and uncertain systems like energy management systems and power converters. Several advantages of FLC over traditional methods include increased robustness, decreased steady state error and increased dynamic response, which makes it attractive for applications related to Maximum Power Point Tracking or MPPTs and Converter Controllers. [21] Fig. 2.8 represents the overall process of fuzzy logic control.

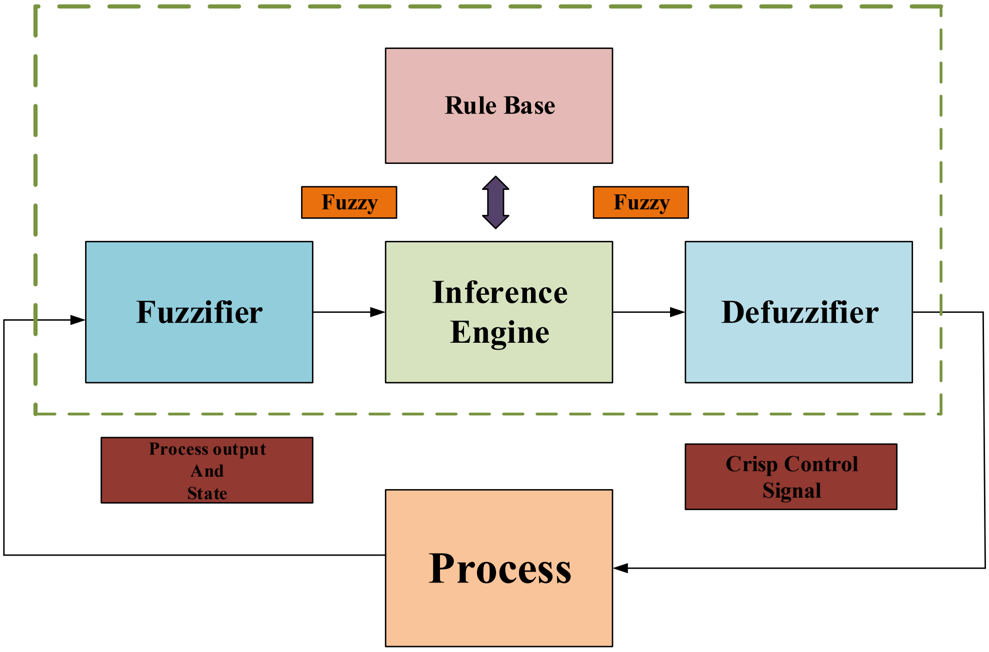

Fig 2. 8 Fuzzy Logic Control

2.7.1 Primary concept of Fuzzy Logic Control:

- **Fuzzy Sets and Linguistic Variable**: Using Linguistic terms (e.g. warm, hot) and degrees of membership (e.g. 0.8 warm, 0.2 hot) rather than Crisp Values (e.g. temperature is 25°C), utilizes a Fuzzy Logic Controller (FLC).
- **Fuzzification**: converts Crisp (digitized) input types of data (e.g. sensor readouts) to create Fuzzy Sets. Fuzzy Inference Engine: employs a set of rules to establish fuzzy outputs (e.g. IF temperature is Warm and Humidity is High, THEN Fan Speed is Medium).
- **Defuzzification:** transforms fuzzy output into a numerical, actionable control signal.

2.7.2. Working Principle of Fuzzy Logic Control

The work flow of the fuzzy logic control is given below:

- **Step 1:** Acquiring input data from the environment (Engine RPM, accelerator position) in real time.
- **Step 2:** Fuzzing the inputs by identifying the degree of the input belonging to each fuzzy set
- **Step 3:** Smearing "if-then" rules to convert the fuzzy inputs into a fuzzy result
- **Step 4:** Transform the fuzzy output into a particular operation.

2.8 Conventional Controllers

Outmoded control systems are boundary when commerce with complex nonlinear, modifying dynamics, or uncertainties. They can require manual tuning when there is poor adeptness, slow response time, and low accuracy. These systems do not have the capability to change their behaviour automatically, and therefore do not enjoy the same benefits of automatic learning and adjustment that modern intelligent control systems offer, such as improved performance, stability, and fault tolerance. Due to their reliance on fixed parameter sets and simplistic mathematical models, traditional control systems cannot provide optimal solutions for applications in which the conditions are constantly changing (e.g., dynamic production lines), resulting in long settling times, excessive overshoot and significant susceptibility to discontinuities.

Conventional controllers, such as Proportional - Integral (PI) and Proportional - Integral - Derivative (PID), are typically simple and easy to implement; therefore, they are widely used. Nevertheless, the performance of these controllers heavily depends on how well the parameters of the controller are tuned for use with a linear system. As operating conditions change rapidly, the robustness of conventional controllers often decrease faster than those of intelligent control methods. [20]

2.8.1 Limitations of Conventional Controllers:

The major Limitations of conventional controllers are below mentioned:

- **Uncertainty:** Systems that rely on linear modeling struggle to cope with processes that are not easily defined or that change with time, due to their inability to adjust for plant process variations or their interactions with complex dynamics (such as conical tanks).
- **Inability to adapt:** Fixed system parameters make it impossible for systems to automatically compensate for system wear and other changing operating parameters, which leads to a necessity for costly retuning (by hand) and results in reduced system efficiency.
- **Slow reaction to Change**: Systems may have long settling and rising times, as well as overshooting and oscillating characteristics when experiencing disturbances.
- **Sensitivity to disturbance**: External shocks or noise can greatly impair system performance. Systems are not designed to operate in a robust manner.
- **Lack of fault tolerance:** Older systems are intended for operation without failures; therefore, they have no built-in features to deal with component failures in comparison to modern controllers.
- **Reliance on wired interfaces and manual intervention:** Many older controller systems are connected to their external devices by way of a manual cable interface. Additionally, many of this system do not automatically store data; therefore; they require a large degree of manual monitoring.

- **Failure to manage lot of predictor:** Older controller systems lack capability to address complex systems which have many independent variables and many dependent variables, along with additional restrictions placed on them

Chapter 3

Literature Review

Lithium-ion (Li-ion) batteries have been widely accepted for use within renewable energy systems, electric vehicles, and consumer electronics owing to their high energy density, long cycle life, and low self-discharge rates. The control of charging and discharging rates is essential for protecting the battery, as it helps increase the efficiency and durability of the battery. Numerous academic investigations have indicated that overcharging and deep discharge of a battery will deteriorate performance and can lead to thermal runaway. Common methods for charging a "Lithium-Ion Battery" are such as "Constant Current", "Constant Voltage method", "Pulse Charge Method", and "Multi-Stage Charge Method". In most cases, the above mentioned methods are employed in simulation and hardware environments involving power electronic converters. Most research has developed "equivalent circuit models" or "electrochemical models" to simulate the charging and discharging processes of "Li-Ion" Batteries, as well to analyze their dynamic response. A comprehensive review of the current directions in terms of "battery charging technique", "flyback convertor based chargers", "MPPT-based charging systems", "fuzzy logic controllers for battery systems" is demonstrated in this chapter.

3.1 Introduction:

Advancements in renewable energy systems, electric vehicles and portable electronic devices, have resulted in a rapidly increasing need for improved energy storage and power management solutions. Of all existing types of energy storage technologies, Lithium Ions have become the most desirable because of their high energy density, ability to retain charge for many cycles, minimal self-discharge rate, as well as their excellent energy-to-weight ratio. Although Lithium Ions have many advantages, their performance, safety, and cycle/lifetime depend on how effectively they are charged/discharged and how well they are interfaced with other power electronics, which require sophisticated control methods to be optimally utilized.

The "DC-DC converter" is an essential component of energy management systems, allowing for power flow from the energy sources such as solar, wind, to the batteries. Flyback converters are particularly suitable for battery charging and discharging because of their inherent electrical isolation, simple structure, wide input voltage range, and ability to handle low-medium power levels. Pairing flyback converters with "MPPT" techniques allows for efficient extraction of energy from renewable sources for better overall efficiency and reliability.

Simulation as a technique for understanding the operation of a "lithium-ion battery" and evaluating the performance of "DC-DC" converters in many different scenarios has become essential. Using computer simulations to develop models of a lithium-ion battery, simulate its charging and discharging behaviour, simulate the different flyback converter configurations, and simulate the control methods used on those configurations is much less costly and risky than building experimental prototypes. There have been numerous simulations conducted in the past on different lithium-ion battery models like charging methods for lithium-ion batteries, MPPT techniques, and flyback converter control strategies, to improve the efficiency of the batteries, reduce losses, and operate the batteries safely. Section 3.2 discusses the related literature review papers. Battery charging technique (Section 3.3), Flyback Convertor based chargers (Section 3.4), MPPT- based charging systems (Section 3.5), Fuzzy logic controllers for battery systems (Section 3.6), and Research gaps (Section 3.7).

3.2 Related works:

In recent years, researchers have begun to focus on using data-driven methods for estimating “SOH” and “RUL” in lithium-ion batteries under real-world operating conditions. An advanced deep learning architecture has been developed, which combines the capabilities of a deep “convolutional neural networ ”, a “long short-term memory” network, and a multi-head attention mechanism for predicting “SOH” and “RUL” based on fragmented discharge data. This differs from traditional methods that depend on charging and discharging cycles, and crafted features; instead, it uses portions of the discharge process at random voltage-current combinations, allowing for effective training on battery degradation characteristics without having to perform complicated feature engineering tasks. Experimental validation with both public and lab datasets indicates that there is a high degree of accuracy in predictions made by this approach, demonstrating both the robustness and practicality of deep learning methods in the context of realistic use cases of batteries that are not completely captured or consistent with regard to data acquisition. This research highlights the promise of intelligent methods based on data to accurately monitor battery health as well as encouraging future investigations into combining advanced controls and energy management methods with battery prognosis methods. [23]. Another significant contribution to data-driven battery capacity estimation was made recently that addressed the practical challenge of limited and fragmented charging and discharging data in industrial environments. Traditional machine learning models for capacity estimation typically require complete charge and discharge cycles and extensive datasets, which are often difficult to collect under real operating conditions. To overcome this, a deep transfer learning framework is proposed that uses partial segments of charging and discharging data and extracts capacity increment features to train a “deep transfer convolutional neural network”. The model is first trained on a comprehensive source domain dataset and subsequently fine-tuned using limited target domain data, effectively reducing distribution differences caused by varying battery types and operating protocols. [24]. In general, model-based methods use empirical, electrochemical, and equivalent circuit techniques to estimate the battery's capacity. These methods are limited in their ability to be adapted for all lithium-ion batteries and require detailed battery specifications for accurate estimations of the capacity of this type of battery, limiting their usefulness in practical applications. In contrast, most data-driven methods use machine learning and deep learning to estimate the capacity of batteries based on their operational data such as charging and discharging. A challenge facing most current data-driven methods for capacity estimation is that existing methods rely on the availability of complete charging and discharging cycles. Also, when batteries are used under varying conditions, both in terms of chemistry and use, the performance of data-driven capacity estimators degrades significantly. More recently, researchers have been exploring the use of transfer learning methods that allow for the estimation of a battery's capacity by using only partial charging or discharging segments of a battery. In contrast, most data-driven methods use machine learning and deep learning to estimate the capacity of batteries based on their operational data such as charging and discharging. A challenge facing most current data-driven methods for capacity estimation is that existing methods rely on the availability of complete charging and discharging cycles. Also, when batteries are used under varying conditions, both in terms of chemistry and use, the performance of data-driven capacity estimators degrades significantly. More recently, researchers have been exploring the use of transfer learning methods that allow for the estimation of a battery's capacity by using only partial charging or discharging segments of a battery. [25].

For lithium-ion batteries, “thermal runaway” and “thermal runaway propagation” pose significant safety risks. This is especially true when the batteries are charged and discharged at high rates, since these higher currents will produce more heat and degrade the performance of the batteries more quickly than low rate charging and discharging would. In previous work, “thermal runway” initiation mechanisms such as overcharging, external heating, and internal short circuits have been investigated extensively. In addition, several studies have examined the dynamics of heat transfer from adjacent batteries and how these dynamics contribute to the propagation of thermal runaway. Cell spacing, state of charge, and heat dissipation can also play a large role in “thermal runway propagation” behaviour. Many previous studies have not adequately examined the synergistic effects of varying cycle count and inter-battery spacing on the propagation of “thermal runway propagation”. In addition, the precise inter-battery spacing needed to prevent “thermal runway propagation” in real-world applications is still an open question. In the referenced study, commercially available pouch-style lithium-ion batteries were subjected to “charge and discharge and cycles” with differing cycle counts and spacings between batteries. The study showed that the repeated cycling of batteries under high rates of charge and discharge can negatively affect the batteries' “state of health” and accelerate the onset of “thermal runway”, while increasing the spacing between batteries can reduce or eliminate “TRP” propagation.. [46].

3.3 Battery Charging Technique

Charging methods are essential for improving a “lithium-ion battery's “ability to perform, be efficient, and last longer. Traditionally, batteries are charged using a continuous current–continuously varying voltage method; however, charging through “CC-CV” is limited in both speed and effect on degrading batteries during maximum working conditions. Therefore, to be more effective, researchers are now beginning to research intelligent and adaptive charging techniques. More recent studies have noted the importance and benefits of real time “SOC” and “SOH” estimation in order to support “Adaptive Charging Strategies”. A machine learning approach is being utilized to have a continuously evolving capacity profile of a battery as it degrades, thereby allowing for more accurate control of charging processes. Additionally, using other types of sensor data, such as strain and temperature data, during the charging process also provides additional insight into the internal behaviors of the battery, thereby enhancing both the safety and efficiency of battery charging techniques [47]. The charging performance of lithium ion batteries is closely tied to how well the electrode material is designed and what happens inside the battery under electrical charge. As commonly used charging techniques have limitations related to how fast ions can be diffused throughout them and how stable they are structurally, particularly for anodes made from graphite, researchers have now been able to demonstrate that advanced types of electrodes with very high amounts of surface area and optimized pore structures greatly improve the ability to transfer charges during battery charging processes. As a result, researchers have concentrated on utilizing “metal-organic frameworks” to fabricate the next generation of lithium ion battery electrodes. Because of how easily pores can be structured within “metal organic frameworks” and the high number of surfaces available for ion transport, researchers sees the “metal organic frameworks” providing a platform to rapidly insert lithium ions while lowering internal resistance during the battery charge. In addition, porous carbon and metallic materials which can be obtained using “metal organic frameworks” provide excellent solutions for volume expansion and thermal stress management associated with high rates of charge. [30]. “MPPT” method enables the maximum energy available from solar “photovoltaic” systems to be extracted. To operate under changing irradiance conditions, this strategy provides extended charging effectiveness . Utilizing the "MPPT" control system helps reduce energy lost while charging batteries and support in the transition among charging steps. This method also works effectively in accommodating changes due to the environment itself. The efficiency of charging renewable energy is maximized when using "MPPT" charging techniques [42]. The solar charge controller that is microcontroller based uses a modified "incremental conductance", "maximum power point tracking" algorithm to control how the solar charger operates in response to the changes of the solar irradiation on the solar panels and to adjust the solar charger's charge speed. Since the "MPPT" improves the accuracy of tracking, it is able to increase the efficiency of the charge. The microcontroller is able to provide stable battery charging in a variety of continuously changing environments. In addition, the microcontroller is an economical, flexible means of controlling a solar charger. The method has the capability of reducing significantly the loss of charge from solar charging. Furthermore, the controller also provides battery protection features. The system has been tested and demonstrates that a solar energy system can operate as a stand-alone system by maximizing the charging power supplied [43]. Machine Learning has been used to create a new charge profile (for lithium-ion batteries) by giving insight into the microscopic processes occurring while charging, thus allowing the use of machine learning to control the Real Time current flowing through the battery and also enable the successful performance of the battery with decreased degradation caused from excessive current during operation. Real-time monitoring of battery condition allows for changing the amount of current that is applied to the battery, thus increasing charging speed but maintaining a high level of safety. As a result, the process creates a long-lasting battery and is especially applicable in areas of high need such as electric vehicle charging applications. Therefore, fast intelligent charging is accomplished [33]. Rapid charge development is applied using "Bayesian optimization techniques" to strike a balance between speed of charging and longevity of battery life, through the use of the techniques associated with "Bayesian optimization". It proposes a less manual approach to the tuning of charge parameters, resulting in significantly less degradation, lowers charging times and adapts itself to various battery characteristics. [34]. As for the constraints and challenges associated with "lithium-ion battery" charging for "Electrically Powered Vehicles", strategies must adhere to safety and dependability regulations and any traditional methods do not have a great deal of flexibility in regards to the realities of today's world. Integration of monitoring and protective systems must also be part of the intelligent charging strategy. Since the efficiency of charge plays a direct role in the range of the vehicle and in the overall life of the battery, charging systems' coordination with the "Battery management systems" is necessary for the safety and efficiency of the charging process. [40]. A new deep learning framework that utilizes both machine-learned and "hand-crafted" features is developed to assess how batteries behave.. This framework allows for the early prediction of battery lifetime so that adaptive control of charging can occur. This improved method allows for the creation of a safer and more capable charging strategy so that we can avoid unexpected battery failures that would otherwise occur during long-term operation. Thus, intelligent lifetime-aware charging will continue to develop as a means of improving our knowledge of the operation of batteries.[48].

3.4 MPPT Based Charging Systems

A rapid “MPPT” strategy is introduced for charging battery-operated “PV” panels when they're partially shaded and incorporated a novel “Hybrid PSO-PID” Control to maximize the amount of power extracted from the panels and minimize steady-state oscillation. The new “hybrid PSO-PID” controller develops an online method for tuning “PID” controls to allow for very quick global maximum power points. As a result, simulations and experimental results were both significantly better than conventional “MPPT” approaches. An additional benefit of this controller is its robustness against shading and changing irradiance levels, which greatly increases charging efficiency and reduces the amount of energy wasted. [44]. The potential of applying an “ANN-based MPPT to the solar-battery powered EV system” is examined. This “MPPT” algorithm is to be developed with an objective to pull more power from photovoltaic panel while providing the support of a “PMSM type driven Electric Motor”. The authors found the ability of an “ANN-based MPPT” to quickly adjust to the non-linear nature of PV and thus adapt quickly to the changing loads of the vehicle during each drive- cycle. The results indicated that the “MPPT” controlled charging system leads to a dramatic increase in efficiency measured by the amount of energy consumed. The implementation of artificial intelligence technologies can be applied to improve the reliability of the entire system of “Electric Vehicle Charging”. [45]. An intelligent “maximization of power point tracking" strategy has been created for a doubly fed induction generator “DFIG-based wind energy conversion system” combined with a battery storage unit. This strategy utilizes the actual wind profiles to provide reliable and efficient power extraction. Further, sophisticated control methods increase the reliability of the “DFIG-based wind energy conversion system” as we experience changing winds, resulting in an effectively coordinating power flow from the generator to the battery. Results indicate that this strategy provides increased energy capture, reduced mechanical stress, and maintained stability while charging batteries under variable conditions. Resilience from intelligent “MPPTs” in hybrid renewable power charging systems is validated by this research. [46]. A “Super-Twisting Sliding Mode Controller” is designed to track “maximum power point” on “photovoltaic” commercial modules using a “circular search” algorithm. This method offers improved speed of tracking and reduces chattering. It also has the capability of maintaining an effective output of irradiance by providing robustness under quickly changing irradiance conditions. Through comparative analysis, it was determined that the performance of the “STM” with a “CS” algorithm is superior to that of the traditional “MPPT” algorithm. Improved dynamic response will result in increased charging efficiency. The use of this controller results in stable and effective operation of battery charging. The use of this approach will provide a solution for a high degree of precision charging systems utilizing “PV” energy [47]. Fuzzy logic control is being applied for battery thermal management of electric vehicle batteries in low temperature environments. While they did not perform a direct “MPPT” study, fuzzy logic also offers support through a unique control strategy that allows chargers using “MPPT” to operate safely and with increased performance at low temperatures due to better control of battery temperature and operating conditions, which allow for an increased battery lifespan and increased efficiency. Thus, this paper supports MPPT assisted charging systems that will be reliable in cold temperatures. The importance of intelligent control that can be added to the auxiliary system of “MPPT” chargers is made evident. [49] The design and optimization of a fuzzy controlled lithium-ion battery charging system is focused by utilizing the capabilities of a “genetic algorithm”. There are advantages to using “GA” in the process of tuning the optimum system that improves the overall efficiency of the charging process, and thus decreases the amount of potential for overcharging. The fuzzy logic control enables the system to adapt based on the current condition of the battery at all times and the “GA” based tuning provides a better overall performance and stability of the system. Additionally, this strategy will provide a safe way to charge from renewable sources and is compatible with the use of maximum power point tracking techniques. Therefore, this technology serves as a conceptual model for designing an intelligent battery charger system. [50] The integration of fuzzy logic with a triple-loop “PI-based energy management system” for hybrid battery storage systems is proposed as an effective means of achieving efficient power transfer between lead-acid and lithium-ion batteries. A combination of these components allows for stable charging when provided with a changing input source. While the strategy does not directly support maximum power point tracking, it improves on using renewable energy sources effectively. In addition to improving battery life and providing reliable operation, the coordinated approach enhances the overall performance of all battery systems during the charging process, making this study supportive of future research into hybrid battery storage systems with MPPT support. [51].

3.5 Fuzzy Logic Controllers

Energy management and voltage control strategy is developed for microgrids using “artificial neural networks”, “proportional-integral-derivative” and fuzzy logic controllers. The utilization of a fuzzy logic controller has been found effective in mitigating the nonlinear effects and ambiguity of battery integration into microgrids. The fuzzy logic controller's ability to adapt to transient load and generation conditions has allowed it to regulate microgrid voltage or Power Balance more effectively than previous methods. Simulation data completed during this study also verified that when comparing the stability level of the microgrid using fuzzy logic-based energy management vs. predictable “PID” controllers, higher levels of system stability were achieved when using fuzzy logic controllers for a battery storage system.. [54]. In What way, Fuzzy Logic Technology is utilized for Intelligent Energy Management for “Electric Drive Vehicles”. By incorporating "adaptive rules" in the Fuzzy Controller, ICE Management has been enhanced which reduces the amount of energy lost and increases efficiency overall. Testing and analyses demonstrate that by utilizing Fuzzy Controllers, overall fuel economy improves, and vehicle systems demonstrate higher reliability due to lower levels of nonlinear behaviour exhibited during battery operation. These results confirm the advantages of applying Fuzzy Logic Technology to battery energy management in electric vehicle applications. [55]. This document proposes an energy management strategy for Electric Vehicles based on the use of the fuzzy logic algorithm. The fuzzy logic was optimized using Particle Swarm Optimization. The PSO fuzzy controller was developed to optimize the power distribution among the various Hybrid Energy Storage Systems components, the battery and super capacitor are two of the “HESS” components, and the “PSO” fuzzy controller optimizes power distribution between the two. The advantages of the “PSO” fuzzy controller when compared to other advanced fuzzy controllers such as “PSO” are that the “PSO” fuzzy controller provides better regulation of power distribution to both super-capacitor and battery in reducing the stress on both components by decreasing peak current, thereby increasing the useful life of the battery. By reducing stress, peak current, and thereby extending the life of the battery, this is reflected in the results of simulated experiments, indicating a strong advantage for the “PSO-optimized fuzzy control method” in terms of energy savings. [53]. Additionally, the authors of this research have produced an extensive reference publication addressing various methods used by Machine Learning to predict state of charge and state of health for electric vehicle battery systems, presenting fuzzy logic combined with other data-driven methods as a hybrid approach to address the uncertainties of battery dimension. In addition to allowing for more accurate

“SOC” and “SOH” estimation through improved information processing ability through the use of fuzzy logic-based tools under different conditions of operation, these systems assist in improving the way batteries are monitored affordably and with high accuracy, and thus enhancing the efficiency of their management processes through intelligent controls in the context of battery systems. [59]. In addition to being primarily machine learning based, this new model works with traditional fuzzy logic used in “battery management systems” while providing more accurate predictions for “SOH”, as the “BMSs” must employ adaptive fuzzy strategies for charging batteries effectively. A reliable “SOH” prediction is also delivered by this framework when conditions are not optimal. Successful prediction of degradation enables for improved fuzzy logic problem-solving is the main advantage of this framework. [62]. Battery performance optimization solution is developed using Machine Learning and “Explainable Artificial Intelligence” technologies. This research also highlights the use of intelligent energy management systems accompanied by “Fuzzy-based decision systems”. Fuzzy Logic is capable of managing the uncertainty associated with the Operating States of “Lithium-ion Batteries”. Explainable models provide greater clarity and transparency with respect to the “Control Actions” taken by the artificial intelligence. These advances improve the effectiveness of the “Battery Charging Process” and ultimately result in longer battery life cycles. The overall performance of the batteries is significantly improved when tested in Real-Time conditions [61]. For predicting lithium ion battery deterioration using state of the art techniques, a novel method is developed. With this method, researchers can select and then incorporate factors into the fuzzy logic controller for the lithium ion battery. Having precise degradation models will also enable batteries to adaptively modify the fuzzy set of rules used to maintain battery health while a battery is charging and discharging. As a result, this method enhances prediction accuracy and dependency on intelligent battery management systems, thereby supporting the methods outlined in other studies utilizing fuzzy logic controller-based approaches to battery management. [58]. Even though there have been many advances in developing techniques using artificial intelligence for estimating battery charge level and how much they will degrade over time, the limitations that still exist when trying to use these methods in actual operating environments will be discussed here. Many studies use controlled datasets when researching these topics. Many studies do not take into account how much they will age, change due to temperature, or restrictions that might make implementation difficult to do in real-time, which shows that there are still many aspects of battery management systems that need further investigation**.** Machine learning filtered approach for the estimation of lithium-ion battery state of charge showed promise in terms of increased accuracy but was only tested on a small number of databases and operating environments. The model's performance when exposed to the ongoing real-world aging effects (i.e., usage deterioration) was not completely assessed. Furthermore, the influence of temperature variations on the accuracy of the results was explored minimally. Finally, no analysis of the computational complexity of the filtering methods on different computer systems as a function of time and transferability between different lithium-ion battery chemistries have been made thus creating further limits that a general and adaptive “SoC” estimators will fill. [56]. A recent work on lithium-Ion battery estimation of “State Of Charge” using machine learning contains promising predictions under predetermined test conditions, but does not thoroughly evaluate the performance of the model as the battery degrades over time or is cycled for longer periods of time. Data driven selection methods were predominant for feature selection with little to no consideration given to the physical significance of the features selected. Several issues associated with the real-time embedding of machine learning based “SoC” estimates into battery monitoring systems were omitted as well as insufficient discussion of noise and sensor uncertainty on the results of machine learning based “SoC” estimates. This work demonstrates an opportunity to improve on this work through further research into how to develop machine learning based “SoC” estimates that are both robust and interpretable. [57] An intelligent method for feature selection is developed for lithium-ion battery degradation prediction in the context of electric vehicle systems. Although this technique does lead to more accurate degradation predictions, it is highly reliant upon good-quality labeled input data. The authors do not confirm whether the features selected are applicable to various battery types. This research does not addressed the integration of the battery degradation models is does not clarified with real-time battery management systems. Models that utilize online learning and update models are not available. However, these key points imply a need for scalable and real-time degradation-aware battery models to support growing demand for electric vehicles. [59].

3.6. Research Gaps:

The research gap being investigated in this study is adaptive intelligent control of the charge and discharge of Lithium Cell Batteries using MPPT flyback converters.

1) **Lack of integration of Machine Learning Technology in Converter-level Control:**
    - There has been considerable research in this area where the focus has been primarily on battery state estimation or fast charging, however, very little work has been completed that integrates real-time machine learning with hardware level control converters for simultaneous charging and discharging.
    - There is a great need for an overall framework that combines machine learning based battery health estimation with adaptive maximum power point tracker “MPPT” converter control to improve the battery efficiency and give longer life to the batteries.

2) **Minimal Research on MPPT-Fuzzy Control Systems used for Reducing Batteries' Aging Effects:**
    - Most current MPPT systems are designed to optimize the amount of electricity generated by solar panels. The majority of these systems ignore the long-term effects on a battery's health.
    - An Integrated “MPPT Controller with Fuzzy Logic” that takes into account both energy harvest and battery longevity will be necessary to develop new strategies for energy harvesting.

3) **Real-time adaptive control between changing dynamic conditions:**

- There are many “MPPT” and converter research papers that assume either an ideal or static operating condition, and do not take into account real-time adaptation due to changing irradiance, shading, or load conditions on a control basis.
- There is a need for a system to provide a complete view of what is taking place regarding “MPPT”, the actual flyback converter, and overall state of the batteries running under dynamic operating conditions.

4) **Limited application of explainable AI for battery energy management**

   - The utilization of machine learning models for predicting the state of the battery is commonplace. However, little attention is given to interpretability and the transparency of the operation of real-time control.
   - Utilizing explainable AI based controller for batteries will improve reliability, safety and performance understanding.

5) **Application of explainable AI in managing battery systems is limited**:

   - Machine learning models are frequently employed to forecast the state of batteries using machine learning techniques; however, the interpretability and transparency for realtime control are seldom considered.
   - Creating AI-based controllers that can be explained will improve reliability, safety, and understanding of performance.
   - There is a lack of electro-thermal coupled models where most research considers only the electrical characteristics of batteries while disregarding any influence on their performance and degradation from temperature.
   - A need exists for adaptive, electro-thermal coupled maximum power point tracking control systems that can represent the realistic behaviour of the battery during the charging and discharging processes.

6) **In EV based applications, scalability is the biggest challenge**

- The majority of existing control techniques have only been tested with a small pack or simulated. Very few have been tested with multiple cells or large scale.
- In order to support both Electric Vehicles and Hybrid Renewable environments effectively, scalable adaptive "MPPT" flyback frameworks utilizing Machine Learning must be developed.

7) **Limited Interaction with Hybrid Renewable Sources:**

- Currently, most systems only develop outputs for a single source of energy. Therefore, integrating advantages of certified Intelligent MPPT, adaptive converter, and battery management technology from a multiple source approach (Solar/Wind) into a single system has not been adequately explored.
- As such, there is a requirement for Real-Time Adaptive control methodologies for hybrid renewable powered batteries.

Chapter 4

System Architecture

In this chapter, we describe the overall methodology and system design adopted to carry out a simulation study on charging and discharging lithium-ion batteries through the use of an “MPPT-based flyback converter”. A novel energy management system has been developed which will enable maximizing the extraction of energy from a renewable energy source while also providing regulation of the charge and discharge of the battery, ensuring optimal operation regardless of operating conditions. Prior to hardware implementation, we used a model-based design process to evaluate the performance of the system in order to reduce both complexity and costs associated with development. This chapter contains the overall architecture of the system (section 4.1), battery mathematical model (section 4.2), flyback convertor (section 4.3), charging and discharging modes (section 4.4), control objectives (section 4.5), Problem formulation (section 4.6).

4.1 Overall System Architecture:

The proposed system integrates a Solar “PV” energy source that generates variable DC power based on the weather conditions. An MPPT-controlled Flyback “DC-DC” Converter that regulates power levels from the solar energy source to the battery, a “Lithium-ion Battery Pack”, and a “Battery Management System”. The Flyback Converter provides a means to isolate both solar energy and battery energy; as such, it allows two different power flows while providing the ability to control both charge and discharge conditions. To obtain the maximum amount of energy from the photovoltaic array, an “MPPT” controller is attached to the Flyback Converter. The “BMS” monitors the voltage, current, level of charge and discharge limits of the batteries to ensure that they are safely operated under charge and discharge conditions. The complete integrated system is modeled and tested using a simulation tool to examine the dynamic behavior under a variety of conditions. The overall system architecture are classified as many components such as Modeling the system which involves creating the environment for analyzing the battery charging and discharging behaviors. The second step is implementing the “MPPT” algorithm which includes executing the MPPT algorithm and develops a dynamic intelligent MPPT select mechanism to select the best algorithm. The third step is generating the control signal which includes creating the duty cycles from “MPPT” to control the flyback convertor and ensure the regulation of battery charging. The fourth step involves monitoring the battery charging and discharging simulation. The Fifth step involves validating the the performance matrics and efficiency of the “MPPT” algorithm and SOC and thermal behaviour. The sixth step includes validating the outcomes, and validating the results. The final step is intetpreting the outcomes which involves understanding the outcomes.

4.2 Lithium-Ion Battery Mathematical Model

An equivalent circuit modeling approach has been used to accurately represent and simulate the electrical and dynamic characteristics of lithium-ion batteries throughout their entire lifecycle by utilizing an open circuit voltage source and internal resistance along with “RC” networks that represent both polarization effects, as well as transient behaviour during charging & discharging cycles; with State Of Charge determined by adding together the current drawn from the battery over time using the “Coulomb” counting method. Through this method of “SOC” determination, it is possible to accurately predict terminal voltages, power capabilities, and efficiencies of Li-ion batteries under varied loads. Although the effects of thermal degradation and aging have not been modelled directly, they are indirectly accounted for by considering the effects that these parameters have on the resistance and voltage performance characteristics of the battery as it ages.

The lithium-ion battery can be represented by an equivalent electric circuit containing an open-circuit voltage source, an internal resistance, and multiple RC duplication circuits used to represent the transient behaviour of the capacitor. The battery's terminal voltage is:

$$V_{bat} = V_{oc}(SOC) - I_{bat}R_{ohm} - V_{pol} \tag{4.1}$$

In which,

V_{oc} is the open-circuit voltage

I_{bot} is the current of the battery

R_{ohm} refers the ohmic resistance, and

V_{pol} denotes the polarization voltage

The SOC term refers the following way,

$$SOC(t) = SOC\ (t_0) - \frac{1}{Q_{nom}} \int_{t_0}^{t} I_{bot}(\tau) d_\tau \tag{4.2}$$

Where Q_{nom} is the capacity of the battery.

Otherwise, it is represented in the discrete form as the following

$$SOC(k) = SOC(k-1) - \frac{I_n(k)\Delta t}{C_n} \tag{4.3}$$

in which,

C_n is the nomial battery capacity

Δt is the sampling interval

The charging and discharging features are accurately and precisely demonstrated by this model and very suitable for this dynamic simulation study.

4.3 Charging operation

In the charging state of operation, the flyback converter can either be operated as a step-down or a step-up converter, depending on the PV voltage range presented to the converter from the PV panel, and battery requirements for charging the battery pack. The control of the converter is accomplished by the MPPT controller through the adjustment of the duty cycles of the converter to achieve "maximum power point tracking" while maintaining battery voltage and current levels at safe limits during charging. In the discharging state of operation, the battery will provide energy to a load via a controlled operation of the converter ensuring that the output voltage remains stable, and battery over-discharge is prevented. The transition between charging and discharging occurs when the SOC of the battery pack reaches threshold levels based on load requirements; thus, providing a seamless transition from charging to discharging states.

4.3.1. Constant current phase:

The terminal voltage of the battery is represented as,

$$V_{bot} = V_{oc} + I_{ch}R_{int} \tag{4.4}$$

In which,

V_{bat} is represented terminal voltage of the battery.

V_{oc} is open-circuit voltage (V)

I_{ch} current (I)

R_{int} internal resistance of the battery (Ω)

The state of charge at the time of the constant current charging phase is written as:

$$SOC(t) = SOC(0) + \frac{I_{ch}}{Q_n}t \tag{4.5}$$

Where,

$SOC(t)$ is the state battery charge at the time (t)

$SOC(0)$ is the Preliminary state of charge in which (t=0)

I_{ch} is the Constant Charging Current (A)

Q_n Nominal Capacity of the battery (Ah).

t is the charging time (hours)

4.3.2 Constant Voltage Phase:

When the battery voltage has reached its maximum allowable voltage, the charging process will switch to the constant-voltage charging phase, where the battery will continue to charge at a fixed voltage. As the battery continues to charge, however, the amount of current needed to continue charging the battery will gradually decrease.

$$V_{bot} = V_{max} \tag{4.6}$$

$$I_{ch}(t) \downarrow as\ SOC\ \rightarrow 100\% \tag{4.7}$$

If the default cutoff value is fails, the charging phase is terminated.

4.4 Discharging Operation

The discharge of lithium-ion batteries refers to how they utilize their stored chemical energy as electricity to power loads external to the battery. In discharging, lithium ions travel within an electrolyte from the battery’s anode to the battery's cathode and electrons travel through an electrical circuit powering a device connected to the batter, thereby decreasing the State of Charge or “SOC” value as current is delivered by the battery to the load. Discharging takes the chemical energy stored in the battery and converts it into usable form of electrical energy. The current associated with discharging is most often designated as negative in all battery modelling. This discharging activity will continue until one of the limits for the battery is reached, either its minimum voltage level or SOC value. The discharge performance of a lithium-ion battery is determined by the amount of current, temperature of the battery, and the condition of the battery. As such, discharging plays an essential role in energy storage and power supply system functions.

4.4.1. Constant Current Discharging Phase:

The battery presents a constant discharge current I_{dix} to the end at the time of constant current discharging phase.

$$V_{bot} = V_{oc} - I_{dis}R_{int} \tag{4.8}$$

At the time of discharging, the state of charge is decreases.

$$SOC(t) = SOC(0) - \frac{I_{dis}}{Q_n}t \tag{4.9}$$

4.4.2. End-of-Discharge Phase

To obstruct the battery degradation, the discharging process is eliminated when the battery terminal voltage reaches the minimum safe value or the SOC reaches SOC_{min}

$$V_{bot} \geq V_{min} \tag{4.10}$$

4.5 Flyback Converter Design and Modeling

Because the flyback converter is easy to use, provides galvanic isolation, and is capable of charging batteries at low and medium power levels, this converter has been chosen as the basis for the battery-charging circuit. The components of the flyback converter include a transformer that operates at high frequencies, a power switch, a rectifier diode, an output capacitor and a snubber circuit. To determine the appropriate transformer turns ratio, the frequency of operation, the amount of magnetizing inductance and the amount of duty cycle required for “continuous conduction mode operation” and maximum efficiency, key design parameters were used to calculate these items. The mathematical model of a flyback converter was derived from a mathematical model using state-space averaging in order to study the effects of changing voltage conversion ratios as well as the dynamic characteristics of the operation of a flyback converter under various types of operation.

4.5.1. Operating Principles

4.5.1.1. Switch ON Phase:

The MOSFET's switch being ON allows for linear increase in primary currents. The energy is stored within the magnetic coil of the transformer, while the diode continues to be reverse biased until turned ON again.

$$i_p(t) = \frac{V_m}{L_m} t \qquad (4.11)$$

In which,

V_m is the input voltage

I_m is the magnetizing inductance of the transformer

t is the time duration the switch is ON

4.5.2. Switch OFF interval

With the switch OFF, the diode provides conduction and moves stored energy to the load at the output. The amount of current that flows from the transformer to the output is defined using the following equation:

$$i_n(t) = \frac{N_1}{N_2} i_p(t) \tag{4.12}$$

The output voltage V_0 in ideal condition is as follows.

$$V_0 = \frac{D}{1-D} \frac{N_2}{N_1} V_{in} \tag{4.13}$$

In which,

D is the duty cycle of the switch

N_1, N_2 is the ratio of the transformer

One of the main goals of transitioning from the battery charging process to the discharging process with lithium ion batteries is to achieve safe operation, high efficiency, and longevity, minimize degradation of the unit, and properly manage loads and systems. Control strategies will monitor electrical characteristics, including voltage, current, power, and "SOC", within the specified limits based on changing operating conditions.

The control objectives are used for the following purposes.

4.5.2.1.Control of Charge Rate

In order to keep the battery from experiencing excessive stress when charging it, it is important to keep the charge rate controlled to within safe limits.

$$0 \leq I_{ch}(t) \leq \ I_{ch}^{max} \tag{4.14}$$

The control objective is written as follows at the time of CC phase.

$$I_{ch}(t) = I_{ref} \tag{4.15}$$

In which I_{ref} is the reference charging current.

4.5.2.2. Control of the Voltage of Battery

It is also important to maintain a maximum limit on the voltage of the battery to avoid overcharging.

$$V_{bot}(t) \leq V_{\max} \tag{4.16}$$

The voltage control objective is defined as follows.

$$V_{bot(t)} = V_{ref} \tag{4.17}$$

4.5.2.3. Control of State of Charge

State of Charge control ensures that the battery is neither undercharged nor overcharged; this necessitates that the battery stay within safe limits of Charging Capacity.

$$SOC(t) = SOC(0) + \frac{1}{Q_n}\int_0^t I(t)\, d\tau \tag{4.18}$$

4.5.2.4. Optimize Power and Energy Use

In order to achieve maximum utilization and efficiency of the battery, the controller will control the power drawn from the battery, as well as how the power is supplied when Charging or Discharging.

$$P_{bot}(t) = V_{bot}\ (t). I(t) \tag{4.19}$$

The control objective is used to track the maximum available power.

$$P_{bot}(t) \rightarrow P_{max} \tag{4.20}$$

4.5.2.5. Minimize Ripples in Current and Voltage

High ripple components will diminish battery life and efficiency; therefore, the control systems will minimize ripple components in current and voltage.

$$\Delta I_{bot} \rightarrow min \tag{4.21}$$

$$\Delta V_{bot} \rightarrow min \tag{4.22}$$

4.5.2.6. Protection Constraints and Safety Constraints

The control strategy will ensure the safe operation of batteries through compliance with the Protection Constraints/ Safety Constraints listed below.

$$I(t) \leq I_{safe} \tag{4.23}$$

$$V(t) \leq V_{safe} \tag{4.24}$$

$$T(t) \leq T_{safe} \tag{4.25}$$

In which, $T(t)$ is the battery temperature.

4.5.2.7. Control of the Duty Cycle of the Converter

The control objective of converter-based systems is to create an appropriate duty cycle for Voltage and Current Control.

$$D(t) = f\left(V_{ref} - V_{bat}\,, I_{ref} - I_{bat}\right) \tag{4.26}$$

4.6 DC–DC Converter Control Strategy

The closed-loop control method will control the output voltage and current of the flyback converter using the voltage and current output of the flyback converter, as indicated by the MPPT and battery charging logic. The flyback converter's switching is regulated by using the “pulse width modulation” signals derived from the controller comparing the MPPT-generated reference voltage and reference current with the measured values of the flyback converter output voltage and current. With this control method, the converter will be able to keep operating stably even when the input voltage changes, the load changes, and between a charging and discharging mode.

The DC-DC Conversion Control Strategy is intended to control energy flow from a source through a lithium-ion battery by maintaining an optimal level of voltage, current, and power in response to various Conditions of Operation. To do so, this Controller will modulate the Converter's Duty Cycle to provide stable & efficient energy Conversion while ensuring that the battery operates safely.

A control system normally has:

- an outer voltage or power control loop;
- an inner current control loop; and
- a pulse-width modulation (PWM) unit.

4.6.1. Averaged Models of DC-DC Converter

A standard DC to DC converter's input voltage will be a function of its average output voltage.

$$V_0 = M(D)\, V_m \tag{4. 27}$$

In which,

V_0 is the output voltate

V_{in} is the input voltage

D is the duty cycle

$M(D)$is the adaptation proportion.

In unceasing transference mode, the flyback convertor process is written as follows:

$$V_0 = \frac{N_s}{N_p} \frac{D}{1-D}\, V_{in} \tag{4.28}$$

4.6.2. Voltage Control Strategy:

By controlling the voltage to a set reference value, the output voltage of a convertor is managed.

$$e_v(t) - V_{ref} - V_0(t) \tag{4.29}$$

4.6.3. Current Control Strategy:

The inner control loop is ensuring the fast reply and existing limitations. .

$$e_i(t) - I_{ref} - I_L(t) \tag{4.30}$$

4.7 MPPT Technique

The goal of “MPPT” is to optimize the energy produced by a photovoltaic system by responding to changing conditions within the environment that can affect production levels. The “MPPT” controller continuously monitors both voltage and current from the PV array. Using this data, it determines the optimal or best operating point for the entire “PV” system so that energy is maximally utilized with minimal waste during the process of charging batteries. The “MPPT” controller generates a reference signal to indicate which duty cycle needs to be applied by the flyback converter's electronic control circuit.

The purpose of the intelligent MPPT algorithm will be to provide greater accuracy in tracking the maximum power point and improved speed in responding to dynamic changes. Measuring voltage and current for the Infinity Solar Module array will allow for quick computations to determine the optimal “MPPT” based upon current solar resources. Intelligent “MPPT” minimizes oscillations about the “MPP” that are often found with other “MPPT” methods and incorporates rapid response to varying levels of solar irradiance. Additionally, intelligent “MPPT” provides exceptional efficiency and reliability through integration into the converters' control loops.

4.8. Design of a Fuzzy Logic Controller

The development of the fuzzy logic controller targets to enhance the performance of the “MPPT” and the directive of the converters at the time of ambiguity and non-linear operation. The “FLC” has been developed to use two variables for input and to provide control commands based upon a set of default conditions. Membership functions and rule inference were developed for speedy response and minimal steady-state error. Therefore, this controller is more robust to uncertainty in the system and variations in the system parameters.

The control loop in the flyback converter contains an example of a Proportional-Integral Controller, used for comparison purposes. By minimizing the difference between the commands of the controller and the measurements of the converter, the output voltage and current from the convertor is managed by the “PI” controller. To assure the steadiness of the closed loop system and satisfactory transient response characteristics, the parameters of the controller are decided by remembering standard strategies. To determine tracking accuracy, efficiency and dynamic response ability, an evaluation is conducted among the fuzzy logic based controller and “PI” Controller. The complete system employing the “MPPT” based Flyback Converter was simulated using “MATLAB and Simulink”. During the simulation period, fluctuations in solar energy generation due to both the variable nature and changes in user demands occurred. These factors are enumerated below. Other performance measures used in this study included the effective charging process; voltage regulation; changes in the state of charge, power ripple, and how well they respond to variable loads. The simulation showed that flyback converters using Maximum Power Point Tracking technology provide an efficient way to charge and discharge lithium-ion batteries.

4.9. Thesis methodology

This section describes a new approach to simulating lithium-ion batteries during charging and discharging through “Maximum Power Point Tracking”. This is accomplished using a non-standard 'flyback converter' which we will develop as part of our accurate model for the battery and charger, and "Controller" for MPPT. We will evaluate the battery under different environmental conditions and operating conditions to see how these factors affect the lithium-ion battery's characteristics. With this information, we will be able to assess both the conventional “MPPT” method as well as the adaptive “MPPT” method which has been shown to provide increased energy efficiency when charging and discharging the battery, thus improving the overall efficiency of the battery, and ultimately allowing for improved performance of the battery.

This research is novel because it has introduced an adaptive machine learning based framework for flyback charging and discharging of lithium-ion batteries. As more advanced intelligence is integrated into the battery management system, dynamic and intelligent method selection for “MPPT” will occur depending upon changing energy input conditions such as solar radiation, ambient temperature, and state of charge of the battery. By being able to intelligently select methods based upon energy input variations, greater flexibility and optimization can be achieved for improved charging and discharging efficiencies across all components of the battery system. The methodology of this thesis is illustrated in Figure 4.1 below.

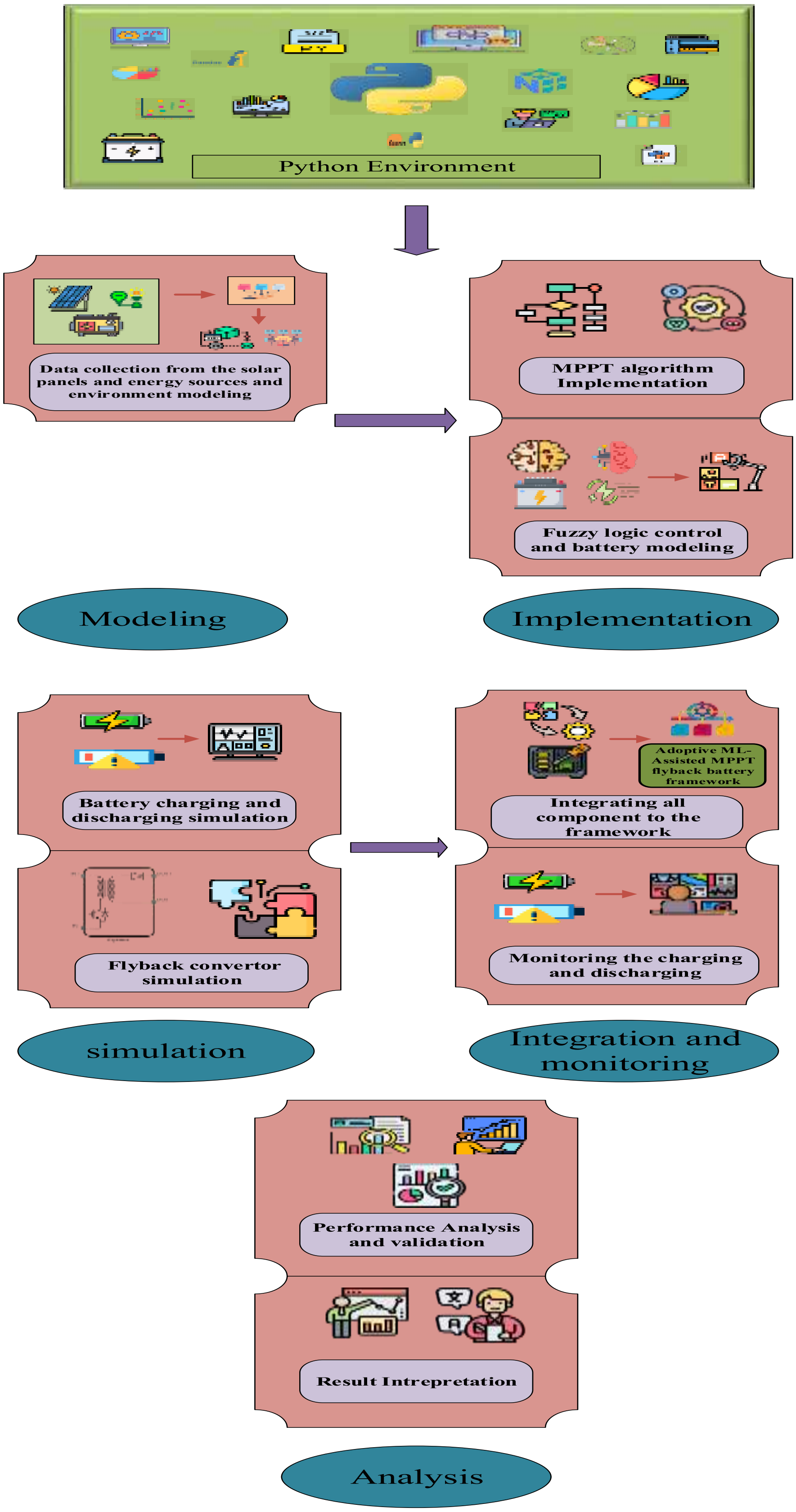
Python Environment
Data collection from the solar panels and energy sources and environment modeling
MPPT algorithm Implementation
Fuzzy logic control and battery modeling
Modeling
Implementation
Battery charging and discharging simulation
Flyback convertor simulation
Adoptive ML-Assisted MPPT flyback battery framework
Integrating all component to the framework
Monitoring the charging and discharging
simulation
Integration and monitoring
Performance Analysis and validation
Result Intrepretation
Analysis

Fig 4. 1 Overall Architecture

4.9.1. System Modeling

The proposed methodology needs for precise system modelling, which will serve as a reference point when creating the methodology itself. An overall energy conversion system will include a solar “PV” array, a lithium-ion battery, and an isolated flyback DC-DC converter.

4.9.2.Solar PV Array Model Development

Modeling the solar PV array provides an accurate representation of the actual operating conditions due to environmental variations in the solar radiation received by the array and the temperature at which the array is operating. The modelling of the PV array allows an valuation of the effectiveness of different maximum power point tracking algorithms under a wide variety of dynamic environment influences, including how changes in solar irradiance and ambient temperature affect "PV" current and voltage and how those changes subsequently impact "PV" power and voltage ratings. As a result, the modelling of the "PV" array allows the performance of an “MPPT” algorithm to be assessed when both the ambient temperature and the solar irradiance level have changed.

4.9.3. Lithium-Ion Battery Model Development

The lithium-ion battery is modeled to reflect both the charge and discharge process connected with the battery. This includes the battery's voltage features, internal resistance and “SOC” dynamics. The charge and discharge processes are modeled to evaluate energy storage efficiency, voltage instability and “SOC” cycles. In addition, observing the voltage of the lithium-ion battery and current and temperature during operation helps to assure the secure operating limits are managed.

4.9.4. Flyback Converter Model Development

A DC/DC Flyback converter that is isolated will be created to control the transfer of energy from the “photovoltaic” source to the storage battery. The Flyback topology provides a means of galvanically isolating voltage, regulating voltages produced by the “PV” Source, and allowing the converter to operate either in a step-up or step-down mode of operation with ease. To ensure efficient operation and stable power transfer at Maximum Power Point Tracking, transformer dynamics, switching actions, and output filtering will be included in the model of the converter.

4.9.5. Implementing MPPT Algorithm

Several “MPPT” algorithms have been used to extract as much energy as possible from the array of “PV” panels.

The traditional “P&O” and “INC” methods are used because they work well when the weather is not changing much. However, their performance can decline rapidly if the weather is changing quickly.

A new method is being developed that allows the system to choose which of the various “MPPT” algorithms will be the best fit for the current state of the battery and system operating environment. These adaptive intelligent selection processes are designed to provide increased convergence rates, fewer fluctuations, and improved overall tracking efficiency.

4.9.6 Control Signal Generation:

To manage the switching of the flyback converter, the MPPT controller produces duty cycles required to control the converter. These duty cycle signals will maintain voltage and current at their regulated levels, allowing for maximum efficiency to transfer energy from the photovoltaic array to the battery.

The following advantages are provided by the control strategies:

- Steady-state voltage and current regulation during battery charging
- Protection against overcharging and overcurrent
- Smoothness in transitioning from the charge and discharge states

The coordinated control of both the power stage and the MPPT controller optimizes safety for the batteries, while also ensuring the best efficiency for the overall system**.**

4.9.7 Simulation of Battery charging and discharging

Both charging and discharging operating modes have been tested using the simulated environment of the proposed system.

4.9.7.1. Charging Mode

The operation of the proposed system in charging mode consists of receiving energy from the PV array via a MPPT based flyback converter to provide optimum charging power to the lithium-ion battery. While charging the system will also monitor the SOC, voltage, current and temperature of the lithium-ion battery throughout the entire process.

4.9.7.2. Discharging Mode

The operation of the proposed system in discharging mode consists of providing energy to the load from the lithium-ion battery. The battery model has been built to provide voltage drop and SOC degradation under loading conditions. The operation in this mode will provide an opportunity to evaluate the efficiency of the discharge as well as the response of the entire system to varying loads.

4.9.8 Performance analysis

This section provides an analysis of performance based on the performance of various MPPT algorithms and control systems.

The key metrics for performance evaluation are:

- MPPT tracking efficiency based on irradiance and temperature
- Converter efficiency and Power Loss
- Battery Charging and Discharging Efficiency
- SOC Accuracy Evaluation
- Thermal Performance of the Battery

This performance analysis shows that the adaptive “machine learning-assisted “MPPT” methodology” has several advantages when compared to traditional methods of “MPPT”.

4.9.9. Validation:

In order to establish the credibility of simulation results, we validate the simulations by comparing them to standard datasets of lithium-ion batteries or to established reference characteristics of a lithium-ion battery. We then carry out consistency checks between battery voltage, current profiles, state of charge trends, and maximum power point tracking performance under the same operating conditions.

4.9.10. Interpretation and Visualization of Results

The last stage of the methodology is interpreted through simulation results. We detail the effects of changes in temperature and irradiance on “lithium-ion battery” charging effectiveness and life cycle, and how MPPT algorithm selection affects them.

Graphical presentations of the simulation results are provided for:

- Photovoltaic system voltage, current, and power output
- Efficiency of the flyback converter
- State of charge of the lithium-ion battery, SOC voltage and SOC current profiles

The flow of power during charging and discharging modes

The graphical results clearly demonstrate and convey the system performance, and provide evidence of the effectiveness of the proposed adaptive maximum power point tracking flyback converter.

The methodology has developed a structured and adaptable simulation framework to allow for the analysis of lithium-ion battery charging and discharging while using MPPT-controlled flyback converters. The intelligent method of maximum power point tracking improves overall system efficiency, maximizes energy use, and optimizes the safety of the lithium-ion battery system. Thus, this methodology represents a strong foundation for the results and discussions of subsequent chapters.

4.10. Overall problem formulation

To efficiently extract energy from solar photovoltaic systems using lithium ion batteries requires the use of a highly efficient method of converting electrical energy and an intelligent control system to ensure that the maximum amount of energy is extracted from PV systems and provided safely to batteries, as well as extending the operational lifetime of lithium ion batteries under changing atmospheric conditions. Factors such as fluctuations in solar radiation, temperature, and battery state-of-charge lead to uncertainties and nonlinearities that adversely affect the efficacy of conventional maximum power point tracking methods along with fixed control schemes.

The Total System consists of a PV array, “MPPT” controlled flyback DC-DC Converter, and Lithium Ion Battery with the ability to operate in two modes for charging and discharging. For controlling the power flowing from the PV power source into the battery for charging purposes is the main objective of the total systems, to load the battery for discharging purposes, while at the same time ensuring proper battery operation and maintaining overall system durability.

Chapter 5

Controller Design

Energy flow management between “Photovoltaic” and “Lithium-Ion batteries” has become increasingly important for increasing system efficiency, battery life, and system reliability. Because the PV Array has a non-linear configuration and the varying environmental conditions, the power output from the “PV” array varies dramatically as well. Without the proper management of the energy supplied by the “PV” arrays, the total solar-power is not utilized.

This chapter provides a comprehensive overview of the design and development of “Maximum Power Point Tracking” and “Fuzzy Logic based Control” methods as applied to flyback converters for lithium-ion battery charging and discharging applications. The first portion of this chapter analyses the Charging and Discharging system of “Electrical Energy” without “MPPT” to show the limitations of this type of control strategy. Following this analysis of “Non-MPPT Charging and Discharging” systems, “MPPT-based control” is then presented and specific details of the MPPT-based algorithms are provided. A “Fuzzy Logic Controller” is then developed with the MPPT control method to provide an “Adaptive Intelligent Control Framework” that incorporates all of the features of the previous control frameworks. This chapter concludes by providing an evaluation of the effectiveness of the “Fuzzy MPPT Flyback Control Method” in achieving improved overall performance, increased charging and discharging efficiency, and increased safety for Lithium-Ion Batteries.

5.1 Charging without MPPT:

A standard PV without MPPT setup connects the PV array directly with a DC–DC converter that runs at a designated fixed duty cycle. Under these situations, operating conditions for a “PV” Array are based on the voltages of the battery and the load characteristics that do not exist within the maximum power point. It is exist on the main circuit.

The result of power of the PV array is illustrated as follows:

$$P_{pv} = V_{pv} \times I_{pv} \tag{5.1}$$

At any given irradiance and temperature, a PV array can be identified by a specific maximum power point at which the maximum power output is produced, however, when functioning without “MPPT” the output is not able to operate at this maximum power point voltage, “MPP” and accordingly, less power will be extracted from the cells.

$$\Delta P = P_{wyp} - P_{actual} \tag{5.2}$$

The following disadvantages are given by the fixed-duty operation:

- lithium-ion batteries being either overcharged or undercharged
- power electronic devices being subjected to maximum stress

- solar energy not being utilized as effectively as possible due to variable weather conditions

the above limitations necessitate the adoption of “MPPT” based Control Strategies.

5.2 MPPT based control Strategy

“Maximum Power Point Tracking” is the control procedure for maintaining optimum output power available to your installed “photovoltaic system”. MPPT works in conjunction with environmental variations, by continually adjusting the operating point on the “IV” curve of your “PV” array in order to extract maximum power. For this reason, the “MPPT” generates control signals for duty cycle regulation of the flyback converter in this proposed system.

Mathematically, the control objective of “MPPT” can be expressed as follows:

$$\frac{dP_{pv}}{dV_{pv}} - 0 \tag{5.3}$$

The maximum power point is demonstrated by the following equation:

$$\frac{d(V_{pv}I_{pv})}{dV_{pv}} - I_{pv} + V_{pv}\frac{dI_{pv}}{dV_{pv}} - 0 \tag{5.4}$$

In the control algorithms, the “PV” array is managed at its optimal operating point by using the above maximum power point.

5.3 Proposed MPPT algorithm

In this thesis, the selected “MPPT” algorithm has two phases which are as follows:

5.3.1 Perturb and Observe algorithm:

One of the most popular methods of “Maximum Power Point Tracking” is the “Perturb” and “Observe” technique because it is upfront and can be easily implemented. In this method, periodic perturbations to the voltage of the “PV” are carried out and the resulting increase or decrease in output power is monitored.

The decision logic is based on the following equations.

$$\Delta P - P(k) - P(k-1) \tag{5.5}$$

$$\Delta V - V(k) - V(k-1) \tag{5.6}$$

5.3.2 Cumulative Conductance Algorithm:

Another MPPT method, the “Incremental Conductance” technique, uses the slope of the power curve for increased tracking precision. The theory behind this technique is based upon.

$$\frac{dI_{pv}}{dV_{pv}} - \frac{I_{pv}}{V_{pv}} \; at\ MPP \tag{5.7}$$

The controller determines whether or not the point lies in the forward or reverse direction relative to maximum power point. To do so, the incremental conductance $\frac{\Delta I}{\Delta V}$

- Firm conjunction
- Fewer fluctuation
- Better operation in speedily changing weather conditions

5.4 Fuzzy logic Controller Design

Fuzzy logic-based controllers can be used instead of traditional maximum power point tracking mechanisms to compensate for their drawbacks. “FLCs” reason using "human-like" thinking and do not require precise mathematical models since they work equally well on nonlinear photovoltaic devices.

5.4.1. Inputs:

The input variables for the fuzzy logic controller is as follows

5.4.1.1. Flaws (F)

The flaws for the fuzzy logic controller are represented as follows:

$$E(k) = \frac{\Delta P(k)}{\Delta V(k)} \tag{5.8}$$

5.4.1.2. Change in Error (CE)

If there is any alteration in the errors, then it is signified as,

$$CE(k) = E(k) - E(k-1) \tag{5.9}$$

The inputs show where the operating point is in relation to the Maximum Power Point, as well as the path that is being travelled.

5.4.2. Membership functions

The fuzzy logic system has a membership function, which is a mathematical representation of how much of the input values fit into a certain fuzzy set. This is very different from classical logic, in which an item either fits or does not fit into a set. With fuzzy logic systems, there is the option of partial members and differing degrees with the “MF” function which takes on values between 0-1.

The fuzzy set for inputs & outputs is defined by terms such as negative large Negative small, zero, positive small, and positive large. We use triangular membership functions because they are easy to calculate and fast to compute. The change in duty cycle is represented as ΔD.

The membership function is used for the following purposes.

5.4.3. Rule base

In a fuzzy logic builder, a “Rule Base” is essentially the “Fixed Rule” that determines how the fuzzy logic controller will react based on a variety of input conditions. This “Rule Base” contains recognized rules that exist as a collection of “if and then” type logical relationships, which represent human-based knowledge and experience on how to link indeterminately defined input variables into indeterminately defined Output Actions using Linguistic Terms.

As a main opinion of decision making within the “Fuzzy Logic” the “Rule Base” provides an assessment of the degree of satisfaction of Input Conditions and the resultant “Output Action” that will result to the achievement of desired system behaviour. A properly constructed “rule base” will permit stable, adaptive control for accurate results within a non-linear system, as well as uncertainty in the system**.**

The fuzzy-based “MPPT” method provides a way to intelligently control the flyback “DC-DC” converter through the use of fuzzy logic for maximum power point tracking. The fuzzy-based “MPPT” continually monitors the conditions of the “photovoltaic” system, and adjusts the duty cycle of the flyback converter based on these readings. The flyback converter's job is to maintain a constant voltage from the “PV” system to the load or battery, and transfer that power as efficiently as possible.

By combining these technologies in a PV-to-battery system, the user can take full advantage of the maximum power that can be generated from the “PV” array regardless of the irradiance or temperature, and achieve optimal performance with respect to voltage regulation, electrical isolation, and safety. By utilizing fuzzy-based “MPPT” combined with a flyback converter, you will increase the efficiency of energy conversion, enhance the dynamic response of the overall system, and enhance the reliability of your battery charging system converted through “PV” systems.

5.5. Control flow diagram:

The system will operate in one of two ways, based on the amount of available power. The first way is enough power from “PV” charge the battery, using a flyback converter from the “PV” Array to the battery. The second is to discharge the battery, supplying load with stored energy from the battery.

The system's main operational parameters are continuously monitored throughout both modes of operation: battery “SOC”, battery current, temperature, voltage, converter efficiency as well as “PV” Power.

Control flow diagram also identifies three stages of performance evaluation, including performance analysis, validation, and results interpretation, to measure the effectiveness of each of the several “MPPT” methods and determine how they impact the charging and discharging efficiency of the battery and the robustness of the system and the overall effectiveness of energy conversion.

This control flow diagram represents the proposed system's operational flow in a comprehensive and organized manner and will provide the foundation for all simulation, analysis, and discussion related to the results in this thesis. Fig 5.1 shows the overall control flow of the proposed system.

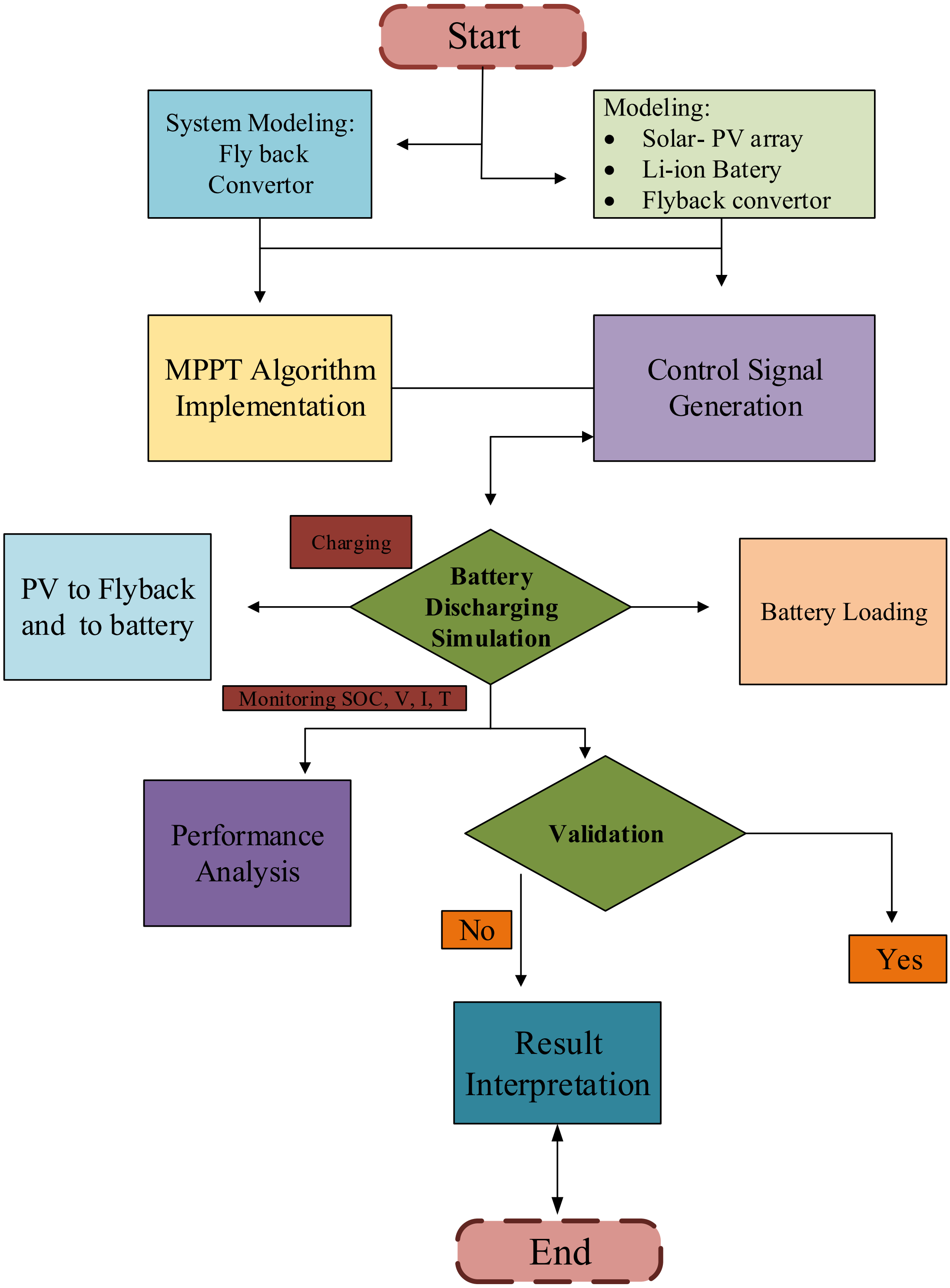

Fig 5. 1 Control Flow Diagram

5.6. System performance

Using organized control methodology and adding a conjunction with the flyback charger for lithium ion batteries significantly enhances the performance of the proposed systems. Improvements can be recognized in the areas of energy harvested, control intelligence, battery protection features and reliability of the overall battery system.

The adaptive “ML-assisted MPPT” allows an increase in energy extended from the “photovoltaic” module. A significant difference in performance between traditional “MPPT” methods, which utilize fixed controls and very simple ways of monitoring is shown by the ability of the adaptive “ML-assisted MPPT” to track both real-time and past environmental conditions through the collection of historical data and the ability of the adaptive “ML-assisted MPPT” to train a more comprehensive predictive model for determining optimum operating performance. With this method, the speed of tracking has been improved, thus minimizing fluctuations around the maximum power point are greatly reduced the energy losses at the time of rapid variations in the environmental conditions.

The adaptive control flow was demonstrated to enhance flyback converter efficiency and dynamic response. The “ML-assisted MPPT’ takes incoming “PV” data and evaluates it to create optimized duty cycle command that correlates both to the optimal PV operating point and the requirements of the battery. The adaptive duty cycle, compared to a fixed duty cycle, reduces the potential for unnecessary switching stress caused by too frequent on or off cycling due to DC variations in the PV source, improves voltage regulation, and provides a smooth power transfer from the isolated flyback converter to the battery. In addition, the decrease in losses in the converter results to improved overall system effectiveness.

The proposed framework provides a mechanism for intelligent and safe battery charging and discharge. The framework provides integrated monitoring of battery “SOC”, voltage, current and temperature, while also including these metrics into the control flow's logic process. Thus, based on the use of machine learning, the intelligent controller alters the charging profile for a particular battery based on battery condition and previous usage history. Hence, optimizing charge acceptance, maximizing charge to discharge efficiency and extending battery life by preventing overcharging, excessive discharge, and thermal damage.

Because of the adaptability of the framework, system transitions improved and there were increased reliability. The “Intelligent Mode Decision Block” provides a way to transition from one operating mode to another as determined by available electrical power or default load level. The capacity to detect power resources and load demand enables mitigating the impacts of significantly changing modes and managing constant operation despite variable loads, using the machine learning based control system to assist.

Moreover, the feedback loop of learning and performance analysis within the control flow ensures that the system is optimized on a continuous basis. During the performance analysis, the System will evaluate its efficiency of “MPPT”, Efficiency of the Converter, and Behaviour of the Battery, and provide that information back to the “ML” Model. This continuous learning ability is one of the main novel features of the System since it will allow the System to improve its performance over time as opposed to operating with fixed control parameters.

Finally, the new “Adaptive ML-Assisted MPPT Flyback Charging and Discharging Framework” allows systems to operate more efficiently by enabling the System to track maximum power faster and more precisely, adapt Converter Control, manage Batteries intelligently, and operate dynamically by the continuous learning and performance analysis. These improvements result in increased energy conversion efficiency, decreased power losses, improved battery health and increased reliability of “Li-Ion Battery energy storage systems”.

Chapter 6

Results Analysis

The chapter contains an comprehensive list of simulations and provides an analysis of the performance of the lithium-ion battery system during both charge and discharge using Flyback converters with all control schemes; however, the intent of this chapter is to prove how effective “Maximum Power Point Tracking” techniques are specifically “Conventional and Fuzzy Logic-Based MPPT”, in maximizing the extraction of power from the photovoltaic array, while being safe for the operation of lithium-ion batteries.

The simulation environment was designed particularly to analyze dynamic scenarios by using variable levels of solar irradiance and ambient temperature. These factors play a important role in the output capacity of “PV” and are also a direct indication of how efficient a battery will function. The initial step of the chapter calculates system function without any “MPPT” technology, serving as the standard against which to measure subsequent test results. In addition, the chapter shows the results generated from a “C-MPPT” solution, as well as showing the performance enhancements achieved from using an “Adaptive Fuzzy Logic

Controller". The performance of "lithium-ion batteries" during both phases has been evaluated and compared based on charging current, voltage level state of charge and energy. In addition, this chapter describes in what way, different types of control strategies is compared against each other using various tables and graphs to show improvements in power usage, charging time, and converter efficiency. Important observations on the benefits of Intelligent Control include increased reliability, decreased energy loss, and increased longevity for batteries.

In summary, this chapter provides all essential information for interpreting in what way, Intelligent Control Systems with Flyback Converter Technology can enhance the efficiency of a "PV based Li-Ion Battery System", thus providing a foundation for further discussions regarding the proposed "Adaptive ML-Assisted MPPT Framework".

6.1 Simulation environment

Simulation of the model was performed using MATLAB and Simulink. The "PV" Array, Flyback Converter, and "Lithium-Ion Battery Models" were created to precisely capture novel operating rules. Dynamic conditions were simulated by using different irradiance levels and ambient temperature profiles for diriment times of the day. The battery model includes the ability to track State of Charge, Voltage, Current, and Temperature. The "Flyback Converter" provided an isolated interface between the PV Array and Lithium-Ion Battery while regulating power transfer between them. The simulation framework allows the three Control Strategies to be compared directly against each other, allowing users to evaluate their effectiveness. Real-time monitoring of all significant variables was provided by “Data Acquisition Blocks”.

6.2 Outcomes without MPPT

If there is no MPPT, there is no adaptation to operate the PV system based on changing conditions. Therefore, the “DC-DC” flyback has a fixed duty cycle and is not adjusted according to the operating conditions of voltage and current at the PV array. The PV array works below the maximum power point usually under these conditions which leads to very low energy efficiency from the PV system.

The following observations were made during the study:

The power generated by the PV array without MPPT is written as follows

$$P_{pv} = V_{pv} \times I_{pv} \qquad (6.1)$$

In which,

V_{pv} is the terminal voltage of PV

$I_{pv}$is the output of the PV current

The expanded power is lesser than the theoretical maximum power, when the operating voltage is not regulated to the optimal value

$$P_{loss} = P_{mppt} - P_{pv} \qquad (6.2)$$

In which,

P_{mppt} Demonstrates the maximum power available PV power at a given irradiance and temperature.

The rate of “SOC” is increases due to the low instable charging when there is “MPPT” is not available. It also results to poor usage of the solar energy and leading to reduced “PV” power extraction, ineffective battery charging and degraded performance of the discharging.

6.3 Results with conventional MPPT

“MPPT”s is based on flyback “DC/DC” converters that use traditional maximum power point tracking methods, including the “Perturb and Observe” and “Incremental Conductance” algorithms. The “P and O” and “IC” methods modify the duty cycle of the “DC-DC” converter so that the converter forces the PV array to always operate as close to the maximum power point as possible, regardless of changing sunlight intensity or weather conditions. Due to their duty-cycle-modifying behaviour, a conventional “MPPT” tracks the changes in a “PV” array's operating voltage and adjusts the power extended from it by the increased efficiency and higher charger performance.

6.3.1 Simulation Result

An established “MPPT” can also extract more power out of photovoltaic panels than operation with a constant duty cycle. With the use of the adaptive duty cycle, batteries are charged more efficiently and solar energy can be utilized more effectively. Moreover, many conventional “MPPT” algorithms need a requirement of their operation, result to oscillations about the maximum of the output power and this will result in a portion of the power being lost under steady state conditions.

6.4 Outcomes with fuzzy MPPT

The method of “Maximum Power Point Tracking” of a photovoltaic array utilizes an intelligent fuzzy-controller in order to track the maximum output of the PV array. Different from the other conventional methods which depend on mathematical models, the fuzzy “MPPT” method utilizes linguistic inference a flyback “DC-DC” and therefore provides a more effective means of tracking the maximum output of the “PV” array as environmental conditions change rapidly and nonlinearly. The fuzzy controller was designed to operate effectively in environments with uncertain or unpredictable characteristics. A fuzzy controller is capable of interpreting vague input data and converting this into smooth and precise control actions, thus achieving effective control of PV systems in less than ideal operating environments.

6.4.1 Simulation result

Based on the outcomes from the simulation, the performance of the fuzzy “MPPT” Controller is much better at gaining maximum power point tracking across various irradiances and temperatures than the generic method of obtaining maximum power point tracking using the generic methods. The decrease of steady-state vacillations in addition to being able to function on a higher energy capture basis result to an increase in battery charging efficiency. The use of smooth duty cycle operation allows for improved steadiness at the system level, and this, in turn, results in a better usage of the battery.

6.5 Charging and discharging performance

The charging capability of the proposed system is decided by in what way it will charge the lithium-ion battery efficiently while keeping the voltage and charging current within compulsory margins. Discharging performance indicates in what way the battery can supply energy to a load while managing voltage constancy and low energy losses. Both charging and discharging performance is evaluated by looking at electrical battery parameters like current, voltage, “SOC” and efficiency.

The battery offers energy to the load by using the flyback convertor at the time of discharging mode. At this time, the battery terminal voltage is represented as:

$$V_{\beta} = V_{oc}\,(SOC) - I_{\beta}R_i \tag{6.3}$$

In which,

$V_c(SOC)$ is the open-circuit voltage dependent on SOC,

I_{β} is the discharge current and

R_i is the internal resistance.

6.6. Comparison

In this segment, the performance of different “Maximum Power Point Tracking” techniques for a “PV-based Li-ion battery charging and discharging system” is analyzed using the performance metrics such as voltage, current, power, and battery State of Charge. All parameters will be monitored throughout a time trial to determine how well each of these three strategies performed relative to one another regarding energy harvest efficiency, system wind resistance, and battery performance. This comparison will lend a better understanding of the strengths and weaknesses of each “MPPT” approach on varying types of loads and weather conditions.

6.6.1 Time (s) Vs Voltage (V):

Time(s)	**Voltage (V)**
1.67	3
20.36	4.1
39.30	3.8
56.01	3.8
74.67	5.9
91.65	2
110.31	0
128.97	5.9
129	-8

145.98	1
164.67	5

Table 6. 1 Time (s) Vs Voltage (V)

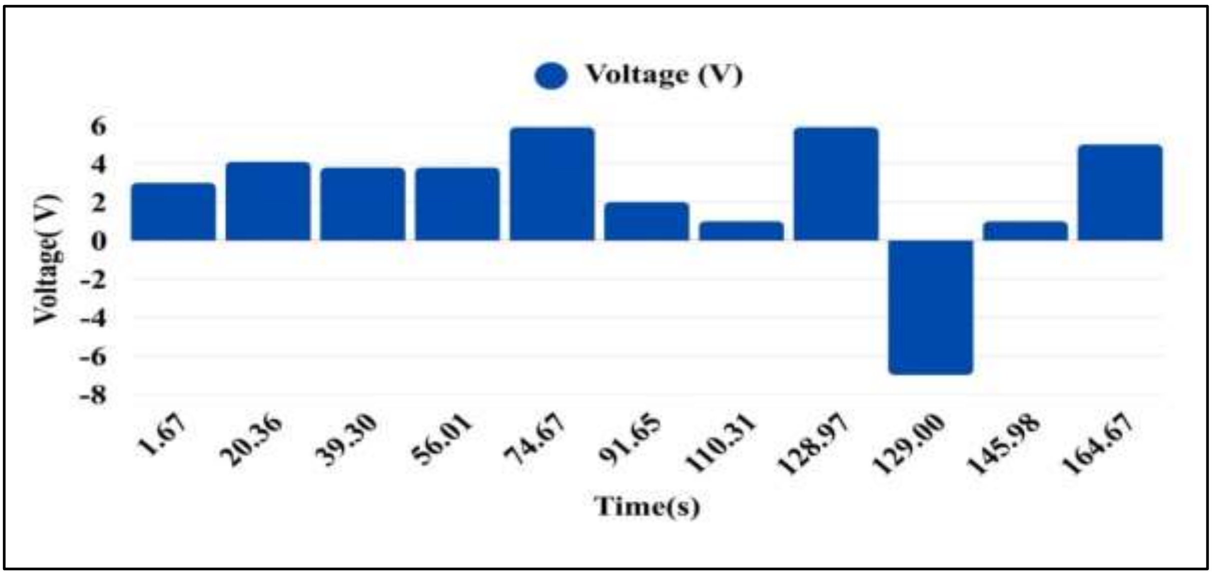

Fig 6. 1 Results of Time(s) Vs Voltage (V)

Table 6.1 and Fig. 6.1 shows the experimental results between the time and voltage. The graph shows a time sequence of the changes in system voltage for the simulation period. It shows how the electrical characteristics of the system change based on some of the parameters of its operating scenario. When looking at the beginning of the simulation we see that the voltage is approximately 3.00 volts, indicating that the system is starting to function properly after undergoing some transition from an unstable state to a stable operating state. The total amount of time needed to stabilize from this low starting voltage of around 3 V to a slightly higher voltage of approximately 4.10 volts was complete by the end of the simulation. The increase in voltage after 1.67 seconds is an indication that the system is now able to effectively deliver power from the input to its load. During the time period of 39.30 to 56.01 seconds the voltage remained relatively steady at approximately 3.80 volts; meaning that the system was maintaining a regulated voltage during this time period, which is an indicator of stable operation; and to provide for a regulated voltage during battery charging, thereby preventing excessive voltage stresses to the battery and supporting the controlled transfer of energy.

6.6.2 Time (s) Vs. Current (W):

Time(s)	Current (W)
0	0
20	-400
40	0
60	0
80	-150
100	150
120	-190
140	1500
160	-200
220	-200

Table 6. 2 Time (s) Vs Current (W)

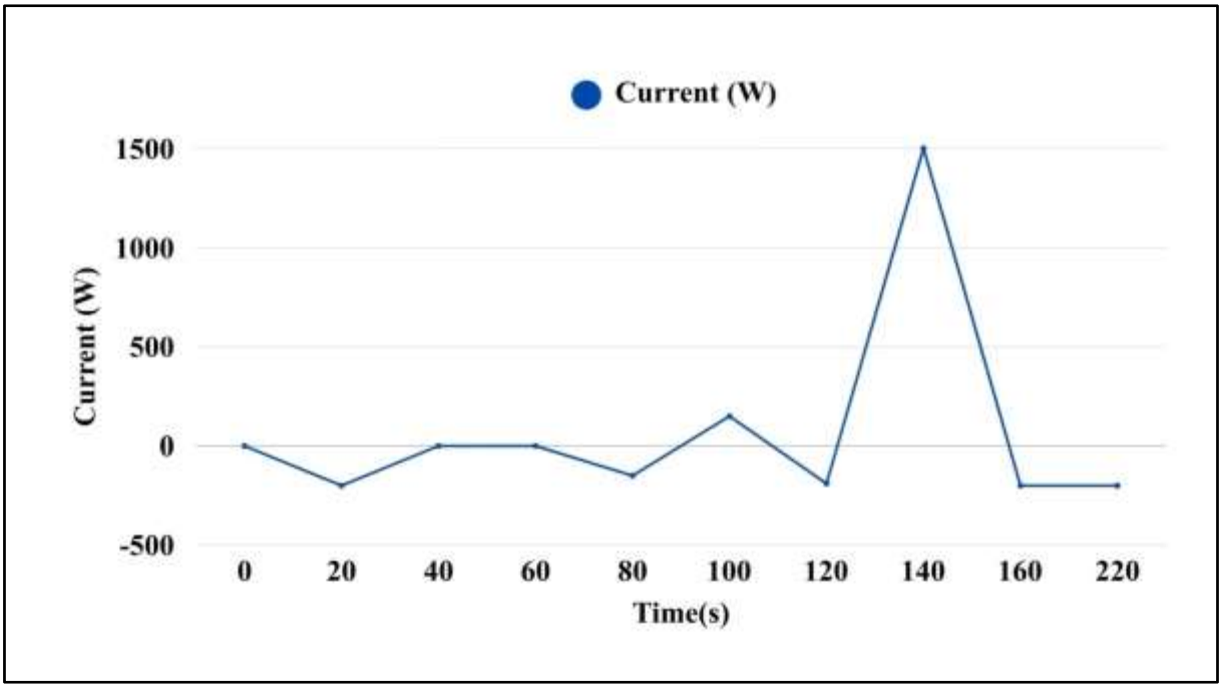

Fig 6. 2 Results of Time(s) Vs Current (W)

Table 6.2 and Fig. 6.2. shows the experimental results between the time (s) and Current (W). In the time graphs, current changes over time have corresponding tabular values. The first observation on both time and tabular data starts at 0 seconds with current being equal to zero watts. After 20 seconds, it appears the current has decreased to -400 watts. The 40 and 60 second data points again show a return of the current to zero watts, showing that the currents between 20 and 40 seconds and from 60 to 80 seconds have not changed from their previous levels of zero watts.

When a current of -150 watts appears at the 80 second point, it rises to 150 watts by 100 seconds. By the 120 second point, the current has returned to a value of -190 watts. Then the next significant occurrence with respect to current is shown at the 140 second point. The maximum current recorded here reached an extremely high value of +1500 watts. The 1500 watts peak current is followed immediately with a sharp decline, down to -200 watts, by the 160 second point which remains unchanged at -200 watts until the 220 second point.

Overall, the time graphs have different values for current as time moves forward; among the graphs with the greatest currents, the highest peak was reached at 140 seconds as noted above. The tabular information shown here reinforces the graphical representation of the current's value at each second of time.

6.6.3 Time (s) vs Power (W):

Time(s)	Power(W)
0	900
20	900
40	0
60	0
80	200
100	210
120	600
140	4200
160	0
180	900

Table 6. 3 Time(s) vs Power (W)

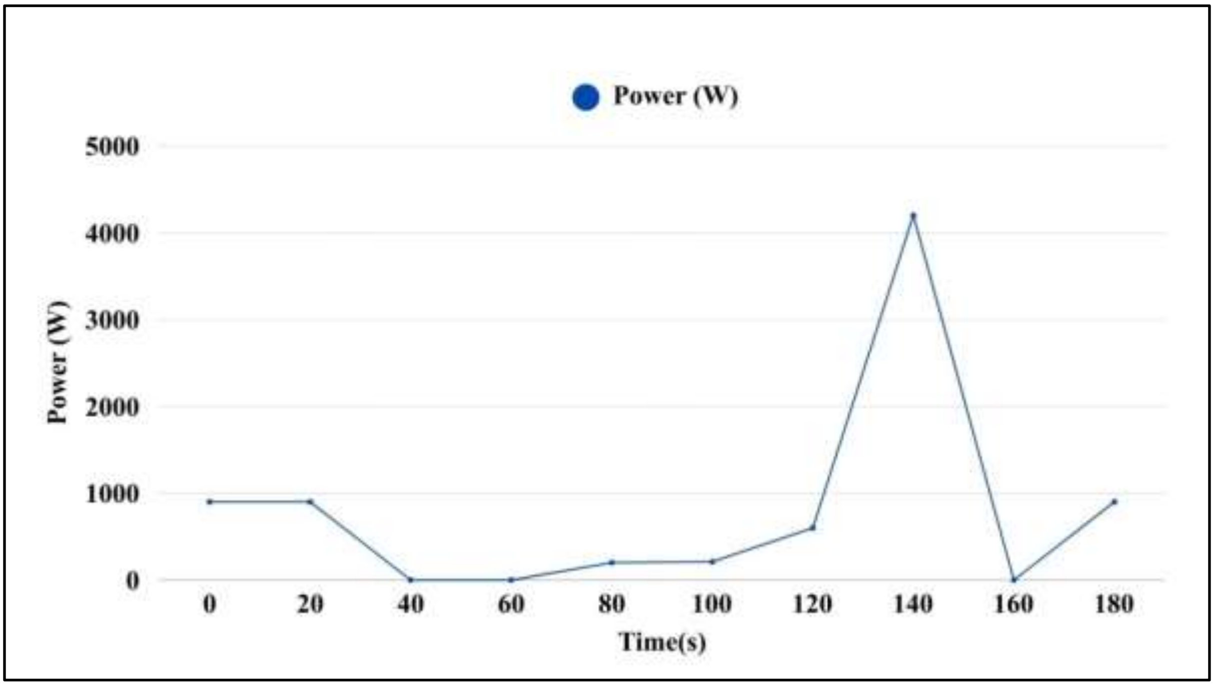

Fig 6. 3 Result of Time(s) vs Power(W)

Table 6.3 and Fig. 6.3 shows the experimental results between the time (s) and power (W) This document shows a chart that represents how power changes over time. It also provides the exact numbers in the chart in the following table. Starting from an initial value of 900 Watts, the power stays the same until it reaches 20 seconds. After that, at 40 and 60 seconds, we can see that no power is being consumed.

Then from 80 to 100 seconds, there are two increases, with the first occurring at 80 seconds where it goes up to 200 Watts and a second increase of just ten watts to 210 at 100 seconds. After that, we can see another increase of 600 Watts at 120 seconds.

At 140 seconds we can see the maximum power value of 4200 Watts has now been reached, followed by a drop in power down to 0 at 160 seconds, after which, at 180 seconds, the power comes back to 900 Watts again.

The information in the graph is consistent with the information provided in the table as it clearly shows a progression from constant power to no power, then through gradual increases and finally to a sudden peak in the middle at 140 seconds.

6.6.4 Time (s) vs State of Charge (%):

Time (s)	State of Charge (%)
0	15
20	46
40	46
60	48
80	85
100	41
120	15
140	15
160	15
180	39

Table 6. 4 Time(s) Vs State of Charge(%)

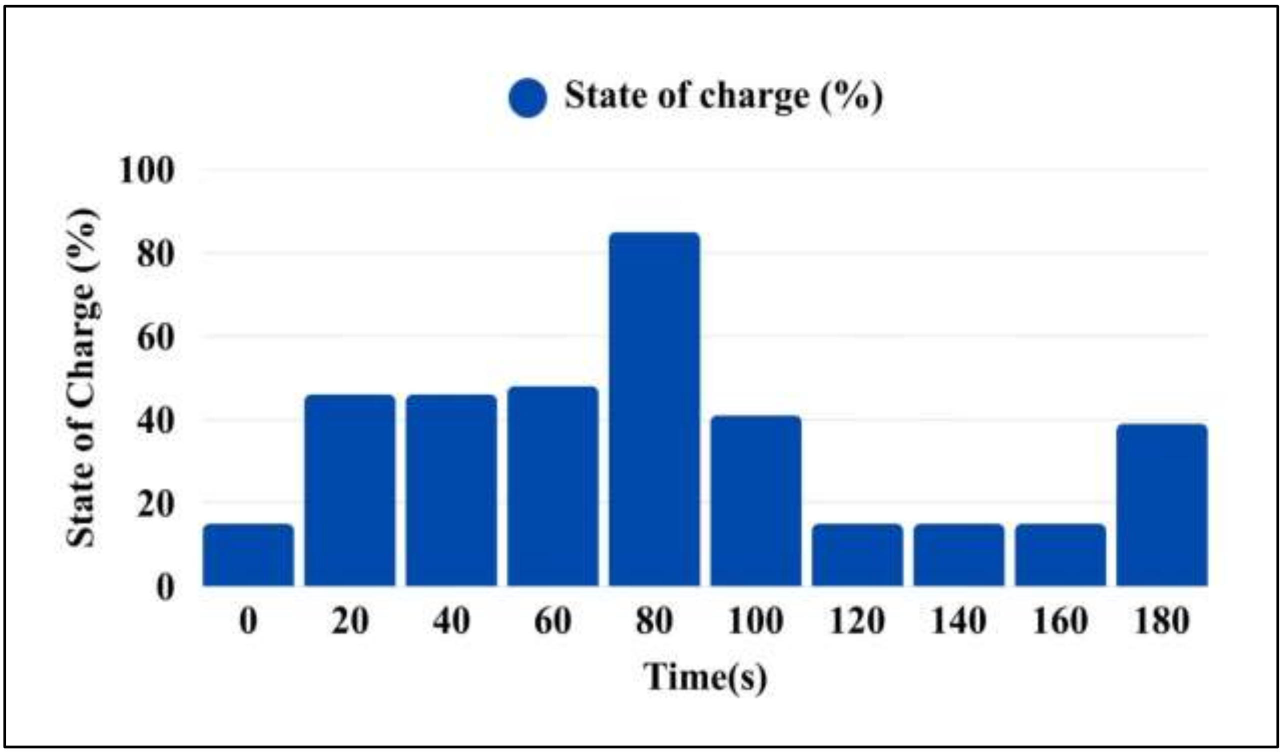

Fig 6. 4 Result of Time(s) vs State of Charge(%)

Table 6.4 and the Fig.6.4, shows the experimental outcomes between the time(s) and the state of charge (%). The Time vs. SOC chart shows how the “SOC” changes as time passes. The numerical values corresponding to the “SOC” on the Time v. “SOC” chart can be found in the table. The image of the graph does not reflect the actual graphical curves; however, there are specific times at which the “SOC” reaches specific values; the specific Times and SOC values are identified in the table 6.4.

At 0 Seconds, the SOC is 15%. At 20 seconds, the SOC climbs to 46%. At 60 seconds, it climbs again, but only slightly to an SOC of 48%. After 80 seconds, the “SOC” goes up from 15% to about 85%. It then drops down again to 41 at 100 seconds and keeps dropping down until 120 seconds as indicated below in the table and above in the “SOC” graph.

6.7. Key findings

The findings of the evaluation will be based upon analyzing the entire range of how effectively lithium-ion battery charge control systems with a flyback converter performed under various charge control regimes, particularly at the time of using both conventional "MPPT" and fuzzy logic-based MPPT methods. The performance assessment was validated according to the current, power, and state of charge characteristics providing a brief description of each.

Based upon the analyses conducted so far, we can better understand the operation and efficiency enhancements associated with the use of "MPPT" techniques. By using both types of "MPPT" will help us create a better understanding of the overall performance of our system.

The key findings are mentioned below:

- The outputs of the simulation studies indicate that when a photovoltaic-battery system is operated without "maximal power point tracking", Power extraction from the "PV" array will be limited, the charging pattern was unstable and there is ineffective use of solar energy is also occurred.
- The use of standard "MPPT" techniques to maximize electrical extraction from "Photovoltaic Arrays" has a significant enhance over a fixed duty cycle with reference to battery charging performance at various degrees of sun and temperature. Although these techniques have greatly increased the efficiency of Battery usage, there is still the presence of steady-state oscillations that occur about the "MPPT", which creates an unfinished extraction of energy during steady-state conditions.
- The use of a fuzzy logic based "MPPT" will provide superior capabilities for tracking

the maximum power point with rapidly varying and nonlinear environmental conditions as compared to that of traditional “MPPT” techniques.

- Reduced oscillations and smoother control of the duty cycle will result from using fuzzy “MPPT”. Thus, increasing the system's ability to provide stable characteristics during operation, and enabling the maximization of effective energy capture.
- Through the use of a flyback converter, both an electrically isolated and a regulated transfer of power between the “PV” array and lithium-ion battery can occur both during the charge and discharge modes.
- The waveform of the power and current varies greatly over time between zero-power intervals, an increasing slope, and a peak, representing a realistic operating experience for “PV” implemented battery systems.
- "Peak power tracking” in operations controlled via maximum power point tracking demonstrates that it is possible to progress toward “maximum power point tracking” and utilize the total solar energy that's available much better than previous methods.
- As stated, the state of charge profile was clear during the various stages of charge and discharge with “MPPT” compared with “MPPT-based charging” compared to traditional charging methods.
- Intelligent control with fuzzy logic for maximum power point tracking through flyback converter enhances battery charging effectiveness, energy loss reduction, improved battery reliability, and increased battery lifetime.

Chapter 7

Conclusion

The conclusions from the study on the Simulation of Charging and Discharging of Lithium-Ion Batteries with PV-Based Flyback Converter, with advanced “MPPT” algorithms, are summarized in this chapter. The study focused on the modeling of a “PV” array, a lithium-ion battery, and a flyback “DC-DC” converter, designed and implemented three “MPPT” algorithms, and evaluated the performance of the system based on changing the environmental conditions.

This chapter summarizes the findings of the study, discusses the benefits of the “Adaptive MPPT Framework”, and provides a basis for detecting Limitations and suggesting Future Research Directions. This chapter represents all the outcomes and insights gained from the thesis and present a clear picture of effectiveness and reliability of the proposed methodologies for improving Renewable Energy Utilization and Battery Management are when used for Electronic Vehicle and PV-Based Applications.

7.1 Summary of the work

This thesis presents a thorough simulation study of the usage of a photovoltaic-based flyback DC-DC converter system with advanced maximum power point tracking methods in order to charge and discharge lithium ion batteries. The first aspect of the work included the development of an overall model of the system. The “PV” array's characteristics when operating at various temperatures and levels of irradiance were described. The second stage focused on modelling the operation of LIBs which included both charge/discharge process characteristics and dynamic behaviour during battery operation. The third and final stage of the modeling phase involved creating a model for flyback DC-DC converters which represent the transfer of power between DC and DC. Following the modeling phase of this study, “MPPT” strategies were researched and tested to optimize energy harvesting from the “PV” array. Strategies were evaluated using the incremental conductance method. The two methods were combined to form a hybridized adaptive method, which could dynamically choose which of the pertinent “MPPT” strategies would be used based upon fluctuations in environmental conditions.

The second major component of the thesis included creating control signals for the fly-back converter current to the “LIB” and thus ensure that the “LIB” was charged safely and appropriately. Simulation testing was done evaluating the transfer of fly-back voltage to battery power while charging and discharging the battery. The test monitored “SOC”, battery voltage, battery current and battery temperature during both charging and discharging functions. A broad-based performance evaluation was performed to determine the effectiveness of the “MPPT” methods on battery charging and fly-back converter performance under a variety of environmental conditions.

7.2 Key Outcomes:

Many useful insights are demonstrated by our simulation outcomes which are mentioned below:

- The “hybrid MPPT system” was the best in terms of energy production when used under changing temperature and light conditions. The hybrid system produced more usable energy than either the P&O or IncCond systems.
- The battery “SOC” comparison was extremely close to what actually occurred, which means we had successfully modeled the way batteries charge and discharge.
- The flyback converter kept a consistent voltage and current when transferring PV, giving batteries a safe approach to store energy without overheating.
- Compared to a single-algorithm “MPPT” approach, the new hybrid system could transfer energy between the “PV” and battery at a higher efficiency level with less wasted energy.
- The thermal profiles show the new hybrid system created less thermal stress, which increases both battery life and safety during battery charge and discharge.

7.3. Benefits of Adaptive or fuzzy MPPT:

Having a fuzzy logic-based “MPPT” or adaptive algorithm implemented into the flyback converter system provided various benefits:

- **Dynamic Adaptability**: Adaptive “MPPT” can continuously monitor changing irradiance and temperature conditions, and adjust the “MPPT” strategy accordingly to obtain optimal power extraction.
- **Lower Steady State Oscillations**: Adaptive “MPPT” has fewer fluctuations around the maximum power point than traditional “P and O” algorithms.
- **Improved Battery Protection**: The risk of overcharging or causing unnecessary thermal pressures to the battery is reduced, as the proposed framework has more precise guidelines
- **Improvement in the complete effectiveness**: The intelligent selection of “MPPT” algorithms results in high consumption of energy generated by the “PV” array.

7.4. Drawbacks:

Although there were many positive outcomes from the study, there were still some limitations noted which are mentioned below:

- The majority of the data collected was obtained through simulations. However, the effects of real-world conditions were not adequately addressed in the analysis due to time and resource constraints.
- The hybrid "MPPT" framework contains more computational complexity compared to using a single algorithm-based approach, which may pose challenges for implementation on low-cost embedded hardware.
- The thermal properties of the flyback converter components under high load conditions were approximated in a simplistic manner and, therefore, some issues related to localize heating may be underestimated or overlooked.

7.5. Future enhancements:

Using the findings of this thesis, a variety of future research opportunities exist.

- **An Experimental Validation**: Create an actual hardware prototype that uses the proposed framework to test the simulation results, and verify that the real world disturbances are accounted for.
- **Battery Aging Models Integration:** To estimate long-term presentation and also to develop both “State of Charge” and “State of Health” estimates, the battery degradation modeling should be integrated.
- **AI and ML Enhancement Methods**: To provide predictive optimization of power production as well as fault detection, extending the adaptive “MPPT” model by using the machine learning.
- **Multi-Battery Storage System & Hybrid Systems Expansion** In order to provide additional flexibility and consistency, the framework should be enhanced for including lot of various battery chemistries or hybrid storage systems. .
- **Grid Connectivity:** For helping with aggregating the level of renewable energy penetration and energy management, adopting the model for working with the grid connection of “PV-battery” systems.
- **Thermal Management Augmentation:** To contribute with optimizing the cooling strategies and maximizing the operational life of the components, there is need for integrate the comprehensive thermal modeling for both batteries and convertors.

In conclusion, the findings of the thesis have shown that the “Adaptive MPPT Flyback Converter Framework” is a feasible method for maximizing the utilization of solar energy from photovoltaic panels while maintaining secure operation of “lithium-ion batteries”. For constant development of intelligent renewable energy storage systems and structure for “Electric Vehicle Charging” is offered by our proposed framework.

References:

1. Zhang, X., Li, Z., Luo, L., Fan, Y., & Du, Z. (2022). A review on thermal management of lithium-ion batteries for electric vehicles. *Energy*, *238*, 121652.
2. Tahir, M. U., Sangwongwanich, A., Stroe, D. I., & Blaabjerg, F. (2023). *Overview of multi-stage charging strategies for lithium-ion batteries*. Journal of Energy Storage, 61, 106739.
3. Krishnamoorthy, U., Ayyavu, P. G., Panchal, H., Shanmugam, D., Balasubramani, S., Al-rubaie, A. J., Al-khaykan, A., Oza, A. D., Hembrom, S., & Patel, T. (2023). *Efficient battery models for performance studies-lithium ion and nickel metal hydride battery*. Batteries, 9(1), 52
4. Li, Y., Zhou, Z., Hu, L., Bai, M., Gao, L., Li, Y., Liu, X., & Song, Y. (2022). Experimental studies of liquid immersion cooling for 18650 lithium-ion battery under different discharging conditions. Case Studies in Thermal Engineering, 34, 102034.
5. Liu, Y., Wang, L., Li, D., *et al.* (2023). State-of-health estimation of lithium-ion batteries based on electrochemical impedance spectroscopy: a review. *Protection and Control of Modern Power Systems, 8*, 41
6. Chen, J., Wang, G., Song, H., Wang, B., Wu, G., & Lei, J. (2022). Stress and displacement of cylindrical lithium-ion power battery during charging and discharging. *Energies, 15*(21),
7. Fayaz, H., Afzal, A., Samee, A. D. M., Soudagar, M. E. M., Akram, N., Mujtaba, M. A., Jilte, R. D., Islam, M. T., Ağbulut, Ü., & Saleel, C. A. (2022). Optimization of thermal and structural design in lithium-ion batteries to obtain energy efficient battery thermal management system (BTMS): A critical review. *Archives of Computational Methods in Engineering, 29*(1), 129–194.
8. Carrera, R., Quiroz, L., Guevara, C., & Acosta-Vargas, P. (2025). State-of-charge estimation of medium-and high-voltage batteries using LSTM neural networks optimized with genetic algorithms. *Sensors*, *25*(15), 4632.
9. Zhou, W., Lu, Q., & Zheng, Y. (2022). Review on the selection of health indicator for lithium ion batteries. Machines, 10(7), 512
10. Ness, S., Boujoudar, Y., Aljarbouh, A., Elyssaoui, L., Azeroual, M., Bassine, F. Z., & Rele, M. (2024). Active balancing system in battery management system for lithium-

ion battery. *International Journal of Electrical & Computer Engineering (IJECE), 14*(4), 3640–3648.

11. Hai, T., Abidi, A., Abed, A. M., Zhou, J., Hasani Malekshah, E., & Aybar, H. Ş. (2022). Three-dimensional numerical study of the effect of an air-cooled system on thermal management of a cylindrical lithium-ion battery pack with two different arrangements of battery cells. Journal of Power Sources, 550, 232117.
12. Wang, Z., Feng, G., Liu, X., Gu, F., & Ball, A. (2022). A novel method of parameter identification and state of charge estimation for lithium-ion battery energy storage system. *Journal of Energy Storage, 49*, 104124.
13. Maddipatla, S., Kong, L., & Pecht, M. G. (2024). Safety analysis of lithium-ion cylindrical batteries using design and process failure mode and effect analysis. Batteries, 10(3), 76.
14. Guo, X., Wang, K., Shan, D., Zheng, D., & Ning, Y. (2024). RUL prediction of lithium ion battery based on CEEMDAN-CNN BiLSTM model. *Acta Energiae Solaris Sinica, 45*(7), 181–189.
15. Zheng, Y., Che, Y., Hu, X., Sui, X., Stroe, D.-I., & Teodorescu, R. (2024). Thermal state monitoring of lithium-ion batteries: Progress, challenges, and opportunities. *Progress in Energy and Combustion Science, 100*, 101120
16. Azad, S., Nazari-Heris, M., Ameli, M. T., & Asadi, S. (2022). Charging and discharging of electric vehicles in power systems: An updated and detailed review of methods, control structures, objectives, and optimization methodologies. *Sustainability, 14*(4), 2137.
17. Zhang, J., Qiao, J., Sun, K., & Wang, Z. (2022). Balancing particle properties for practical lithium-ion batteries. Particuology, 61, 18–29
18. Lee, J., & Won, J. (2023). Enhanced Coulomb counting method for SoC and SoH estimation based on coulombic efficiency. IEEE Access, 11, 15449–15459.
19. Li, J., Peng, Y., Wang, Q., & Liu, H. (2024). Status and prospects of research on lithium-ion battery parameter identification. *Batteries, 10*(6), 194.
20. Zou, M., Yang, Y., Liu, M., Wang, W., Jia, H., Peng, X., Su, S., & Liu, D. (2022). Optimization model of electric vehicles charging and discharging strategy considering the safe operation of distribution network. *World Electric Vehicle Journal, 13*(7), 117.
21. Gul, S., Malik, S. M., Sun, Y., & Alsaif, F. (2024). An artificial neural network based MPPT control of modified flyback converter for PV systems in active buildings. *Energy Reports*, *12*, 2865-2872.

22. Ramos-Paja, C. A., Bastidas-Rodriguez, J. D., & Saavedra-Montes, A. J. (2022). Sliding-mode control of a photovoltaic system based on a flyback converter for microinverter applications. *Applied Sciences*, *12*(3), 1399.
23. Belman-Flores, J. M., Rodríguez-Valderrama, D. A., Ledesma, S., García-Pabón, J. J., Hernández, D., & Pardo-Cely, D. M. (2022). A review on applications of fuzzy logic control for refrigeration systems. *Applied Sciences*, *12*(3), 1302.
24. Dong, M., Li, H., Yin, S., Tian, B., Yang, S., & Chen, Y. (2025). An Overview of DC-DC Power Converters for Electric Propulsion. *Aerospace*, *13*(1), 36.
25. Li, Y., Li, K., Liu, X., Li, X., Zhang, L., Rente, B., ... & Grattan, K. T. (2022). A hybrid machine learning framework for joint SOC and SOH estimation of lithium-ion batteries assisted with fiber sensor measurements. *Applied Energy*, *325*, 119787.
26. Shen, M., & Ma, H. (2022). Metal-organic frameworks (MOFs) and their derivative as electrode materials for lithium-ion batteries. *Coordination Chemistry Reviews*, *470*, 214715.
27. Yao, X. Y., Chen, G., Pecht, M., & Chen, B. (2023). A novel graph-based framework for state of health prediction of lithium-ion battery. *Journal of Energy Storage*, *58*, 106437.
28. Natella, D., Onori, S., & Vasca, F. (2022). A co-estimation framework for state of charge and parameters of lithium-ion battery with robustness to aging and usage conditions. *IEEE Transactions on Industrial Electronics*, *70*(6), 5760-5770..
29. Fei, Z., Zhang, Z., Yang, F., Tsui, K. L., & Li, L. (2022). Early-stage lifetime prediction for lithium-ion batteries: A deep learning framework jointly considering machine-learned and handcrafted data features. *Journal of Energy Storage*, *52*, 104936.
30. Lin, C., Tuo, X., Wu, L., Zhang, G., & Zeng, X. (2024). Accurate capacity prediction and evaluation with advanced SSA-CNN-BiLSTM framework for lithium-ion batteries. *Batteries*, *10*(3), 71.
31. Jafari, S., Shahbazi, Z., Byun, Y. C., & Lee, S. J. (2022). Lithium-ion battery estimation in online framework using extreme gradient boosting machine learning approach. *Mathematics*, *10*(6), 888.
32. Wei, Z., Yang, X., Li, Y., He, H., Li, W., & Sauer, D. U. (2023). Machine learning-based fast charging of lithium-ion battery by perceiving and regulating internal microscopic states. *Energy Storage Materials*, *56*, 62-75.

33. Jiang, B., Berliner, M. D., Lai, K., Asinger, P. A., Zhao, H., Herring, P. K., ... & Braatz, R. D. (2022). Fast charging design for Lithium-ion batteries via Bayesian optimization. *Applied Energy*, *307*, 118244.
34. Zabetian-Hosseini, A., Ghazanfari, A., & Boulet, B. (2024). A finite-state machine-based control design for thermal and state-of-charge balancing of lithium iron phosphate battery using flyback converters. *Battery Energy*, *3*(4), 20230055.
35. Lee, Y. L., Lin, C. H., Tsai, P. H., Liu, H. D., & Lu, S. D. (2022). A Multifunctional, Non-Constant Current Charger Based on a Dual-Switching, Bidirectional Flyback Converter. *Processes*, *10*(8), 1522.
36. Ullah, M. A., Ahmed, A., Uppal, A. A., & Ahmed, Q. (2025). NMPC based Performance evaluation of Active Balancing Networks of Li-Ion Batteries for Overnight EV Charging. *IEEE Access*.
37. Shieh, Y. T., Liu, C. Y., Wu, C. C., Chieng, W. H., & Chang, E. Y. (2022). Flyback Converter Using a D-Mode GaN HEMT Synchronous Rectifier. *Energies*, *15*(9), 3197.
38. Lim, W. C., Siek, L., & Tan, E. L. (2025). Adaptive Hybrid Switched-Capacitor Cell Balancing for 4-Cell Li-Ion Battery Pack with a Study of Pulse-Frequency Modulation Control. *Journal of Low Power Electronics and Applications*, *15*(4), 61.
39. Habib, A. A., Hasan, M. K., Issa, G. F., Singh, D., Islam, S., & Ghazal, T. M. (2023). Lithium-ion battery management system for electric vehicles: constraints, challenges, and recommendations. *Batteries*, *9*(3), 152.
40. Kumar, G. P., & Dasarathan, S. (2025). Metaheuristic-tuned droop control for PV-based DC microgrid optimization under dynamic load conditions. *IEEE Access*.
41. Yadav, I., Sachan, S., Maurya, S. K., & Deb, S. (2023). Effective battery charging system using step voltage and step duty size-based MPPT controller for solar PV system. *Energy Reports*, *10*, 744-755.
42. Endiz, M. S. (2024). Design and implementation of microcontroller-based solar charge controller using modified incremental conductance MPPT algorithm. *Journal of Radiation Research and Applied Sciences*, *17*(2), 100938.
43. Al-Muthanna, G., Fang, S., AL-Wesabi, I., Ameur, K., Kotb, H., AboRas, K. M., ... & Mas' ud, A. A. (2023). A high speed MPPT control utilizing a hybrid PSO-PID controller under partially shaded photovoltaic battery chargers. *Sustainability*, *15*(4), 3578.

44. Viswa Teja, A., Razia Sultana, W., & Salkuti, S. R. (2023). Performance explorations of a PMS motor drive using an ANN-based MPPT controller for solar-battery powered electric vehicles. *Designs*, *7*(3), 79.
45. Chojaa, H., Derouich, A., Zamzoum, O., Watil, A., Taoussi, M., Abdelaziz, A. Y., ... & Mossa, M. A. (2023). Robust control of DFIG-based WECS integrating an energy storage system with intelligent MPPT under a real wind profile. *IEEE Access*, *11*, 90065-90083.
46. Ghazi, G. A., Al-Ammar, E. A., Hasanien, H. M., Ko, W., Lee, S. M., Turky, R. A., ... & Jurado, F. (2024). Circle search algorithm-based super twisting sliding mode control for MPPT of different commercial PV modules. *IEEE Access*, *12*, 33109-33128.
47. Raj, P. J., Prabhu, V. V., Krishnakumar, V., & Anand, M. C. J. (2023). Solar powered charging of fuzzy logic controller (FLC) strategy with battery management system (BMS) method used for electric vehicle (EV). *International Journal of Fuzzy Systems*, *25*(7), 2876-2888.
48. Zhang, S., Li, T., & Chen, L. (2023). Fuzzy logic control of external heating system for electric vehicle batteries at low temperature. *World electric vehicle journal*, *14*(4), 99.
49. Károlyi, G., Pózna, A. I., Hangos, K. M., & Magyar, A. (2022). An optimized fuzzy controlled charging system for lithium-ion batteries using a genetic algorithm. *Energies*, *15*(2), 481.
50. Lencwe, M. J., Zau, A. T. P., Chowdhury, S. D., & Olwal, T. O. (2022). Integrated fuzzy-logic and triple-loop pi-based management strategy for a lead-acid/lithium-ion hybrid battery energy storage system. *Applied Sciences*, *12*(14), 6910.
51. He, H., Xiong, R., & Fan, J. (2011). Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach. *energies*, *4*(4), 582-598.
52. Omakor, J., Alzayed, M., & Chaoui, H. (2024). Particle swarm-optimized fuzzy logic energy management of hybrid energy storage in electric vehicles. *Energies*, *17*(9), 2163.
53. Al Sumarmad, K. A., Sulaiman, N., Wahab, N. I. A., & Hizam, H. (2022). Energy management and voltage control in microgrids using artificial neural networks, PID, and fuzzy logic controllers. *Energies*, *15*(1), 303.

54. Guler, N., Ismail, Z. M., Hazem, Z. B., & Naik, N. (2024). Adaptive fuzzy logic controller-based intelligent energy management system scheme for hybrid electric vehicles. *IEEE Access*, *12*, 173441-173454.
55. Sun, X., Zhang, Y., Zhang, Y., Wang, L., & Wang, K. (2023). Summary of health-state estimation of lithium-ion batteries based on electrochemical impedance spectroscopy. *Energies*, *16*(15), 5682.
56. Zazoum, B. (2023). Lithium-ion battery state of charge prediction based on machine learning approach. *Energy Reports*, *9*, 1152-1158.
57. Rauf, H., Khalid, M., & Arshad, N. (2023). A novel smart feature selection strategy of lithium-ion battery degradation modelling for electric vehicles based on modern machine learning algorithms. *Journal of Energy Storage*, *68*, 107577.
58. Haraz, A., Abualsaud, K., & Massoud, A. (2024). State-of-health and state-of-charge estimation in electric vehicles batteries: a survey on machine learning approaches. *IEEE Access*.
59. Oyucu, S., Ersöz, B., Sağıroğlu, Ş., Aksöz, A., & Biçer, E. (2024). Optimizing Lithium-ion battery performance: Integrating machine learning and explainable AI for enhanced energy management. *Sustainability*, *16*(11), 4755.
60. Kohtz, S., Xu, Y., Zheng, Z., & Wang, P. (2022). Physics-informed machine learning model for battery state of health prognostics using partial charging segments. *Mechanical Systems and Signal Processing*, *172*, 109002.