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**Study And Diagnosis of Battery Charging State in Photovoltaic
Energy Systems**

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Abstract

In recent years, global interest in renewable energy sources has significantly increased, particularly (PV) solar energy, as an effective solution to meet the growing energy demand while reducing the environmental impacts associated with fossil fuel consumption. Batteries are considered one of the most important components of standalone PV systems, as they ensure energy storage during periods of solar irradiation and provide power when generation is low or unavailable.

This study aims to analyze and diagnose the battery State of Charge (SOC) in PV energy systems by investigating the electrical and operational characteristics of batteries during charging and discharging processes. It also seeks to evaluate different SOC estimation methods and their effectiveness in improving system performance and ensuring a reliable power supply.

First, a theoretical study of PV energy systems and their main components was conducted, including solar panels, charge controllers, inverters, and energy storage systems. Subsequently, the study focused on the different types of batteries used in PV applications, highlighting their technical characteristics, operating principles, and the factors affecting their performance and lifespan.

The research further examines the concept of State of Charge and its importance in energy management. Several SOC estimation and diagnostic techniques were reviewed, including voltage-based methods, Coulomb Counting, mathematical modeling approaches, and intelligent algorithms. The advantages and limitations of each method were analyzed in terms of accuracy, complexity, and practical implementation.

The results demonstrate that accurate monitoring of the battery State of Charge plays a crucial role in enhancing the efficiency of PV systems. It helps prevent overcharging and deep discharging conditions that may degrade battery performance and shorten its service life. Furthermore, modern diagnostic techniques contribute to improving system reliability, optimizing the utilization of stored energy, and reducing maintenance and replacement costs.

In conclusion, battery State of Charge diagnosis is a fundamental aspect of PV energy system management. The development of accurate and efficient SOC estimation methods directly contributes to improving system energy performance, extending battery lifetime, and enhancing the sustainability and reliability of renewable energy systems in both residential and industrial applications.

Photovoltaic (PV) Systems

Keywords

- **Solar Energy**
- **Battery State of Charge (SOC)**
- **Battery Diagnostics**
- **State of Charge Estimation**
- **Energy Storage Systems**
- **Battery Management System (BMS)**

الملخص

تزايد الاهتمام العالمي في السنوات الأخيرة باستخدام مصادر الطاقة المتجددة، وعلى رأسها الطاقة الشمسية الكهروضوئية، باعتبارها حلاً فعالاً لمواجهة الطلب المتزايد على الطاقة وتقليل التأثيرات البيئية الناجمة عن استخدام الوقود الأحفوري. وتعد البطاريات من أهم مكونات الأنظمة الكهروضوئية المستقلة، حيث تضمن تخزين الطاقة المنتجة خلال فترات الإشعاع الشمسي واستغلالها عند انخفاض أو انعدام الإنتاج.

تهدف هذه الدراسة إلى تحليل وتشخيص حالة شحن البطاريات (State of Charge - SOC) في أنظمة الطاقة الشمسية الكهروضوئية، وذلك من خلال دراسة الخصائص الكهربائية والتشغيلية للبطاريات أثناء مراحل الشحن والتفريغ. كما تسعى إلى تقييم الطرق المختلفة المستخدمة في تقدير حالة الشحن ومدى فعاليتها في تحسين أداء النظام وضمان استمرارية التغذية الكهربائية.

في البداية، تم تقديم دراسة نظرية حول الطاقة الشمسية الكهروضوئية ومكوناتها الأساسية، بما في ذلك الألواح الشمسية، منظمات الشحن، العواكس، وأنظمة التخزين. بعد ذلك تم التطرق إلى أنواع البطاريات المستخدمة في التطبيقات الكهروضوئية، مع التركيز على خصائصها التقنية وآليات عملها والعوامل المؤثرة في أدائها وعمرها الافتراضي. كما تناولت الدراسة مفهوم حالة الشحن وأهميته في إدارة الطاقة، حيث تم استعراض أبرز طرق التقدير والتشخيص المعتمدة، مثل طريقة قياس الجهد، وطريقة عدّ الأمبير-ساعة (Coulomb Counting)، والطرق المعتمدة على النماذج الرياضية والخوارزميات الذكية. وقد تم تحليل مزايا وعيوب كل طريقة من حيث الدقة والتعقيد وإمكانية التطبيق العملي. وأظهرت نتائج الدراسة أن المراقبة الدقيقة لحالة شحن البطارية تلعب دوراً أساسياً في تحسين كفاءة النظام الكهروضوئي، إذ تسمح بتجنب حالات الشحن الزائد والتفريغ العميق التي تؤدي إلى تدهور أداء البطارية وتقليص عمرها التشغيلي. كما تبين أن استخدام تقنيات التشخيص الحديثة يساهم في رفع موثوقية النظام وتحسين استغلال الطاقة المخزنة وتقليل تكاليف الصيانة والاستبدال.

وتخلص هذه الدراسة إلى أن تشخيص حالة شحن البطاريات يمثل عنصراً أساسياً في إدارة أنظمة الطاقة الشمسية الكهروضوئية، وأن تطوير أساليب دقيقة وفعالة لتقدير حالة الشحن يساهم بشكل مباشر في تحسين الأداء الطاقوي للنظام، وزيادة العمر الافتراضي للبطاريات، وتعزيز استدامة أنظمة الطاقة المتجددة في مختلف التطبيقات المنزلية والصناعية.

الكلمات المفتاحية:

• أنظمة الطاقة الشمسية الكهروضوئية (PV)

• الطاقة الشمسية

• حالة شحن البطارية (SOC)

• تشخيص البطاريات

• تقدير حالة شحن البطارية

• أنظمة تخزين الطاقة

• نظام إدارة البطارية (BMS)

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General Introduction

The growing global demand for clean and sustainable energy has accelerated the development and deployment of renewable energy systems, particularly (PV) systems. These systems play a critical role in transitioning away from fossil fuels and reducing greenhouse gas emissions. However, the intermittent nature of solar energy necessitates the use of efficient energy storage solutions, among which lithium-ion batteries have emerged as the most prevalent technology due to their high energy density, long cycle life, and relatively low self-discharge rate[1].

Effective management of lithium-ion batteries requires accurate real-time monitoring of key parameters, most notably the State of Charge (SOC), which quantifies the remaining energy capacity relative to the battery's total capacity. Precise SOC estimation is essential for ensuring safe operation, optimizing battery performance, and extending battery lifespan. However, SOC cannot be measured directly and must be estimated through indirect methods, which presents a significant technical challenge owing to the nonlinear electrochemical behavior of lithium-ion batteries and their sensitivity to temperature, aging, and operating conditions[1].

Among the various estimation approaches available, model-based observer techniques — particularly the Extended Kalman Filter (EKF) — have demonstrated superior performance in terms of accuracy, robustness to noise, and adaptability to dynamic operating conditions. These methods rely on accurate mathematical models of the battery, typically represented by equivalent electrical circuits, to reconstruct the internal state of the system from measurable input-output data[2].

The central research question addressed in this thesis is: How can the state of charge of a lithium-ion battery be accurately and reliably estimated using state observer techniques?

To address this question, the present thesis is organized into four chapters:

Chapter One provides a comprehensive overview of PV energy systems and battery storage fundamentals, covering solar radiation principles, PV cell technologies, system configurations, and the role of energy storage in renewable energy applications[30].

Chapter Two presents and analyzes the principal electrical equivalent models used for battery simulation, including the ideal model, the simple model, the Thevenin model, and its various modifications, with emphasis on their ability to capture the dynamic behavior of lithium-ion batteries[2].

Chapter Three introduces the theoretical foundations of state of charge estimation, covering physical, electrical, and impedance-based methods, as well as the construction of state

observers. The Luenberger observer is examined in detail, along with the principles of observability and the Extended Kalman Filter formulation[3].

Chapter Four addresses the practical implementation of the proposed SOC estimation approach, presenting the nonlinear state-space model of the lithium-ion battery, the design of the EKF-based observer, and the Matlab/Simulink simulation results validating the accuracy of the proposed method under various operating conditions[3].

1.

first Chapter I :

*Photovoltaic (PV) Energy Systems and
Battery Storage Fundamentals*

1.1. Introduction

The global shift toward renewable energy sources has significantly increased the adoption of photo-voltaic (PV) systems as a sustainable solution for electricity generation. These systems efficiently convert solar energy into electrical energy using solar cells and can be deployed in both standalone and grid-connected configurations[1].

Grid-connected PV systems, in particular, have gained increasing importance due to their ability to support public utility networks and reduce reliance on conventional energy sources. However, these systems face several technical challenges, most notably the continuous variation in operating conditions such as solar irradiance and temperature, which directly affect their efficiency[1].

To overcome these limitations, MPPT techniques are employed to extract the maximum available power from PV panels at all times. Among the various MPPT algorithms, the Perturb and Observe (P&O) method is widely used due to its simplicity and ease of implementation.

In addition to MPPT, efficient power flow regulation to the grid requires a robust control structure involving both DC-DC and DC-AC converters. Given the inherent non-linearity and parameter uncertainties of PV systems, advanced control strategies like SMC become essential to ensure stable performance and reliable maximum power tracking[2].

This chapter provides a technical overview of PV systems and their components laying the foundation for the control challenges addressed in the subsequent chapters of this thesis.

1.2. Renewable Energy System

1.2.1. Definition of Renewable Energy

Renewable energy can be defined as energy derived from natural resources that are inexhaustible and are constantly renewed. Renewable energy is also known as energy resulting from natural sources that are renewed at a rate greater than what is consumed. Renewable energy is also called by several terms, including clean energy and environmentally friendly energy. The uses of renewable energy are concentrated in generating electrical energy, while other uses such as heating and cooling water as well as use in transportation are still not sufficiently exploited.

significantly reduces greenhouse gas emissions that contribute to rising global temperatures reduces local air pollution and water contamination.

- provides energy security by developing local sources that are flexible and can respond to community needs[3].

-
- improves local economy by creating jobs and placing value on lands that supply renewable energy sources.

1.2.2. The importance of energy in the modern world:

Renewable energy is one of the most sustainable solutions that can help achieve the world's goals in tackling climate change and reducing carbon emissions. It offers alternatives to fossil fuels, which cause air and water pollution and contribute to global warming.

1.3. Solar energy

PV solar energy is the most competitive and the fastest-growing and most widely installed energy source in the world. This clean energy boasts remarkable environmental, economic, and social benefits, aligning its advantages with sustainable development goals. But despite its strengths, it is not without its challenges. These limitations, while surmountable, merit careful consideration, especially for those considering investing in this sector[2].



Figure 1-1: Types of Solar Radiation Affecting Solar Panels.

1.3.1. Historical Evolution of PV Technology

The development of PV technology spans more than a century, with significant milestones marking its evolution. The first practical PV cell was developed in 1954 by researchers at Bell Telephone Laboratories. This silicon-based solar cell had an efficiency of approximately 6% and marked the beginning of PV technology as a viable energy source.

During the late 1950s and 1960s, PV cells found their first major application in space technology, where they were used to power U.S. satellites. Their reliability and ability to generate power in isolated environments made them ideal for space missions.

In the late 1970s, PV systems began to be deployed in remote and off-grid areas on Earth—locations without access to conventional electricity infrastructure. These early terrestrial applications proved the utility of PV technology in diverse environments.

A major shift occurred after 2004, with the widespread adoption of grid-connected PV systems. These systems, installed on rooftops, buildings, and large-scale solar farms, feed electricity directly into the power grid. The expansion of PV deployment was driven by technological advancements, reductions in production and installation costs, and favorable policy measures such as tax incentives and net metering programs.

By the mid-1990s and continuing to the present day, the number of installed PV systems has increased exponentially. In countries like the United States, millions of grid-connected systems are now operational, contributing significantly to national energy portfolios.

This historical development reflects not only the technological maturation of PV systems but also their growing role in global efforts toward sustainable and renewable energy[4].

1.4. Solar radiation

Solar radiation is radiant (electromagnetic) energy from the sun. It provides light and heat for the Earth and energy for photosynthesis. This radiant energy is necessary for the metabolism of the environment and its inhabitants. The three relevant bands, or ranges, along the solar radiation spectrum are ultraviolet, visible (PAR), and infrared. Of the light that reaches Earth's surface, infrared radiation makes up 49.4% of while visible light provides 42.3%. Ultraviolet radiation makes up just over 8% of the total solar radiation. Each of these bands has a different impact on the environment[2].

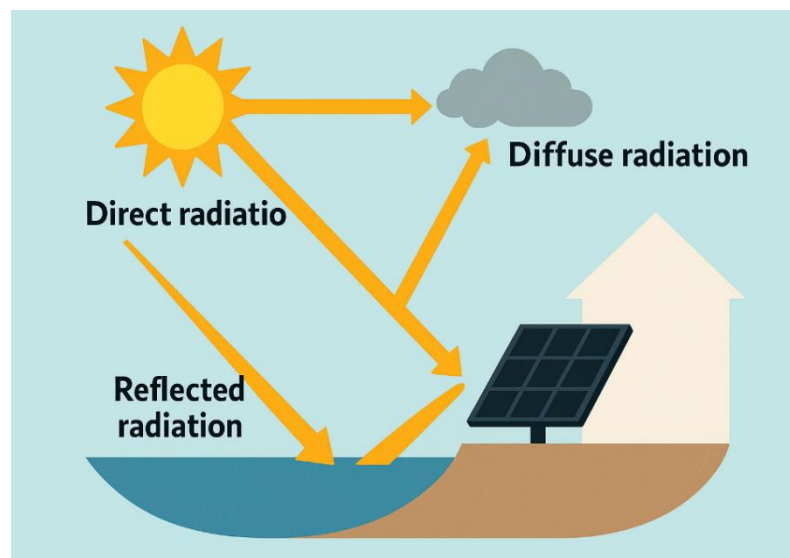


Figure 1-2: Types of Solar Radiation Affecting Solar Panels.

1.4.1. Direct radiation

This type of radiation penetrates the atmosphere and reaches the Earth's surface without dispersing at all on the way[2].

1.4.2. Diffuse radiation

This is the radiation that reaches the Earth's surface after having undergone multiple deviations in its trajectory, for example by gases in the atmosphere[3].

1.4.3. Reflected radiation or ground albedo

This is the fraction of solar radiation that is reflected by the earth's surface itself, in a phenomenon known as the albedo effect[4].

1.4.4. Global radiation

It is the radiation, received on a horizontal surface, coming from the Sun and the entire celestial vault; it is measured with a pyranometer.

Is the sum of these various radiations. It reaches a value of 1000 W/m^2 on a clear, cloudless day. This radiation can be measured using a pyranometer or a solarimeter. Most of the time, solar energy is determined by cumulative radiation.

To do this, daily global radiation is calculated; this is the integral of global radiation over a day at a given location with a given inclination (usually horizontal). The cumulative radiation is measured in Wh/m^2 per day. This data is accumulated from year to year, and averages for each month of the year are thus determined. These values are available with the PVGIS (PV Geographical Information System) information system[5].

1.5. Solar panels

1.5.1. Definition

Solar panels are devices that convert sunlight into electricity through the (PV) effect. Their efficiency, performance, and applications depend on various factors, including the technology used, environmental conditions, and installation method[8].

1.5.2. The PV cell

(PV) cells, commonly known as solar cells, are devices that convert sunlight directly into electricity through a process called PV . These cells are constructed from semiconductor materials that absorb photons, freeing electrons and generating an electric current. The PV effect was first noted by French physicist Alexandre-Edmond Becquerel in 1839, and significant advancements have been made since then, including the development of the first silicon solar cell in 1954, which marked a turning point in solar technology. [9]

The PV cell (also known as a PV cell) is a device that converts sunlight into electricity through the PV effect, a phenomenon discovered in 1839 by the French physicist Alexandre-Edmond Becquerel. Over the years, other scientists, such as Charles Fritts

and Albert Einstein, contributed to perfecting the efficiency of these cells, until reaching the current silicon ones, whose use has become increasingly more accessible and efficient. [10]

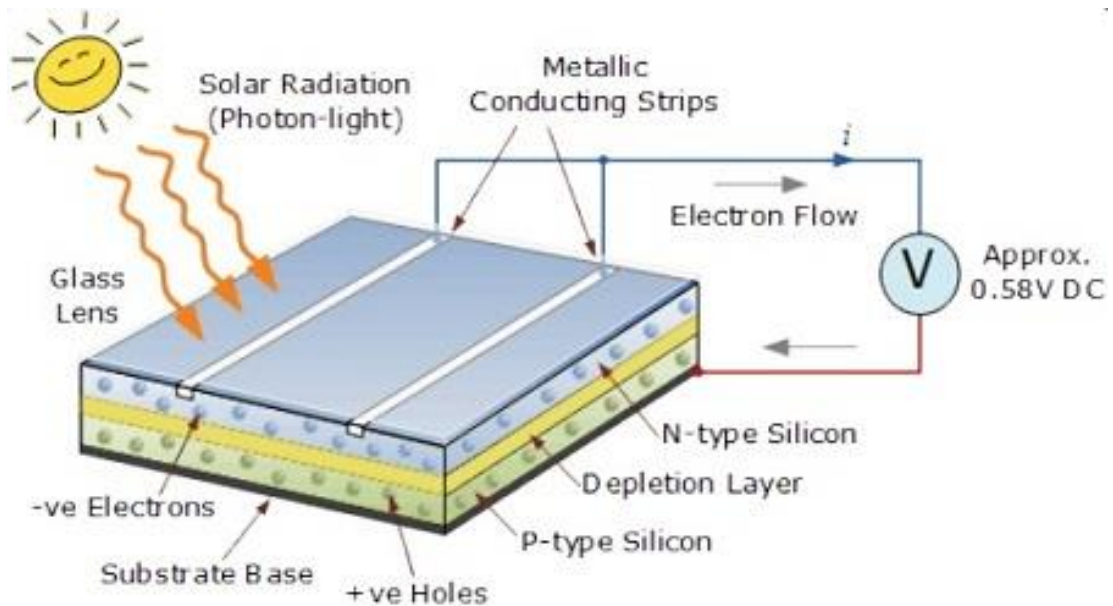


Figure 1-3: Model showing a PV cell.

1.6. Type and performance of PV cells

1.6.1. Monocrystalline Silicon Cell

The most effective of the solar PV cells with 15% efficiency, mono-crystalline silicon is therefore the more expensive option. They require less space than other cells simply because they produce more energy and can yield up to four times more power than thin-film solar panels. They also last longer than other panels and perform better at low light.

The main disadvantage is the cost which often means that it's not the first choice for home owners. It can also be affected by dirt or shade, which can break the circuit and the production process is often seen as wasteful because the cells have to be cut into wafers.

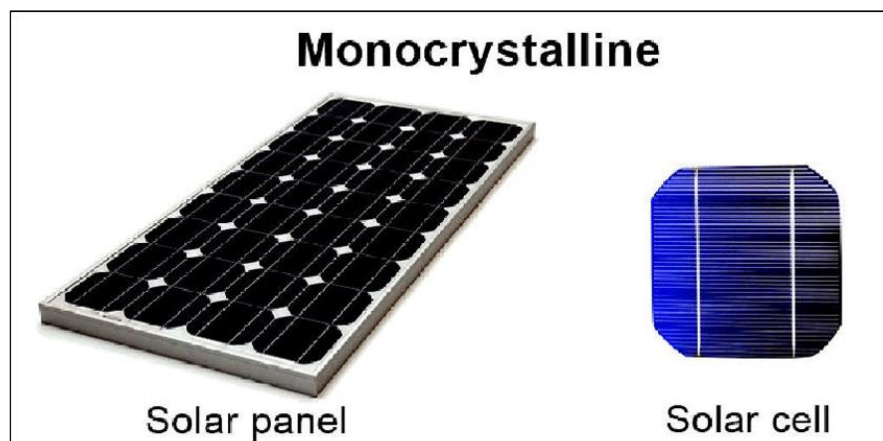


Figure 1-4: Monocrystalline Silicon Cell.

1.6.2. Polycrystalline Silicon Cell

With an efficiency of 13%, polycrystalline solar panels are often seen as a better economic choice, particularly for home owners. They are made from a number of smaller silicon crystals that are melted together and then recrystallized. The process to create them is simpler and less wasteful than with monocrystalline panels. They do suffer more at high heats that can reduce their lifespan but overall perform just as well as their more expensive counterpart.

The main disadvantage for polycrystalline solar panels is that you need more of them because of the lower energy conversion efficiency.

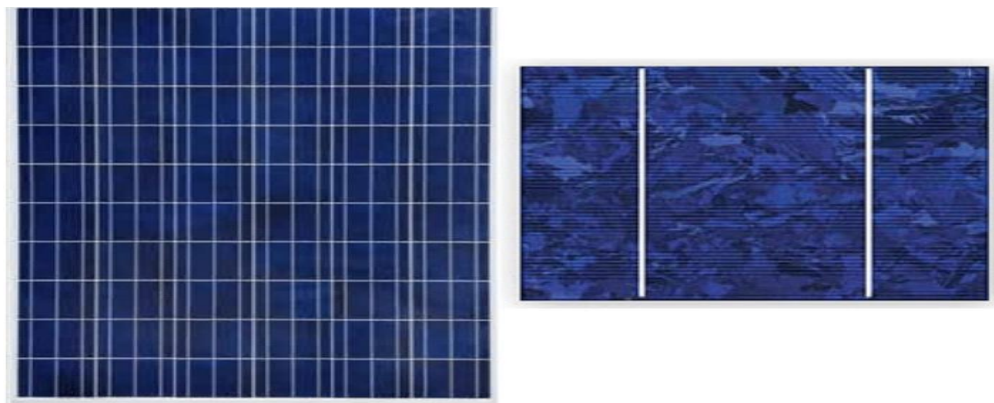


Figure 1-5: Polycrystalline Silicon Cell

1.6.3. Amorphous/thin film Cell

At 7%, thin film solar panels are among the least efficient on the market but they are the cheapest option. They work well in low light, even moonlight, and are made from non-crystalline silicone that can be transferred in a thin film onto another material such as glass. The main advantage is that it can be mass produced at a much cheaper cost but is more suitable for situations where space is not a big issue.

The main disadvantage for thin film solar panels are not generally used for residential purposes and will degrade quicker than crystalline cells.



Figure 1-6: Amorphous/thin film Cell

1.6.4. Hybrid silicon cell

With an efficiency of 18%, hybrid solar panels are made from a mix of amorphous and monocrystalline cells to generate maximum efficiency. There are a variety of types of hybrid cells and they are still very much at the research and development stage which is why they are currently a more expensive option.

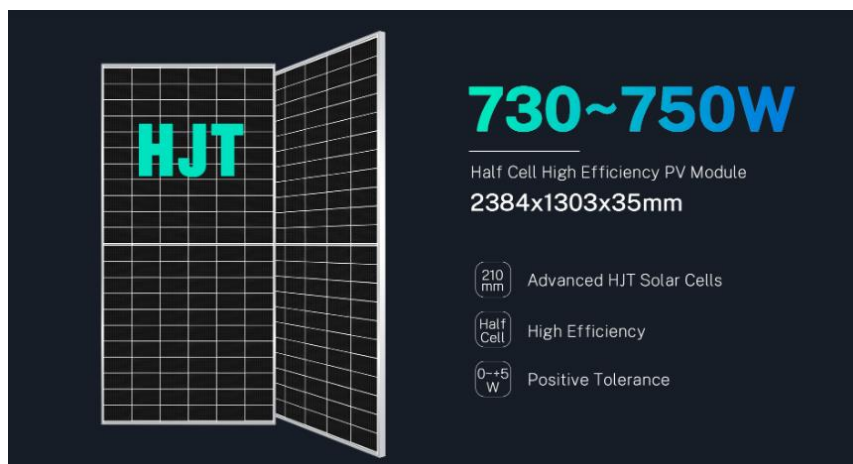


Figure 1-7: Real photograph of a hybrid (HJT) silicon solar panel module used in modernPVsystems

1.7. Types of Photovoltaic Systems

PV systems can be categorized based on their connection to the electric grid, their use of energy storage, and their integration with other power sources. The main types are:

1.7.1. Grid-Connected (Grid-Tied) PV System

- Connected directly to the utility grid.
- Solar panels generate electricity, which is either used on-site or fed back into the grid.
- Do not require batteries, as the grid acts as a backup when solar production is insufficient.
- Common for Operate independently from the utility grid.
- Rely on batteries to store excess energy for use at night or during cloudy periods.
- Often used in remote locations where grid access is unavailable.
- May be designed residential, commercial, and utility-scale installations.

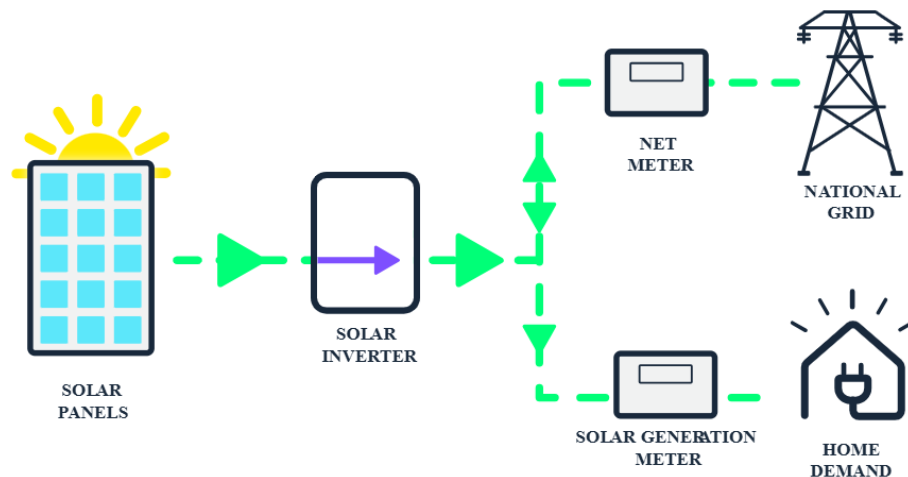


Figure 1-8: On-Grid Solar System.

1.7.2. Stand-Alone (Off-Grid) PV System

- ❖ as DC-only systems (for direct loads) or include inverters for AC loads.

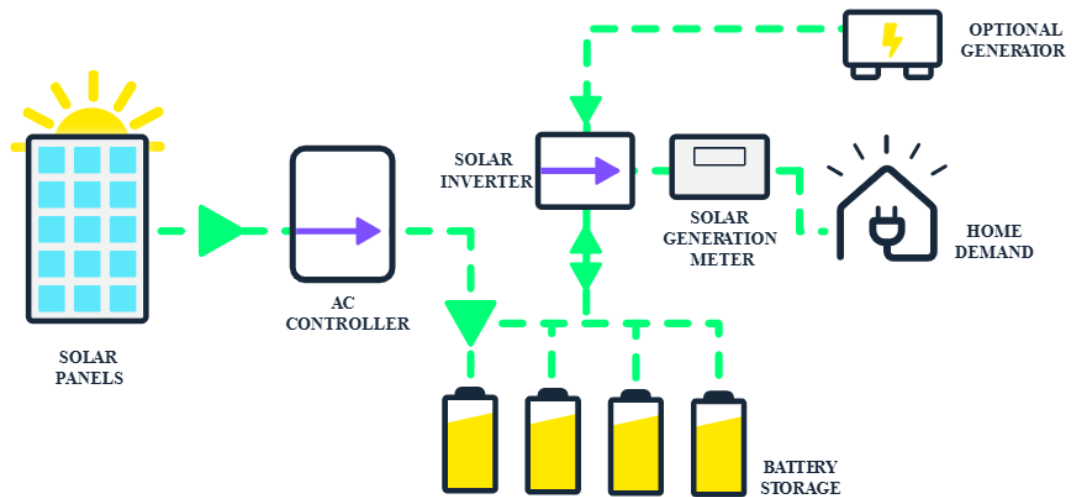


Figure 1-9: Off-Grid Solar System.

1.7.3. Hybrid PV Systems

- Combine solar PV with other energy sources, such as diesel generators, wind turbines, or the grid.
- Include batteries for energy storage, enhancing reliability and flexibility.
- Useful in areas with unreliable grid access or where continuous power supply is critical.

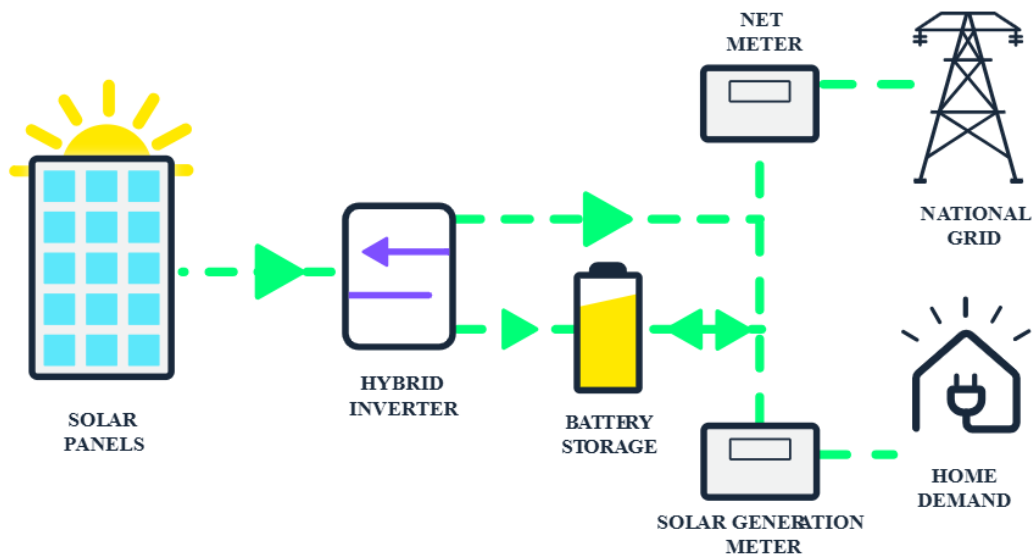


Figure 1-10: Hybrid Solar System

1.7.4. Grid-Connected PV Systems with Storage

- Similar to grid-tied systems but include battery storage.
- Provide backup power during grid outages and allow for energy management (e.g., time-of-use optimization).

- Sometimes referred to as "hybrid" or "backup power" systems.

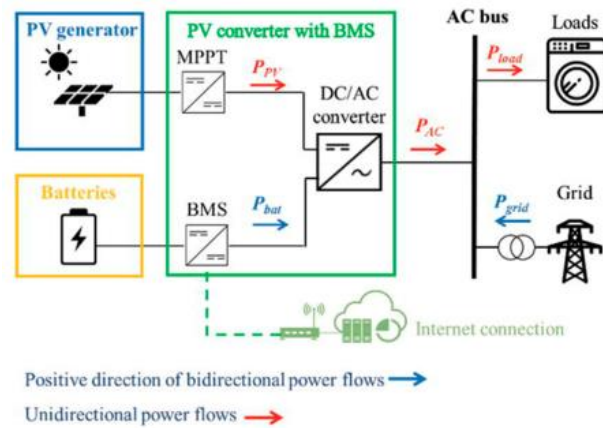


Figure 1-11: Solar PV-Battery Energy Storage System

1.8. PV generator

A PV generator is a key component in a solar power system, consisting of multiple PV modules connected together to convert solar energy into electrical energy. It is typically made up of groups of solar modules connected in series to form "strings," and these strings are then connected in parallel to form the entire generator. The total voltage of a string is the sum of the voltages of each module, while the total current of the generator is the sum of the currents from each string. This configuration allows the PV generator to produce a usable electrical output for various applications.

In summary, a PV generator is an assembly of solar modules configured to convert sunlight into electrical energy, forming the heart of any PV system and enabling the generation of clean, renewable electricity.

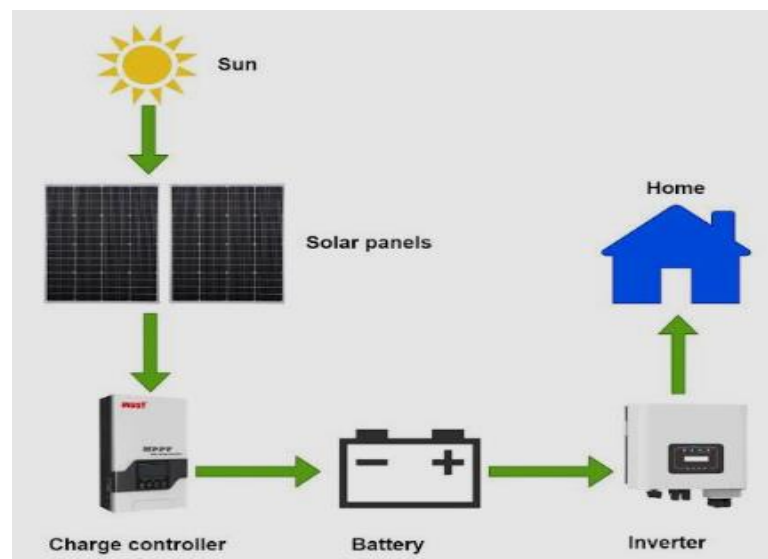


Figure 1-12: Block diagram of a standalone (P V) system

1.9. Solar Panel String

The “solar panel string” is the most basic and important concept in solar panel wiring. This is simply several PV modules wired in series or parallel.

1.9.1. Series Connection

Solar panels feature positive and negative terminals. Wiring solar panels in series means wiring the positive terminal of a module to the negative of the following, and so on for the whole string. This wiring type increases the output voltage, which can be measured at the available terminals.

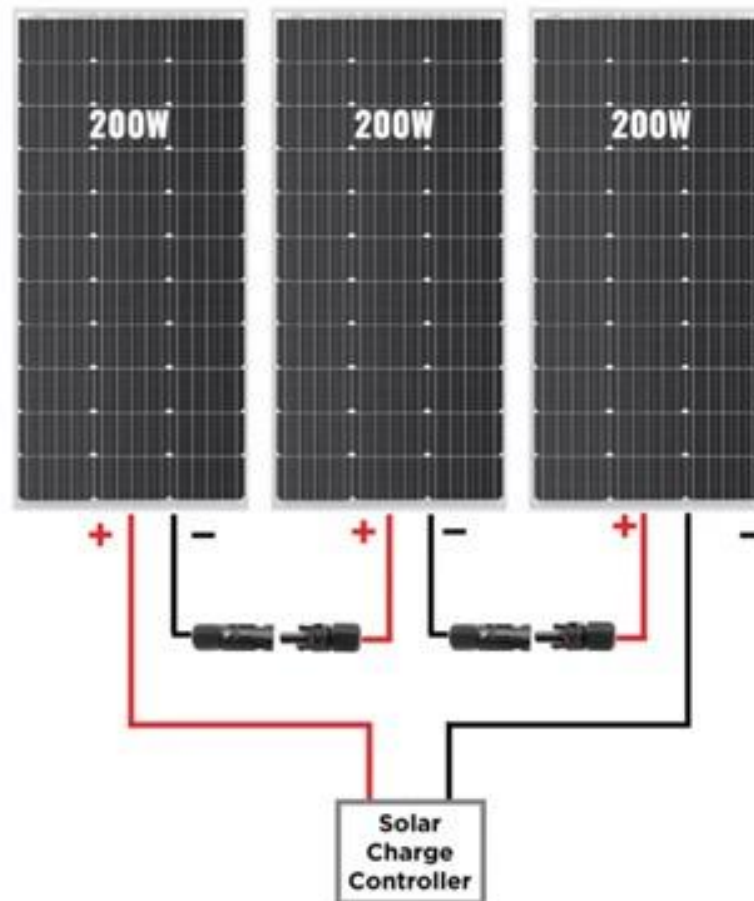


Figure 1-13: Solar panels in series.

1.9.2. Parallel Connection

Wiring solar panels in parallel increases the output current, while keeping the voltage constant. The output current is the sum of all currents generated by the modules in the string.

Solar panels wired in parallel also have to meet NEC regulations. This includes conductor size and overcurrent devices. This is calculated by oversizing the Short Circuit Current (Isc) by 125%, considering the number of modules in the system, as specified in the NEC Article 690.8. [12]

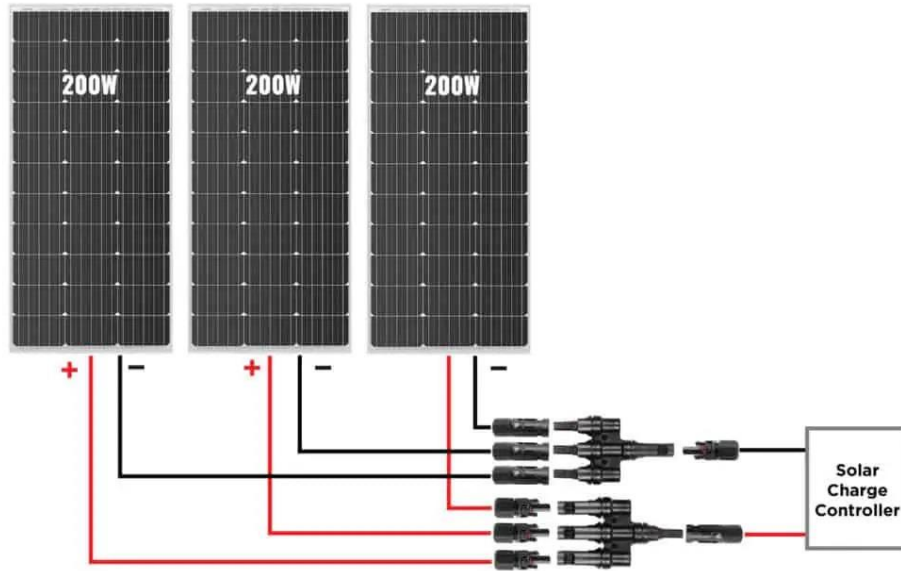


Figure 1-14: Solar panels in parallel.

1.9.3. Series-Parallel Connection

There is a solar panel wiring combining series and parallel connections, known as series-parallel. This connection wires solar panels in series by connecting positive to negative terminals to increase voltage and connects these strings in parallel. All solar panel strings connected in parallel have to feature the same voltage, and they also have to comply with the NEC 690.7, NEC 690.8(A)(1), and NEC 690.8(A)(2). Modules need to be the same model in all cases in order to provide optimum performance on the system.

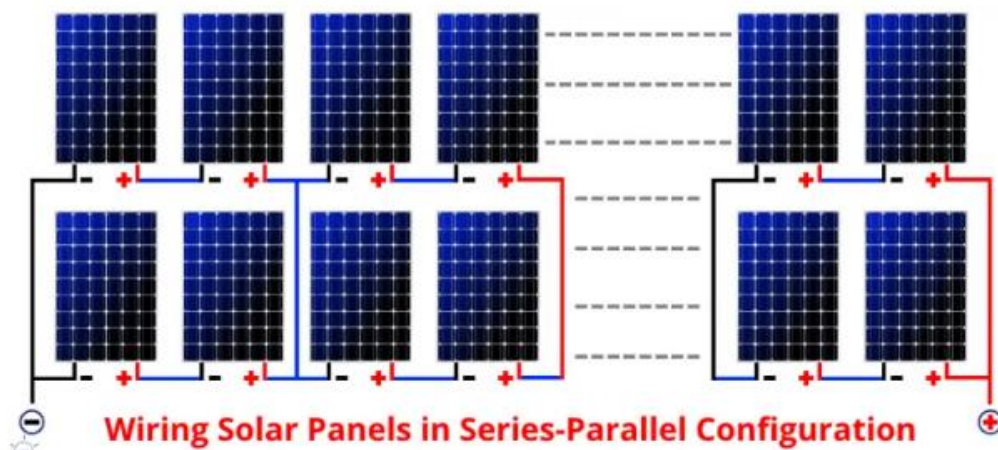


Figure 1-15: Solar panels in series-parallel.

1.10. Advantages and disadvantages of PV systems

1.10.1. Advantages

- **Sustainable energy source:** PV systems use the sun's energy, making them a sustainable energy source that is independent of fossil fuels.
- **Cost-effectiveness:** although the initial cost of a PV system can be high, it can be very cost-effective in the long run because energy production is free and operating costs are minimal.
- **Low maintenance:** PV systems require little maintenance and have a long-life span, making them a very reliable energy source.
- **Flexibility:** PV systems can be installed in many different places, such as on the roofs of buildings, on open spaces or on mobile platforms. This allows for a high degree of flexibility in placement and use.
- **Independence from electricity suppliers:** by installing a PV system, you become more independent of the electricity supply and can ensure your own energy supply.

1.10.2. Désavantages

- **Weather dependency:** the power generated by a PV system is weather dependent and can be greatly reduced by bad weather, such as clouds. This can affect the efficiency of the system.
- **Initial cost:** the initial cost of a PV system can be high, although the cost has decreased in recent years.
- **Space requirements:** a PV system needs sufficient space to be used effectively, which is often a challenge in urban environments.
- **Power storage:** storing excess energy can be a challenge, as it often comes at an additional cost.
- **Dependency on sunlight:** Since power generation from a PV system depends on sunlight intensity, it is not always the best choice for locations with limited sunlight.

1.11. Modeling of a PV Cell

A single solar cell can be represented as a component of an electrical circuit. It contains a p–n junction called as a diode, a photo-current generator represented a generation of current from light and two resistors, one is arranged in series and another one is in parallel which described the Joule effect and recombination losses. Then this combination is called as a single diode solar cell model (KRS 18). The solar PV device can be represented as an ideal solar cell in Figure 1.9.

The current source I_{ph} represents the cell photo-current. R_p and R_s are the intrinsic parallel and series resistances of the cell, respectively. Usually, the value of R_p is very large and that of R_s is very small, hence they may be neglected to simplify the analysis.

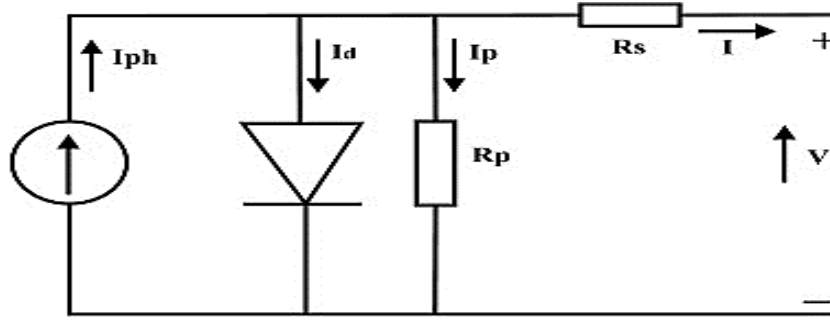


Figure 1-16: Model of a PV cell.

The PV panel can be modelled mathematically as given in equation (1)-(4).

Module photo-current:

$$I_{ph} = [I_{SCr} + K_i(T - 298)] * \lambda/1000 \quad (1)$$

The module reverse saturation current - I_{rs} :

$$I_{rs} = I_{SCr} / [\exp(qV_{OC}/N_s kAT) - 1] \quad (1.2)$$

The module saturation current I_0 varies with the cell temperature, which is given by

$$I_0 = I_{rs} \left[\frac{T}{T_r} \right]^3 \exp \left[\frac{q^* E_{g0}}{Bk} \left\{ \frac{1}{T_r} - \frac{1}{T} \right\} \right] \quad (1.3)$$

The current output of PV module is:

$$I_{PV} = N_P * I_{ph} - N_P * I_0 \left[\exp \left\{ \frac{q^*(V_{PV} + I_{PV} R_s)}{N_s A k T} \right\} - 1 \right] \quad (1.4)$$

Where $V_{PV} = V_{OC}$, $N_p = 1$ and $N_s = 36$

1.12. Characterization of the PV module

In this study, we simulated the KC200GT PV module, which consists of 54 mono crystalline silicon solar cells measuring 125.125mm connected in series.

The module can produce a maximum power of 200 watts at 32 volts. This allowed us to determine the power as a function of voltage and the current as a function of the voltage of the module studied for an irradiance of 1000 W/m².

The electrical characteristics of the KC200GT PV module under standard test conditions are shown in Table 1.1:

Table 1.1: Electrical characteristics of the PV module KC200GT under standard test conditions.

Total number of cells in series (N_s)	54
Rated power (W)	200.143 W
Short-circuit current (I_{sc})	8.21 A
Open circuit voltage (V_{oc})	32.9 V
Current at Maximum power (I_{mp})	7.61 A
Voltage at Maximum power (V_{mp})	26.3 V

1.13. Simulation of the PV array

Based on the mathematical model of the solar cell developed in the MATLAB / Sim-power System tool, the SIMULINK schematic block is shown in Figure 1.17.

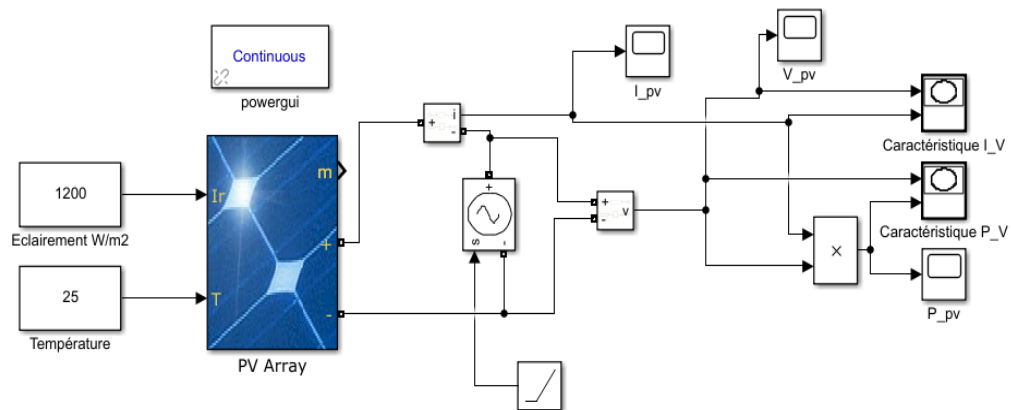


Figure 1-17: Block diagram of the solar module in SIMULINK» KC200GT ».

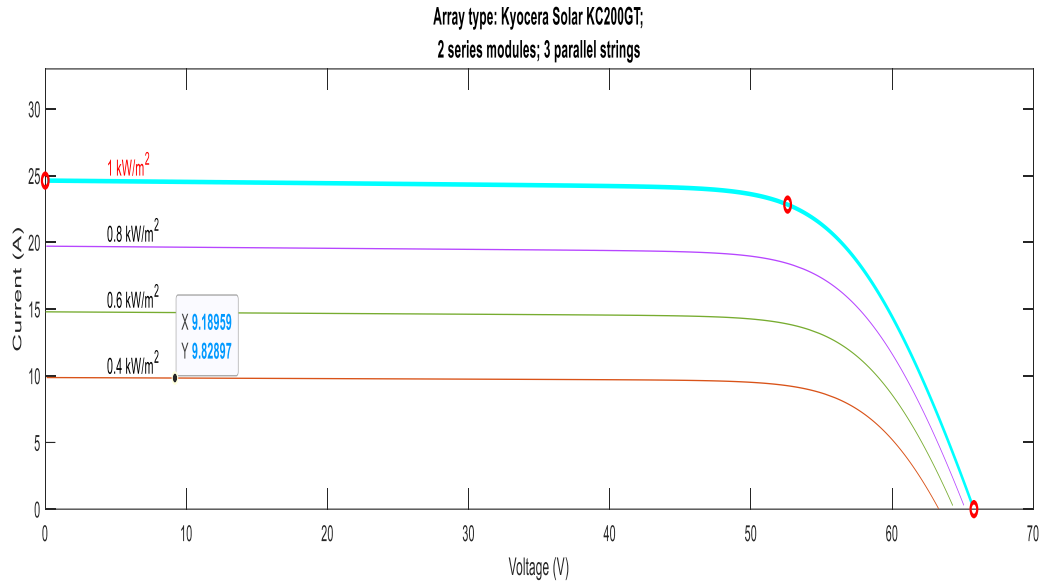


Figure 1-18: Effect of Irradiance on the Current-Voltage Characteristic.

The diagram in (figure 1.18) shows the voltage-current (I-V) curves of a solar panel under different irradiance levels, where the current increases with higher solar irradiance. The voltage remains relatively stable, while the maximum power point shifts with changing irradiance.

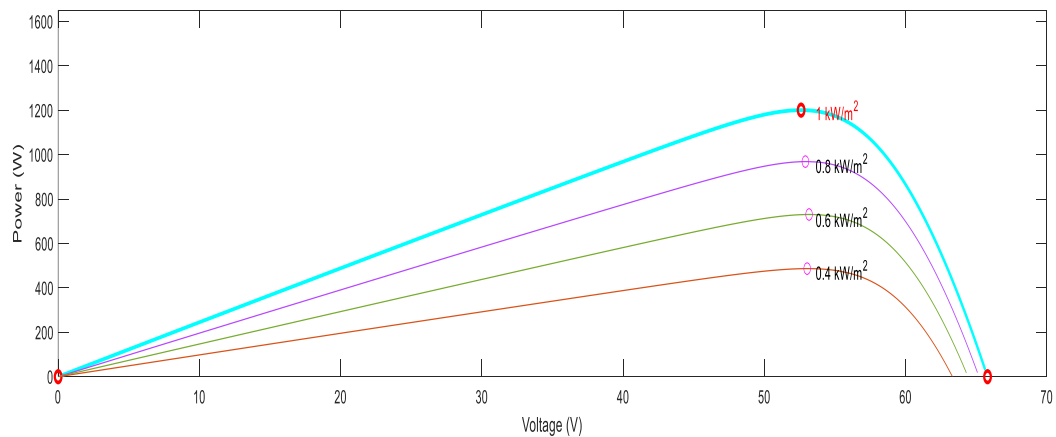


Figure 1-19: Effect of Irradiance on the Power-Voltage Characteristic.

The diagram in (figure 1.19) shows the power-voltage (P-V) curves of a solar panel under different irradiance levels, where the output power increases with higher irradiance and reaches a maximum at the Maximum Power Point (MPP), which shifts depending on the irradiance level

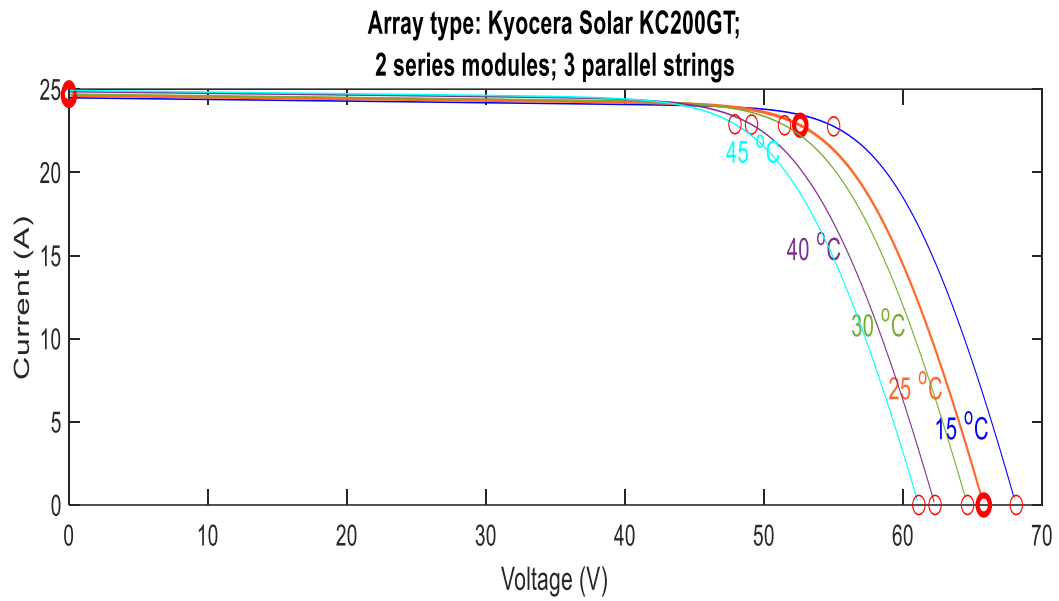


Figure 1-20: Effect of Temperature on the Current-Voltage Characteristic.

The diagram in (figure 1.20) shows the current-voltage (I-V) characteristics of a solar panel at different temperatures (from 15°C to 45°C). The current remains nearly constant, while the voltage decreases significantly with increasing temperature, leading to a reduction in overall power output.

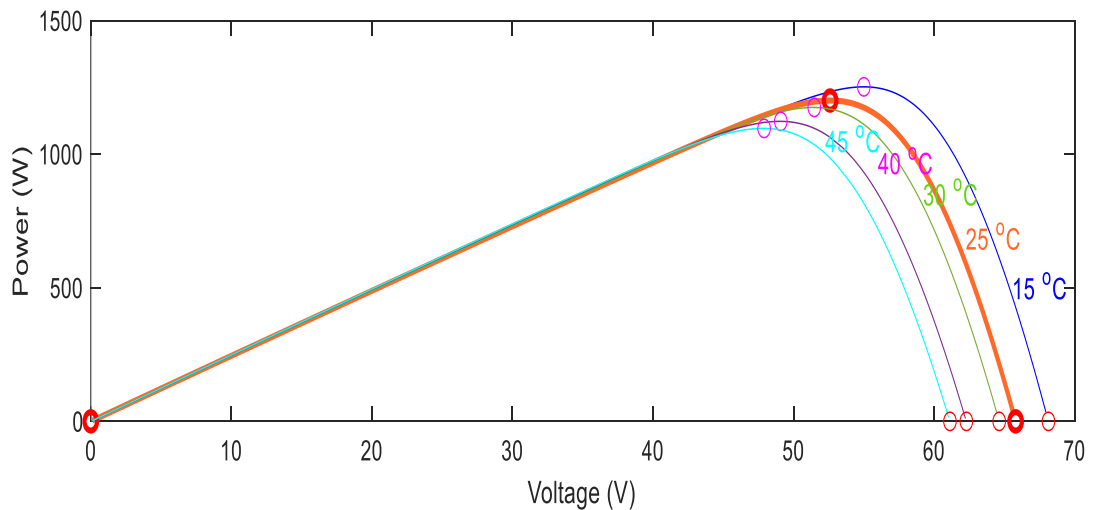


Figure 1-21: Effect of Temperature on the Power-Voltage Characteristic.

The diagram in (figure 1.21) shows the power-voltage (P-V) characteristics of a solar panel at different temperatures (from 15°C to 45°C). The output power decreases with increasing temperature due to the reduction in voltage at the Maximum Power Point (MPP), indicating better performance at lower temperatures.

3. BATTERIES:

A battery is a device that stores energy that can be used by the process of conversion of chemical energy into electric energy. The process of this energy conversion happens through an electrochemical oxidation-reduction reaction. Both oxidation and reduction occur together so this process is often called redox reaction. The key to this reaction is the transfer of electrons from one material to another via an electric circuit. Oxidation occurs at the electrode called the anode, and through this process, a material loses one or more electrons. On the other hand, reduction occurs at the cathode, and in this process, the material gains one or more electrons. These two electrodes are connected through a wire that conducts electrons and measures current or electric potential[8].

Batteries usually produce electricity through the use of their electrochemical cells.

A cell is a single unit in a battery that produces electricity generating power through a chemical, thermal, or optical process. A typical cell is made of two terminals – electrodes, separated by a barrier that allows electric charge to pass from one electrode to another and an electrolyte. The electricity flow happens because of this exchange of electrons that develops a difference in potential or voltage between two electrodes[9].

There are two main types of cells:

a. Primary cells – These cells experience permanent change after the chemical reaction between the electrodes and the electrolyte. That means that these batteries can be used only once and they are not rechargeable. They are also often called "dry cells".

b. Secondary cells – Current is generated in the opposite direction of the primary cells. The chemical action occurs in reverse and is effectively restored. Therefore, it allows a battery to be rechargeable. This type of cell is usually called a "wet cell" because it contains a liquid electrolyte. Example Lithium-Ion Battery Operation

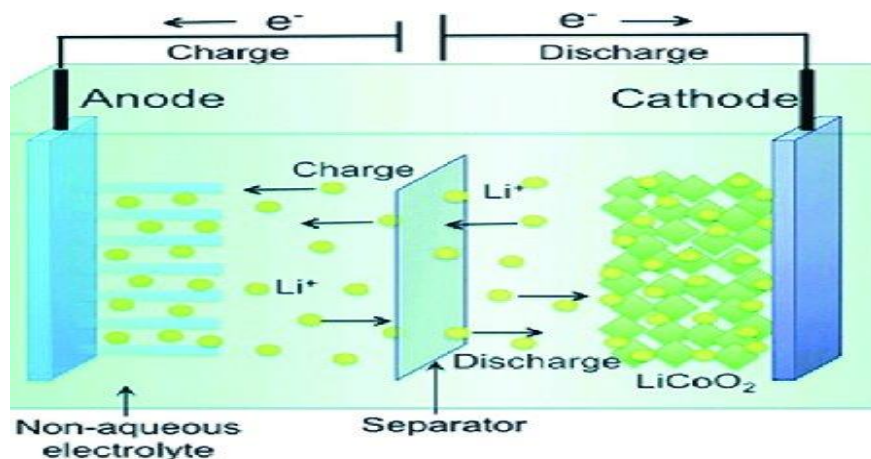


Figure 1-21: Lithium-Ion Battery

3.1 PERFORMANCE CHARACTERISTICS OF BATTERIES

3.3.1 Battery capacity

It represents the amount of time that a battery will last expressed in Ampere hours (Ah). That means that the battery with a capacity of 1 Ah will last for one hour operating at one ampere. It is also possible to rate a battery by its energy capacity expressed in watt-hours or kilowatt-hours (kWh)[17].

3.3.2 Energy density

It represents the amount of energy that can be stored in a battery. Energy density can be measured in two ways: per volume or mass. Volumetric energy density is more common and it shows how much energy a battery contains in comparison to its volume. It is typically expressed in watt-hours per liter (Wh/l).

A battery with higher energy density is an advantage because it means it can store the greater amount of energy. Moreover, it means the battery is lighter than one with similar capacity and lower energy density. This characteristic is very important for many applications, not only in portable systems, but also in PV systems because it lowers the costs of their transport to remote locations[6].

3.3.3 Specific energy

It is also called the gravimetric density and it represents a measure of how much energy a battery contains in comparison to its mass. It can also be said that specific energy illustrates the ability of a battery to hold power.

Specific energy is typically expressed in watt-hours per kilogram (Wh/kg).

3.3.4 Power density

While energy density does not give us information on how quickly energy can be used, we can know this from batteries' power density. It is a measure of power output per unit volume, which means that we can know the rate at which the battery can deliver energy. If a battery has a high-power density, it means it can release its energy quickly and recharge quickly. Power density is expressed in watts per liter (W/l) or kilogram (W/kg)[5].

3.3.5 Voltage

One of the fundamental battery characteristics is battery voltage. It is determined by the chemical reactions inside the battery, the concentrations of the battery components, as well as the polarization. It refers to the difference in electrical potential between the positive and

negative terminals caused by the potential difference. The greater the potential difference, the greater the voltage of a battery.

3.3.6 Discharge curve

A plot of voltage dependent on the percentage of capacity of a battery is called a discharge curve. It shows whether the voltage remains constant as the battery is used up. The most desirable case is a flat discharge curve which means that the voltage remains stable[6].

3.3.7 Temperature dependence

The temperature inside a battery is one of the most important factors that influence the battery's performance and lifecycle. In most cases, an optimal operation temperature for batteries is within a temperature range of 25-45 degrees Celsius. Neither very high nor very low temperatures are good for batteries. When the temperature of the battery increases, that means faster chemical reactions inside the battery. Even if this can contribute to a higher performance of a battery, it will decrease the lifecycle of a battery[10].

On the other hand, if the temperature is too low, it means that the battery will need more time and effort to charge and the capacity will be lower.

3.3.8 Cycle life

Battery starts losing the ability to return to its original state with several uses and recharges. The number of charge and discharge cycles before the battery starts losing performance is what we call the lifecycle of a battery. Typically, cycle life ranges from 500 to 1200.

3.3.9 Cost

When we talk about the cost of a battery, it is important to consider the initial cost of a battery, as well as the costs of operating and maintaining it.

3.4 TYPES OF SOLAR BATTERIES

Solar batteries represent a crucial component of a solar system if we want to get the most of the generated energy. To use resources wisely and contribute to the green energy and sustainability movement, every waste of energy would contradict these ideas[21].

There are many benefits of using solar batteries, such as energy independence, increased self-consumption, backup power, load shifting, grid support, reduction of greenhouse gasses, and many more.

The main types of batteries that are used in PV systems are:

1. Lead-acid.
2. Lithium-ion.
3. Flow batteries.
4. Nickel Cadmium.

Based on their volumetric and specific energy density, batteries are different in size and weight. Energy density comparison of weight and size is shown in figure 1.22.

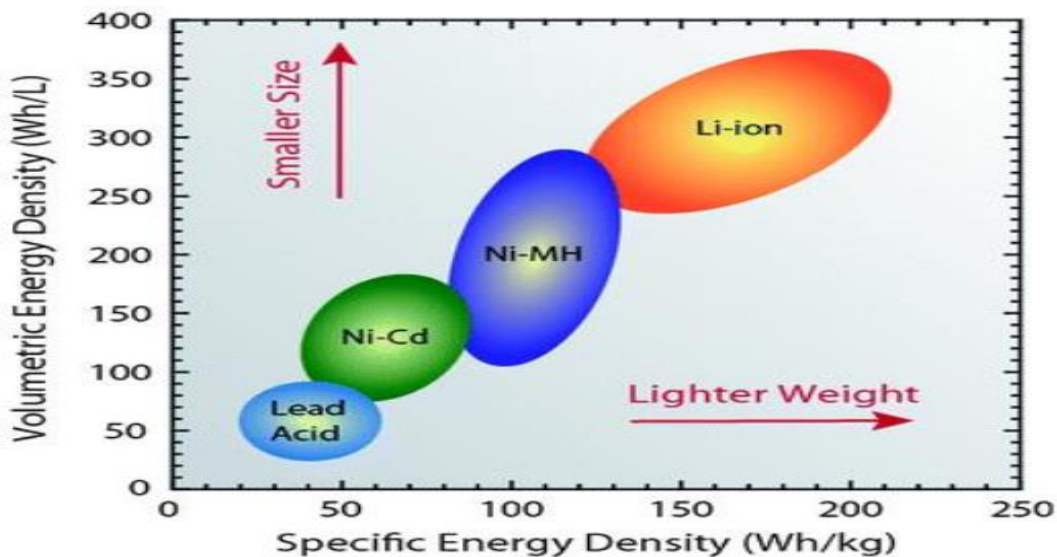


Figure 1-22: Energy density comparison of weight and size

Among these 4 types of solar batteries, lithium-ion batteries are generally considered the most superior lately, and, as such, they have gained the most popularity in the market. This is mainly because of their higher performance and superior characteristics, such as higher energy density, longer cycle life, higher depth of discharge, faster charging, lighter weight, and smaller size of a system in comparison to other battery technologies.

However, the energy storage market is very dynamic, and new technologies are always developing. One of them is a solid-state battery which is considered a very promising technology that even offers advantages over current popular lithium-ion batteries.

Given all the reasons above, Li-ion and solid-state batteries act as promising candidates for energy storage in the future. Even though the commercialization and widespread adoption of solid-state batteries are still in the early stages, and they have not yet become a common choice for PV systems, acknowledging its characteristics and advantages in comparison to Li-ion could accelerate deeper research and future development, with possible future application in PV systems.

To be able to perform a comparative analysis of these two types of batteries, it is crucial to get familiar with their structure, working principles, and main characteristics.

3.5 LI-ION BATTERIES

3.5.1 Structure

Li-ion batteries are built of four main components:

1. **Cathode** – The positive electrode where reduction reactions occur during the discharge or utilization of the battery's stored energy. This part of the Li-ion battery determines the capacity and voltage. Also, it is the electrode in which lithium oxide is inserted and used as an active material.

2. **Anode** – The negative electrode where oxidation reactions occur during the discharge or utilization of the battery's stored energy. The choice of material is crucial because it impacts batteries' performance characteristics, such as energy density, capacity, cycle life, etc. It is usually made of carbon-based material, such as graphite due to its ability to store and release lithium ions. Also, graphite is known for its structural stability and low electrochemical reactivity. Therefore, it is considered suitable for the anode.

3. **Electrolyte** – It represents a medium that is the key component in enabling the electrochemical reactions in a battery. The main function of electrolytes is to enable the movement of only lithium ions between the cathode and anode. Therefore, electrolytes need to have high ionic conductivity, low viscosity, and excellent stability in a wide range of temperatures. They are usually a liquid composed of lithium salts dissolved in organic solvents.

4. **Separator** – A physical barrier that keeps the cathode and anode apart to prevent short circuits. It also prevents the direct flow of electrons and lets only the ions pass through the internal microscopic hole. The separator plays a crucial role in maintaining the battery's safety. It is typically made from a polymer material that performs good chemical and thermal stability, as well as excellent mechanical strength and low electrical conductivity.

Structure of a Lithium-ion battery is shown in figure 1.23.

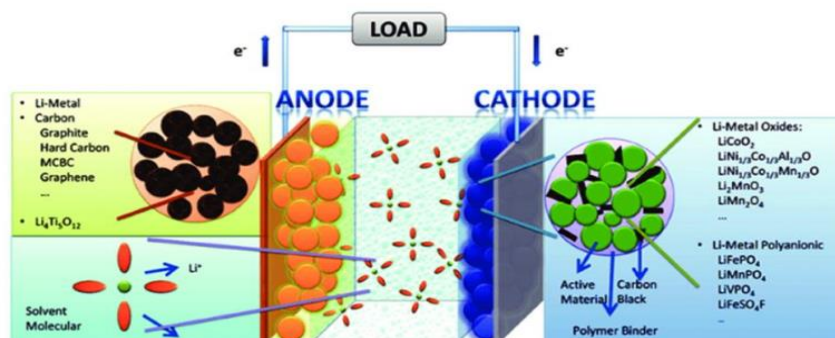


Figure 1-23: Structure of a Li-ion battery

3.5.2 Working principle

Two essential processes for a battery are charge (storing energy) and discharge (using stored energy).

❖ Charging process

At the beginning of a charging process, the lithium ions are mostly located in the cathode. When a charger is connected to the battery, electrons from the charger flow into the battery through the anode. As electrons enter the anode, lithium ions are extracted from the cathode, and these ions start moving through the electrolyte toward the anode. The electrolyte allows the lithium ions to flow but prevents the flow of electrons. When they reach the anode, lithium ions are intercalated into the anode while the negatively charged electrons which were released at the beginning of the process flow through the external circuit towards the cathode. In this way, electron flow completes the circuit. Meanwhile, lithium ions from the electrolyte combine with the electrons at the cathode, which causes a reduction reaction allowing the cathode to store the lithium ions. Once a battery reaches the desired state of charge, the process ends and at this point, the battery is considered fully charged with a higher concentration of lithium ions stored in the anode and cathode.

Charging process is shown in figure 1.24.

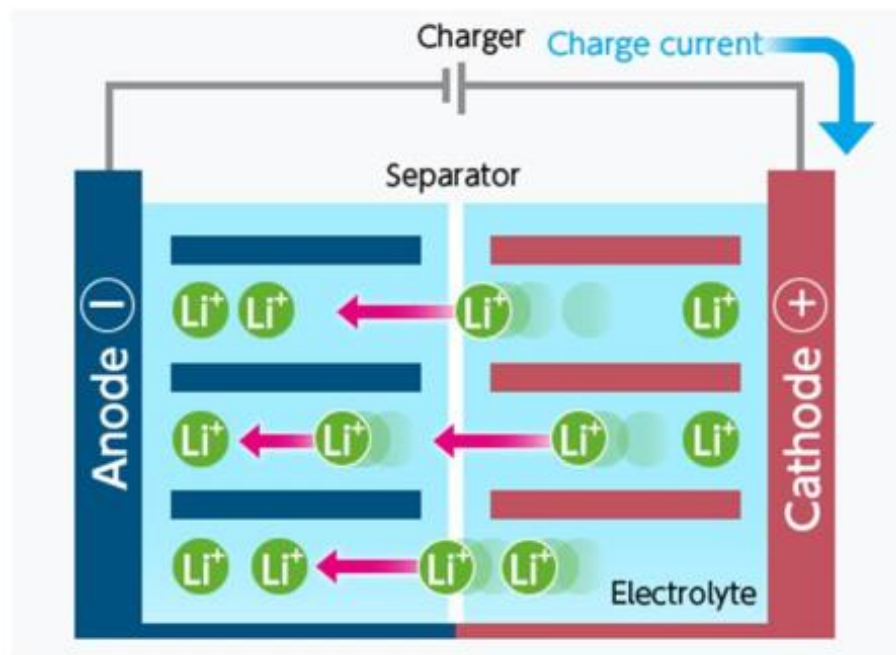


Figure 1-24: Charging process of a Li-ion battery

❖ Discharging process

Exactly the opposite of a charging process, the discharging process (figure.1.25) involves the release of stored energy. At the beginning of the discharging process, when the circuit is completed with a device connected to the battery, the electrons flow from the anode to the cathode through the external circuit. This electron flow powers the connected device. At the same time, lithium ions are released from the anode. They move through the electrolyte towards the cathode. As these ions reach the cathode, they combine with the electrons that arrive from the external circuit. This causes the reduction reaction at the cathode and it allows the cathode to release stored energy and transfer the lithium ions back to the electrolyte. The point of a discharge process is the conversion of chemical energy stored in the battery to electrical energy which powers the connected device. The discharge process ends when stored energy is depleted and the voltage drops below a certain level.

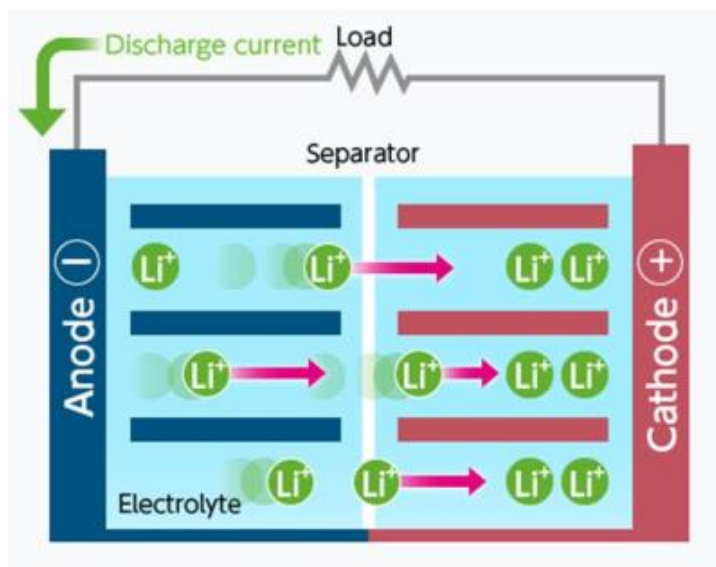


Figure 1-25: Discharging process of a Li-ion battery

3.1. Lead–Acid Battery

The lead–acid battery, created in 1859, is the first kind of rechargeable battery ever developed. Lead–acid batteries have a suboptimal energy density when compared to contemporary rechargeable batteries.

Lead–acid cells are composed of lead alloy grids (solid electrodes) that operate as current collectors and mechanically support the positive and negative active elements.

The grids are interlaced with a permeable, electrically isolator and arrayed as positive and negative plates. The plate stack is embedded into an adequately contoured polymer housing to embody the cell elements and the electrolyte with the coupled positive and negative plates,

terminals, a lid and venting arrangements. The construction of a lead–acid battery is shown in Figure.1.25.

The operating voltage of the lead–acid cell is reasonably high at approximately 2.05 V.

The positive active material (PAM) is considerably permeable lead dioxide (PbO₂) and the negative active material (NAM) is delicately isolated lead. The electrolyte utilized in the discharge process is thinned liquefied sulfuric acid (H₂SO₄). H₂SO₄ ions move to the negative electrode during discharge, producing H⁺ ions and lead sulfate (PbSO₄). Lead dioxide reacts with the electrolyte at the positive electrode to yield lead sulfate particles and water (H₂O), as shown in Figure.1.26. Both electrodes are discharged to a feeble conductor, lead sulfate (PbSO₄), and the electrolyte is incrementally diluted as the discharge progresses.

On charging, the reactions are reversible

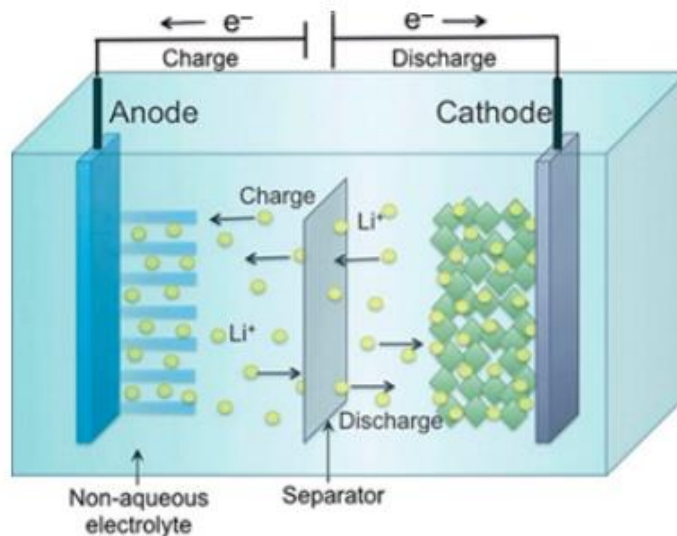


Figure 1-26: Lead–acid battery constru

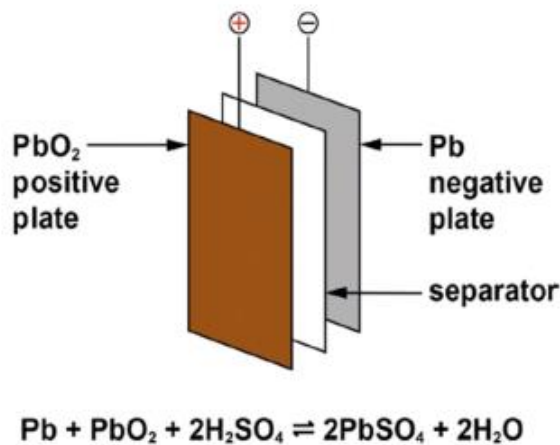


Figure 1-27: Chemistry of lead–acid battery. Chemistry of lead–acid

The most recent innovations have used enhanced lead batteries in a variety of grid-related plans as well as smaller-scale industrial and domestic energy storage applications. In recent years, systems with integrated super-capacitors have been described in addition to conventional lead–acid batteries; they are commonly referred to as carbon enhanced (LC) lead batteries. These could have a negative electrode made of a mix of lead–acid and supercapacitor negatives made of carbon. The positive electrode is exactly like the one in a typical lead–acid battery in every way. The current tendency in operating renewable energy sources, especially solar PV sources, is for periodic discharges rather than a continuous restoration of the battery to a full state of charge (SOC). This partial state-of-charge (PSoC) behavior can be detrimental to lead–acid batteries since it induces permanent corrosion of the negative electrode, and sustainable development strategies are still being investigated

❖ Flow Batteries

Utility-scale energy storage has some promise thanks to flow batteries. There are many different compositions, but they all have energy-producing cells with electrode material stored remotely, making it possible for very large storage batteries to be made. Vanadium redox batteries (VRB) are made up of cells with carbon composite electrodes submerged in a fluid containing aqueous acid and vanadium sulfate, with different valence states separated by an ion-selective membrane. At the positive electrode during discharge, V^{5+} is converted to V^{4+} , while V^{2+} is converted to V^{3+} at the negative electrode. The volume of the vanadium sulfate solution, and hence the battery's capacity, is potentially limitless because it is kept in a storage tank. Recharging causes reverse reactions, which replenish the materials. The batteries are complicated to use and made of heavy materials, but their expected lifespan is very lengthy. Only a few prototype systems have been implemented so far, and given the size of the battery, VRB batteries are only practical for utility energy storage. Figure 10 depicts the chemistry and main parts of a vanadium redox flow battery.

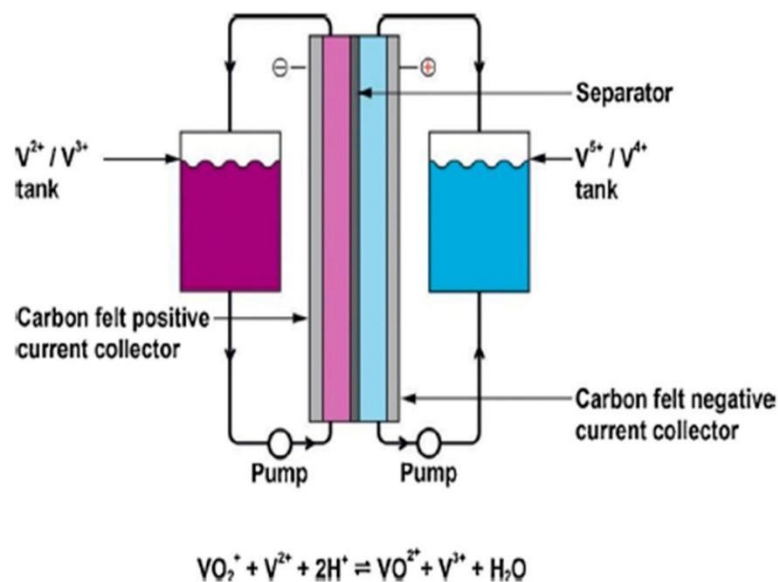


Figure 1-28: Chemistry and principal components of a vanadium redox flow battery.

Another kind of flow battery is the zinc–bromine (Zn–Br₂) battery, as shown in Figure 1.28. Zinc bromide is synthesized when Zn reacts with Br₂ within the cell. Br₂ is injected into cells with carbon electrodes and a microporous plastic separator in an aqueous solution as an organic complexing agent

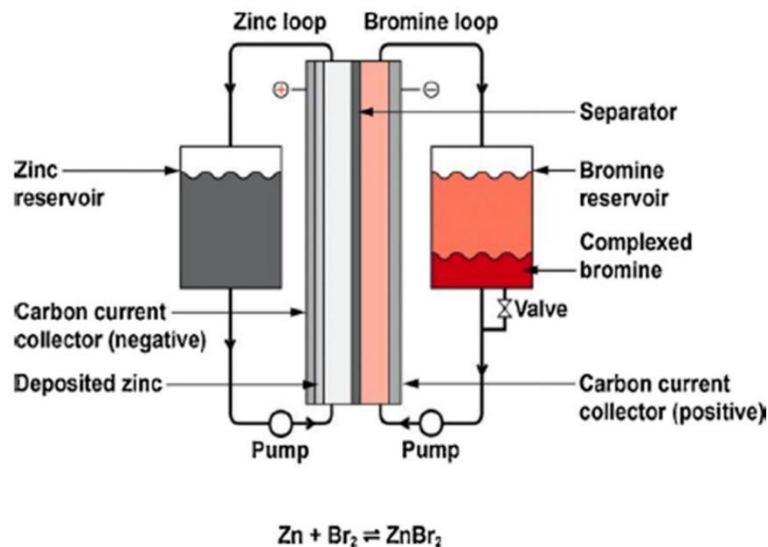


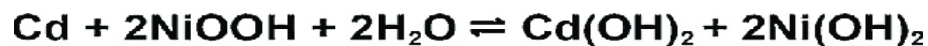
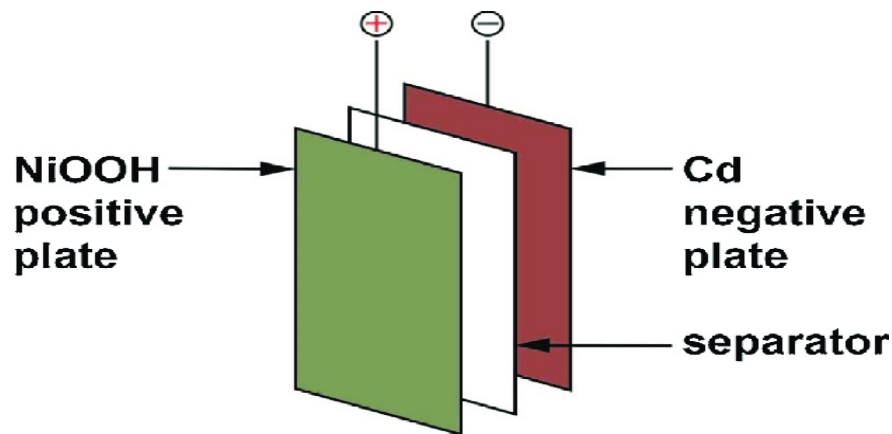
Figure 1-29: Chemistry and principal components of a zinc–bromine battery.

Metallic Zn is formed on charging, and while Br₂ is housed in tanks, the Zn electrode enforces a limit on the capacity for any specific design. The price is cheaper than VRB batteries, but the average lifetime is less. The discharge of bromine is a perceived threat that must be avoided. Zn–Br₂ batteries, like other flow batteries, have only been employed in moderate

numbers for utility usage. There are a few similar types of flow batteries, such as iron–chromium batteries; however, they are not broadly utilized.

❖ Nickel-Cadmium Batteries

Nickel-Cadmium batteries are an older technology but are still used in some applications. These batteries have a longer lifespan than lead-acid batteries and can withstand extreme temperatures, making them ideal for harsh environments . However, they are less efficient and have lower energy density than newer battery technologies such as lithiumion or flow batteries. Regular maintenance is required to prevent memory effects and extend their lifespan



4. Battery System Design and Selection Criteria

Battery system design and selection criteria involves many decisions and trade-offs. Choosing the right battery for a PV application depends on many factors. While no specific battery is appropriate for all PV applications, common sense and a careful review of the battery literature with respect to the particular application needs will help the designer take the decision.

Some decisions on battery selection may be easy to arrive at, such as physical properties, while other decisions will be much more difficult and may involve making tradeoffs between desirable and undesirable battery features. With the proper application of this knowledge, designers should be able to differentiate among battery types and gain some application experience with batteries they are familiar with.

5. Life Expectancy of Solar Rechargeable Batteries

Batteries used in solar power systems can last from one to twenty years, depending on type and how they are used. Factors such as improper charging and temperature all take their toll on solar batteries.

5.1. Type

Solar batteries are typically deep-cycle, which allows them to discharge up to 80% before recharging. Used properly, they can last several years. Each battery is rated for a certain number of full cycles, i.e. it can be discharged then recharged a certain number of times.

5.2. Typical Lifespan

According to Northern Arizona Wind & Sun, an AGM deep-cycle battery lasts four to seven years and a gelled deep cycle battery lasts two to five years. A regular deep cycle battery lasts four to eight years.

5.3. Industrial Batteries

Less common options are industrial batteries. Premium deep cycle batteries may last 7 to 15 years, industrial type batteries may last 10 to 20 years and surplus telephone (float) batteries can last 2 to 20 years.

5.4. Abuse

The lifespan of batteries can be greatly reduced by abuse. Lifespan is reduced by storing batteries in temperatures over 77 C, because they discharge more quickly. Overcharging is also an easy way to kill batteries.

5.5. Efficiency

Battery life can be extended by fully discharging them before recharging, i.e using them as designed. Keeping the batteries at a steady temperature, neither overcharging nor excessively draining them, all help.

6. Battery standards

Standards are produced to facilitate replacement of battery cells (standardised dimensions and designs) and the understanding of performance data (standardised testing methods), etc. The standardisation bodies represent groups of companies and organisations with a common interest in the production or availability of comparable products from multiple suppliers or comparable measures of different parameters.

6.1 IEC standards

The International Electrotechnical Committee (IEC) develops and publishes standards for batteries. Several standards are covering the lead-acid battery and its different versions and applications. The most relevant standards are:

- IEC 95 Lead-acid starter batteries
- IEC 254 Lead-acid traction batteries
- IEC 896 Stationary lead-acid batteries
- IEC 1429 Marking of secondary cells and batteries with the international recycling symbol
- IEC 1431 Guide for the use of monitor systems for lead-acid traction batteries.

6.2 Other standards

Other bodies are also developing standards for specific purposes or for geographical regions. It is important to investigate if some standards are valid for your application and put specific demands on the installation at its specific location.

Standards are for example produced by:

- CENELEC produces standards for Europe
- SAE produces standards for the (American) car industry
- DIN produces German national standards
- JISC produces Japanese national standards

7.Safety precautions

The lead-acid battery is an energy pack. It is quite sensitive to abuse. When treated in a wrong way, it is easy to pass over the limits to unstable conditions. Never stress the battery mechanically, electrically or thermally beyond the limits.

7.1 Always use insulated tools

The tools used for connecting batteries have to be insulated to avoid the potential shorting of batteries. Plastic tubes or plastic tape can easily be used for home manufacturing of insulated tools.

7.2 Protect eyes and skin

- Safety goggles must always be worn when working with batteries.
- Rubber gloves should preferably be used to avoid skin contact with the electrolyte.
- Special clothing is recommended to avoid droplets of acid destroying the normal dress. Such droplets are not always recognised until the clothes are washed and the acid has already made holes in the dress.

-
- Large amounts of water should be used for rinsing if acid has come into contact with the skin, clothes or the construction of the installation.
 - It is very important to have a water bottle available within easy reach in the working area.

7.3 Protection against explosion

Explosions may result from different abuse situations. An explosion forces the cell case to burst and parts will fly around together with a spray of acid. A fire may also start as a result of the explosion.

The battery should be protected against short circuit by an electrical fuse sized correctly to protect the battery from currents above the maximum load and charge values. The fuse is preferably placed in the middle of the voltage string in the battery pack. The location of the fuse in the middle of the voltage string will be safer if a shortcut only involves some part of the battery. In a small 12V monoblock battery system the fuse should be placed as close as possible to the positive terminal.

When assembling the parts of the installation, never connect the battery terminals until all cabling is finished and checked for faults.

Mechanical abuse may well result in an explosion. Protect the battery from pieces that could fall down on the battery or be injected from the side. Mechanical damage to the battery may result in an explosion, which starts as an internal short circuit when the plates or connectors of different polarity are contacting each other as a result of the damage.

A gas explosion is commonly created by an external spark. When batteries are fully charged and in the gassing mode, the internals of the cells are filled with an explosive gas mixture and gas is issuing through the vents. This gas is highly explosive and a cigarette, a match or even by an electrical spark, can easily ignite it. Such a spark may result from a static discharge when two materials are statically charged or from an electrical circuit.

A gas explosion in one cell will immediately propagate from one cell to all other cells damaging the whole battery.

7.4 How to carry a battery

Now and then it is necessary to move a battery from one place to another. Since a battery is a heavy piece of equipment it is recommended to use a special strap which is placed around the terminals. Never try to carry a battery without it.

First of all, this could do severe harm to your back and secondly there is a definitive risk of you dropping the battery on the floor. The result is possible harm to your feet not only from the impact when the battery reaches the floor but also from sulphuric acid if the case breaks.

7.5 Disposal of the battery at end of life

Batteries are considered hazardous items as they contain toxic materials such as lead, acids and plastics which can harm humans and the environment..

For this reason, it is important to reuse the materials for the manufacturing of new batteries.

Such processes for recovery of the metal content of lead-acid batteries are established. If batteries are thrown away, they may leak poisonous metals and acid into the soil

Under no circumstances should a batteries be disposed of in landfills, or the electrolyte allowed to seep into the ground, or the battery burned.

Be careful to collect old batteries for metal recovery or renovation (mainly in developing countries).They may represent a significant value in some countries.

Conclusion

This research provides a comprehensive scientific examination of photo-voltaic (PV) systems, highlighting their critical role in advancing the transition to sustainable energy and reducing reliance on traditional fossil fuel-based power sources. PV technology has become a cornerstone of contemporary energy systems, driven by continuous innovations in materials, power electronics, and energy storage solutions.

The study delves into the historical evolution of PV systems, showcasing notable achievements in conversion efficiency, system reliability, and large-scale implementation. It also offers an in-depth analysis of solar radiation components—direct, diffuse, and global—and their quantitative impacts on the electrical performance of PV modules.

A comparative evaluation of solar cell technologies, including monocrystalline, polycrystalline, thin-film, and hybrid cells, is presented to outline the trade-offs between efficiency, production complexity, cost-effectiveness, and durability. This analysis provides a foundation for making informed decisions regarding the optimal design and selection of PV systems for varying operational contexts.

Furthermore, the research explores the electrical modeling and simulation of PV modules using the single-diode equivalent circuit model. This approach accurately captures the nonlinear current-voltage characteristics of solar cells. Simulations illustrate that increased solar irradiance leads to a proportional rise in output current, while higher operating temperatures result in reduced open-circuit voltage and overall power output, subsequently affecting system efficiency.

The role of energy storage systems is emphasized as vital for boosting the stability, adaptability, and autonomy of PV installations. A detailed evaluation of various battery technologies highlights lithium-ion batteries as the forefront solution, given their high energy density, exceptional efficiency, and long cycle life. Solid-state batteries are also identified as a promising next-generation option with potential to address current challenges such as safety concerns, energy density limitations, and durability constraints.

Lastly, this research underscores the importance of adhering to international standards and safety regulations governing PV and battery systems. Compliance with these standards is essential for ensuring operational safety, reliability, and long-term performance while supporting the seamless integration of PV systems into modern electricity grids.

2.

Chapter II: Modeling of Electric Batteries

2.1. Introduction.

Developing a battery system using model-based design requires a battery cell model that accurately represents its real-world behavior and its dependencies on environmental and operating conditions.

Most existing models for battery simulation can be divided into three subgroups:

- Empirical Model
- Electrochemical Model
- Electrical Model

However, specially developed electrical circuit models can be used for accurate prediction of battery charge and discharge. The state of charge must be taken into consideration.

There are different battery models to represent the electrochemical and electrical behaviour of a battery. Here are some of the most commonly used models.

2.2. Battery Modeling Approaches

2.2.1. The electrochemical model

This model takes into account the electrochemical processes of the battery, such as ion diffusion and electrochemical reactions, using mathematical equations to describe the battery's behavior. This model is more accurate than the equivalent electrical model, but it is more complex and requires more input data to be used.

2.2.2. The Thermal Model

This model takes into account the effect of temperature on battery performance, using thermal equations to describe the variation of capacity and internal resistance as a function of temperature. This model is useful for thermal management of the battery, but does not take into account electrochemical processes.

2.2.3. The neural network model

This model uses artificial neural networks to predict battery behavior based on the history of battery charges and discharges. This model can be used to predict the state of charge of the battery with high accuracy, but it requires a lot of input data and computation time.

2.3. The Equivalent Electrical Model

This model uses an equivalent electrical circuit to represent the electrical characteristics of the battery, such as voltage, internal resistance, and capacity. This model is easy to use and can be applied to different types of batteries, but it does not take into account the electrochemical processes of the battery.

2.3.1. Ideal Model

An ideal electrical model of the battery is a simplified model that assumes the battery is a constant voltage source that can supply unlimited electrical power without discharging.

A more realistic electrical model of the battery takes into account the internal impedance of the battery, which represents the internal resistance of the battery and the voltage losses that occur during battery discharge. It also takes into account the battery capacity, which represents the amount of energy stored in the battery and how it discharges.

$$V_t = V_B - IR_i \quad (2.1)$$

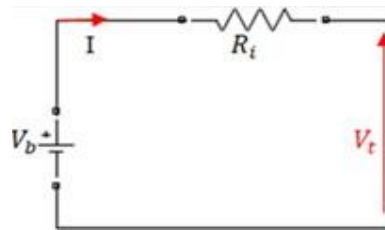


Figure 2-1: Ideal battery model

2.3.2. Simple Model

A simple electrical model. This model assumes that the battery V_0 is a constant voltage source that does not vary with battery charge or discharge. This model is highly simplified and does not account for the effects of the battery's internal impedance or battery capacity. V_t

$$V_t(t) = V_0 - R_i I_b(t) \quad (2.2)$$

is the terminal voltage at the battery terminals.

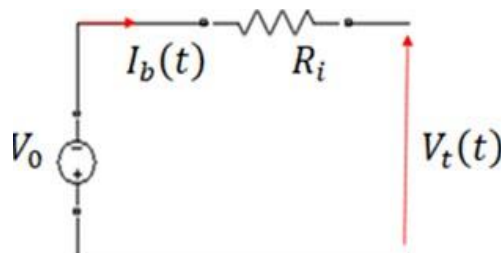


Figure 2-2: Simple Model.

2.3.3. Modified Electrical Battery Models

Equivalent electrical circuit model: This electrical model consists of representing the battery using an equivalent electrical circuit, which includes resistors, capacitors, and voltage sources. This model is simple to use and can be adapted to different types of batteries, but it does not account for the electrochemical processes inside the battery.

2.3.3.1. The Thevenin Model

The Thevenin model is a commonly used simplified equivalent electrical model to represent a battery. This model is based on the principle of electrical circuit theory that a complex electrical circuit can be replaced by a simpler equivalent circuit (Figure 2.3). It consists of an ideal voltage source V_0 , an internal resistance R_0 , a capacitor representing the polarization of the metal plates of the accumulator, and an overvoltage resistance R_0 due to the contact of the plates with the electrolyte.

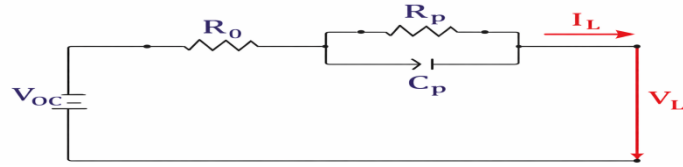


Figure 2-3: Thevenin Model

$$\begin{cases} \dot{V}_P = \frac{V_p}{R_P I_p} + \frac{I_L}{I_L R_0} \\ V_L = V_{OC} - V_P - I_L R_0 \end{cases} \quad (2.3)$$

In this model, all elements of the equivalent circuit are assumed to be constant and different during charging and discharging. In reality, however, these parameters also vary as a function of the state of charge and the discharge rate.

2.3.3.2. Resistive Thevenin Equivalent Model

The resistive Thevenin equivalent model represents the battery as an ideal voltage source in series with an internal resistance. The voltage source represents the nominal battery voltage, while the internal resistance represents the resistance the battery opposes to the current flow.

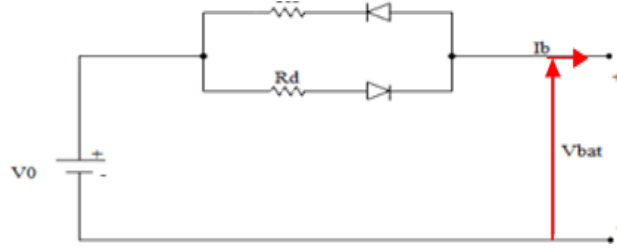


Figure 2-4: Resistive Thevenin Equivalent Model.

The previous model can be improved by using two internal resistances R_c and R_d representing the charge and discharge of the battery respectively.

This model is better than the previous one, but it does not represent the capacitive effect that characterizes the transient conditions occurring in the battery.

It cannot be used for the design of high-performance batteries or for battery management in critical applications.

For this reason, a capacitance C_p is added to the circuit (Figure 2.5) in order to introduce the internal dynamics.

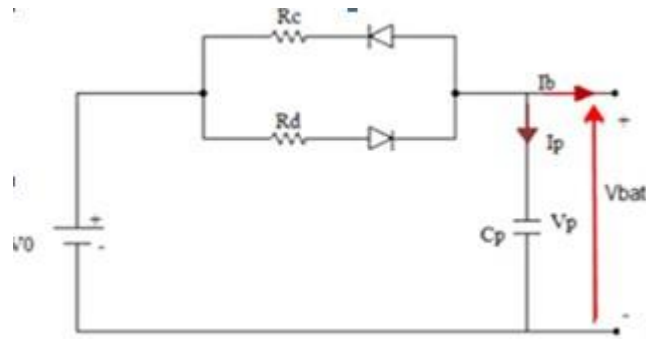


Figure 2-5: Resistive and Capacitive Thevenin Equivalent Model .

$$\boxed{V_0 = V_p + R_c I_c} \quad (2.5)$$

$$\boxed{V_p = \frac{1}{C_p} \int I_p dt} \quad (2.6)$$

$$\boxed{I_p = C_p \dot{V}_p} \quad (2.7)$$

During charging:

$$V_0 = V_p + R_c(I_p + I_b) \quad (2.8)$$

$$V_0 = V_p + R_c(C_p \dot{V}_p + I_b) \quad (2.9)$$

During discharging:

$$\boxed{V_0 = V_p + R_d(I_p + I_b)} \quad (2.10)$$

$$\boxed{V_0 = V_p + R_d(C_p \dot{V}_p + I_b)} \quad (2.11)$$

Then we:

$$\begin{cases} \dot{V}_p = -V_p \frac{1}{R_d C_p} + V_0 \frac{1}{R_d C_p} - I_b \frac{1}{C_p} & \text{Si } V_p < V_0 \\ \dot{V}_p = -V_p \frac{1}{R_c C_p} + V_0 \frac{1}{R_c C_p} - I_b \frac{1}{C_p} & \text{Si } V_p \geq V_0 \\ V_{bat} = V_p & \boxed{\quad} \end{cases} \quad (2.12)$$

2.3.3.3 Modified Thevenin Model

The modified Thevenin model represents the battery as an ideal voltage source in series with a variable internal resistance. The voltage source represents the nominal battery voltage, while the modified internal resistance accounts for the variation of the battery's internal resistance as a function of the state of charge and temperature. Figure (2.6) presents the modified Thevenin model with the following characteristics [22]:

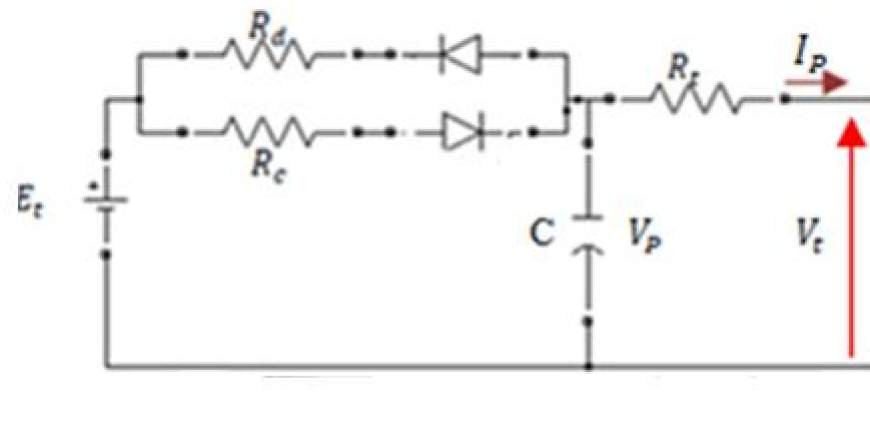


Figure 2-6: Modified Thevenin Model [22].

In this case, during charging:

$$E_t = V_p + R_c I_c \quad (2.13)$$

$$V_p = \frac{1}{C_p} \int I_p dt \quad (2.14)$$

$$\begin{cases} E_t = V_p + R_c I_c \end{cases} \quad (2.15)$$

$$\begin{cases} \dot{V}_{C_0} = \frac{I_2(t)}{C_0} \end{cases} \quad (2.16)$$

$$\begin{cases} V_{bat} = V_0 - R I_b - V_{C_0} \end{cases} \quad (2.17)$$

$$I_c = I_p + I_b \quad (2.18)$$

From Kirchhoff's law:

$$I_c = \frac{E_t - V_p}{R} \quad (2.19)$$

Like:

$$I_p = C_p \dot{V}_p$$

and the equation (2.16) à (2.14) give:

$$E_t = V_p + R_c (C_p \dot{V}_p + I_b) \quad (2.20)$$

$$\begin{cases} \dot{V}_p = -V_p \frac{1}{R_d C_p} + E_t \frac{1}{R_d C_p} - I_b \frac{1}{C_p} & \text{Si } V_p < E_t \\ \dot{V}_p = -V_p \frac{1}{R_c C_p} + E_t \frac{1}{R_c C_p} - I_b \frac{1}{C_p} & \text{Si } V_p \geq E_t \\ V_{bat} = V_p - R \cdot I_b & \end{cases} \quad (2.21)$$

During discharge, the same principle applies by replacing R_c with R_d and I_c with I_d . The dynamic equations of this model are:

2.3.3.4. Dynamic Linear Equivalent Thevenin Circuit

The Thevenin model can be used to provide the best representation of the voltage-time response of a battery cell. This equivalent circuit makes it possible to predict the behavior of the battery in a more complex circuit, taking into account the battery voltage and its internal resistance. The temporal voltage response of battery cells consists of transients of different durations. Figure (2.6) represents this structure.

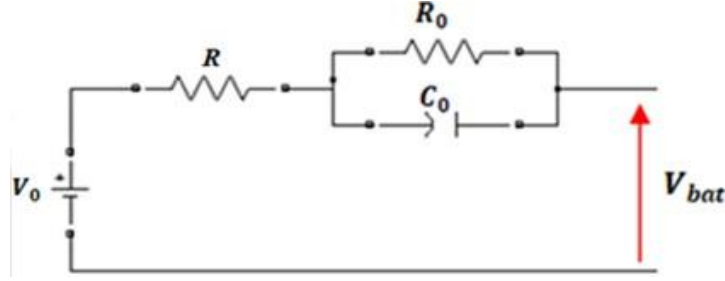


Figure 2-7: Dynamic Linear Equivalent Thevenin Circuit [23].

In general, the battery is considered as a voltage source (equivalent to the battery voltage) and an internal resistance (equivalent to the battery's internal resistance). The battery can then be represented by a simple electrical circuit called the Thevenin equivalent circuit. Several (R/C) circuits with different time constants (τ) must be added so that the model can reproduce them. In this architecture, series (R/C) circuits are used to represent impedances related to charge transport, double layer effects, and diffusion.

Figure (2.7) represents a dynamic linear equivalent circuit composed of:

- An ideal battery voltage V_0
- The internal resistance R
- A capacitor C_0 representing the capacity of the parallel plates
- An overvoltage resistance R_0 representing the nonlinear resistance contributed by the plate-to-electrolyte contact resistance

The voltages and currents describing the network characteristics shown in Figure (2.7) are given by:

$$\boxed{V_0 = I_b R + V_{C_0} + V_{bat}} \quad (2.22)$$

$$\boxed{V_{C_0} = \frac{1}{C_0} \int I_2 dt} \quad (2.23)$$

$$\dot{V}_{C0} = \frac{I_2(t)}{C_0} \quad (2.24)$$

$$V_{bat} = V_0 - I_b R - V_{C0} \quad (2.25)$$

$$I_b = I_1 + I_2 \quad (2.26)$$

According to Kirchhoff's Current Law (KCL), we have:

$$\dot{V}_{C0} = \frac{-V_{C0}}{R_0 C_0} + \frac{I_b}{C_0} \quad (2.27)$$

By substituting (2.26) into (2.25) and then into (2.24), we obtain:

$$\begin{cases} \dot{V}_{C0} = \frac{-V_{C0}}{R_0 C_0} + \frac{I_b}{C_0} \\ V_{bat} = V_0 - V_{C0} - I_b R \end{cases} \quad (2.28)$$

The dynamic equations of this model are given by:

2.3.3.5. Nonlinear Dynamic Thevenin Model

This model accounts for the variation of different parameters with the state of charge and temperature of the battery. The model is shown in Figure (2.6). As can be seen in the model, it employs two different internal resistances during charging and discharging. The diodes in the model are ideal, and they are used to bypass the internal resistances during charging or discharging. There is a capacitor in the model that represents the cut-off behavior of the battery.

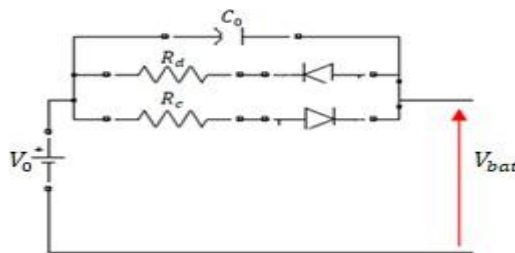


Figure 2-8: Nonlinear Dynamic Thevenin Circuit.

2.3.4. RC Battery Model

The RC model represents the battery as a series electrical circuit composed of a resistance and a capacitor. The resistance represents the internal resistance of the battery, while the capacitor represents the battery's ability to store electrical energy.

The RC model was introduced by SAFT Battery Company. The diagram of this model is illustrated in Figure (2.9).

This model includes a large capacitor C_b indicating the stored capacity, and a small capacitor C_c representing polarization. Equations (2.27) and (2.28) describe the electrical behavior of the RC circuit model.

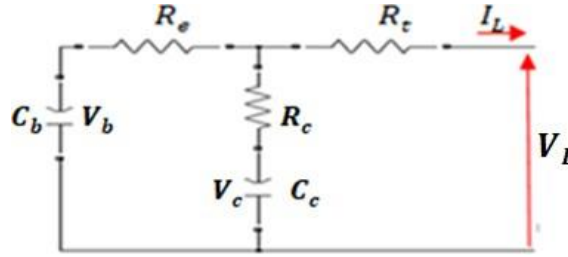


Figure 2-9: RC Equivalent Circuit Battery Model

$$\begin{bmatrix} \dot{V}_b \\ \dot{V}_c \end{bmatrix} = \begin{bmatrix} \frac{-1}{C_b(R_e + R_c)} & \frac{1}{C_b(R_e + R_c)} \\ \frac{1}{C_c(R_e + R_c)} & \frac{-1}{C_c(R_e + R_c)} \end{bmatrix} \begin{bmatrix} V_b \\ V_c \end{bmatrix} + \begin{bmatrix} \frac{-R_c}{C_b(R_e + R_c)} \\ \frac{R_c}{C_c(R_e + R_c)} \end{bmatrix} \quad (2.29)$$

$$V_L = \begin{bmatrix} \frac{R_c}{(R_e + R_c)} & \frac{R_e}{C_b(R_e + R_c)} \end{bmatrix} \begin{bmatrix} V_b \\ V_c \end{bmatrix} + \begin{bmatrix} -R_c & \frac{R_e R_c}{(R_e + R_c)} \end{bmatrix} I_L \quad (2.30)$$

Where R_t , R_c , R_e are respectively the terminal resistance, the capacitor resistance, and the final resistance [25].

2.3.5. CIEMAT Model

This model is based on the electrical diagram of the electrochemical battery model. The battery is then described by two elements: a voltage source and an internal resistance R_i whose characteristics depend on a number of parameters (temperature and state of charge)

$$U_{bat} = n_b E_b - n_b - R_b \cdot I_{bat} \quad (2.31)$$

2.3.6. Cauer and Foster Model :

In this model, R_i represents the internal resistance, and the RC circuit and Warburg impedance Z_w respectively represent the charge transfer phenomenon and the propagation phenomenon that occurs while the battery is operating. It is therefore a fairly complete model and represents the dynamics of the battery [26].

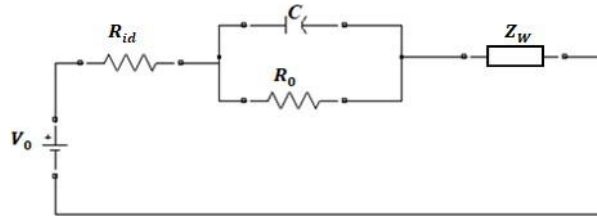


Figure 2-10: Cauer and Foster Model .

The Warburg impedance has been modeled by two structures called: Cauer structure and foster structure:

Cauer Structure: The Warburg impedance is represented by four RC circuits as shown in the diagram below:

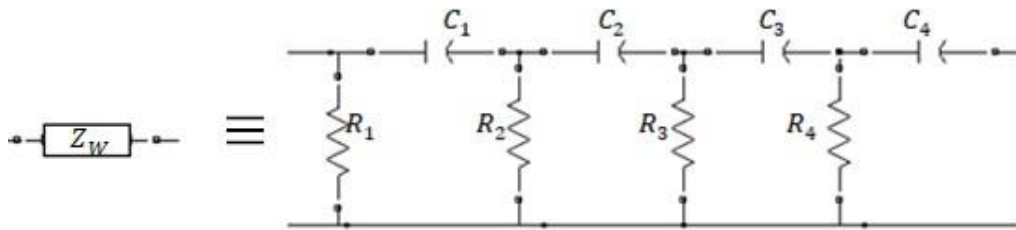


Figure 2-11: Cauer Structure .

Foster Structure: In this case the impedance is simply a set of parallel RC circuits in series. Foster limited himself to four RC circuits.

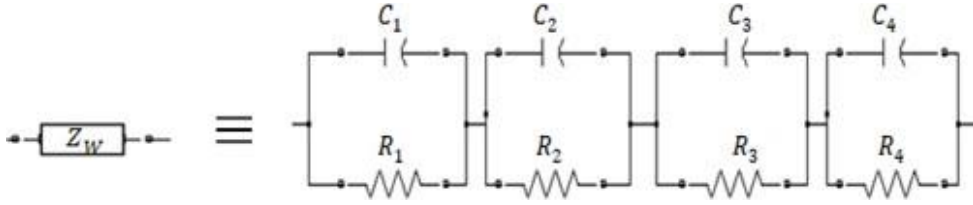


Figure 2-12: Foster Structure.

For this type of model with both structures, parameter identification is performed by an experimental electrochemical method called impedance spectroscopy, which is quite complex to implement.

2.3.7. Shepherd Model

The Shepherd model is a simplified model that does not take into account all aspects of Li-ion battery behavior.

This model was presented by Shepherd. It assumes that the discharge current and internal resistance are constant. This model is based on an equation that allows reproducing discharge curves for a fairly large number of accumulators. The parameters of this equation are calculated from a number of discretized points on a manufacturer's curve.

This model does not take into consideration temperature, degradation, aging effects, and cyclic aging.

Therefore, the simulation results may not be 100% accurate, but they can give a good idea of battery behavior under given conditions.

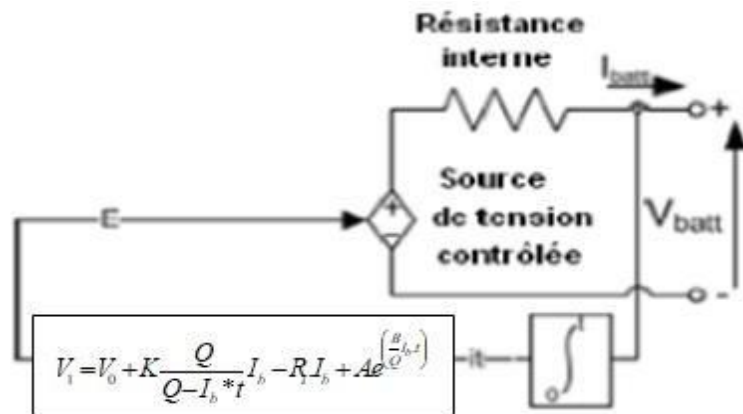


Figure 2-13: Shepherd Model.

However, the Shepherd model is widely used in Li-ion battery simulations due to its simplicity and computation speed. It can be used to evaluate different charge and discharge scenarios, to optimize battery design, and to predict battery performance in specific applications.

The model is expressed by the following equation:

$$V_1 = V_0 + K \frac{Q}{Q - I_b \cdot T} I_b \quad (2.32)$$

Adding the ohmic voltage drop to this equation:

$$V_1 = V_0 + K \frac{Q}{Q - I_b \cdot T} I_b - R_i I_b \quad (2.33)$$

This equation does not include the voltage drop at the beginning of discharge. This part of the curve can be represented by adding an exponential function. The equation then becomes:

$$V_1 = V_0 + K \frac{Q}{Q - I_b \cdot T} I_b - R_i I_b + A \cdot e^{\left(\frac{B}{Q} I_b t\right)}$$
 In this equation, V_0 , K , Q , R_i , A and B represent constant parameters to be determined graphically, which requires several points from the manufacturer's discharge curve. In addition, Shepherd uses two discharge curves to determine the six parameters. Sometimes, the exponential part of the curve is difficult to observe because it is very short and can be neglected, and the discharge curve can be represented by the polarization zone — the Shepherd equation.

2.4. Conclusion

As we have seen, in this chapter there are different models in the literature, each with its own characteristics. If more precision is desired, then a more detailed model is needed that takes into account all the parameters that can affect battery performance. The nonlinear dynamic model is very interesting because it presents a charge and discharge circuit and all parameters are a function of the state of charge.

The nonlinear dynamic model is widely used to represent the phenomenon of charge transfer and diffusion (chemical phenomena), which will be presented in chapter 4.

In the next chapter, some definitions related to the observability of dynamic systems will be given before proceeding to the construction of observers. Each observer is most of the time specific to a particular mathematical model and responds to conditions specific to it.

3.

Chapter III : State of Charge Estimation of the Battery

3.1. Introduction

Estimating the state of charge (SOC) of a lithium-ion battery is an important measurement for efficient battery management. The SOC indicates the amount of energy stored in the battery relative to its total capacity. It is a crucial indicator for battery life, safety, and battery performance. SOC estimation can be performed using different algorithms and techniques. The most common methods are based on monitoring electrical variables such as voltage, current, temperature, and internal resistance of the battery. These data can be combined with mathematical models to predict the state of the battery.

However, accurately estimating SOC can be a challenge due to the variability of battery behavior due to factors such as temperature, age, use, and charge and discharge conditions. Therefore, further research is needed to develop more advanced algorithms for accurate SOC estimation.

In summary, estimating the state of charge of a lithium-ion battery is an important research area to ensure efficient battery management, improve safety, and extend battery life.

3.2. State of Charge of the Battery (SOC)

The level of charge of an electric battery relative to its capacity is called the state of charge (SOC). SOC units are expressed as a percentage (0% = discharged; 100% = fully charged).

In general, SOC is used to describe the current state of the battery in use, while DOD (depth of discharge) is often used to discuss battery life after repeated use. SOC cannot generally be measured directly, but it can be estimated from direct measurement variables in two ways: offline and online. In offline techniques, the battery is charged and discharged at a constant rate. This method gives an accurate SOC estimate, but it is time-consuming, expensive, and disrupts the main battery performance

3.3. Depth of Discharge (DOD)

The depth of discharge (DOD) corresponds to the quantity or percentage of a battery's capacity that has been used after a full charge. It is inversely proportional to the state of charge (SOC), which decreases when it increases. DOD is generally measured in ampere-hour (Ah) units or as a percentage (100% being empty and 0% being full). It is possible that the actual capacity of a battery may be greater than its nominal value, which can cause a DOD higher than the nominal value (e.g., 55 Ah for a 50 Ah battery, i.e., 110%). DOD can be expressed as follows:

$$\text{DOD}(t)=1-\text{SOC}(t) \quad (3.1)$$

3.4. State of Charge Estimation

There are three (03) main methods for estimating the state of charge of a battery:

- **01_ Physical Methods:** based on measuring physical changes, such as electrolyte concentration, that occur in the battery during discharge.
- **02_ Electrical Methods:** based on changes in electrical parameters such as voltage or current, either of individual cells or the entire battery during the discharge phase.
- **03_ Impedance Measurement Methods:** consist of applying an alternating signal to the DC voltage of a battery to evaluate its internal state.

3.4.1. Physical Method

The techniques used rely on observing the physical and chemical changes that occur in the battery during charging or discharging. Among these techniques, measuring the gravity (or specific density) of the electrolyte is a common method. This operation is performed using a densitometer or hydrometer and provides an indication of the battery's state of charge. If the density is high, the state of charge of the battery is also high .

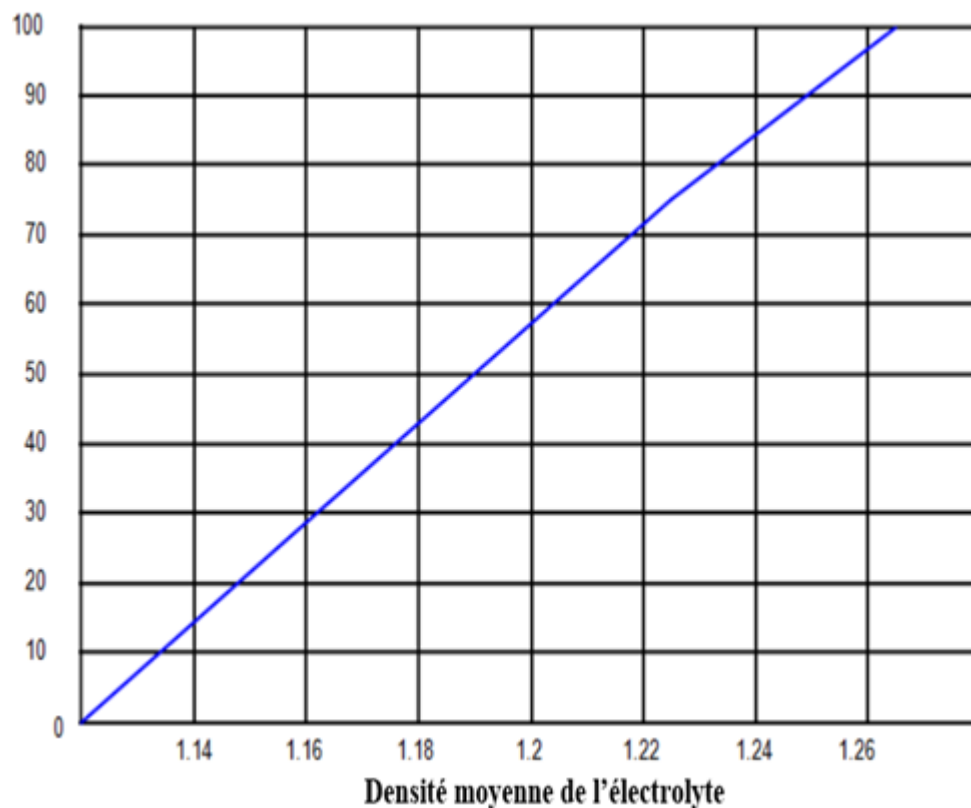


Figure 3-1: State of charge of a 12V battery as a function of electrolyte density .

3.4.2. Electrical Method

Most batteries can be tested using these methods, which are based on measuring electrical parameters such as voltage, current, internal resistance, and impedance. Methods include :

3.4.2.1 Estimation Based on Current Integration

The most common method for calculating the state of charge consists of taking into account the current supplied or removed from the battery during charging or discharging[49].

If the initial state of charge (SOC₀) is known, the integral value of the current allows indicating the state of charge (SOC). The state of charge can be determined using the following equation:

$$SOC(t) = SOC_0 - \frac{\int_{-t}^t I_b(\tau) d\tau}{Q} \quad (3.2)$$

expressed as a percentage of the total charge

- SOC_0 : This denotes the initial state of charge.
- I_b : This is the battery discharge current.
- $\int_t^{t'} I_b(\tau) d\tau$: This represents the amount of charge delivered by the battery at a given moment.

Q is the nominal charge of the battery. In practice, it is recommended to maintain the battery's state of charge within a narrow range, generally between 40% and 80%, in order to avoid overcharging and deep discharge.

3.4.2.2. Estimation Based on open circuit voltage :

This method is based on the assumption that there is an approximate linear relationship between the state of charge and the open circuit voltage. From this, the idea is to deduce the state of charge estimation from the open circuit voltage based on the measurement of current and voltage. The battery is modeled using an electrical circuit similar to that of Thevenin . According to this method, the relationship between the state of charge and the open circuit voltage is expressed by the following equation:

$$SOC(t) = \frac{V_0(t) - a}{b} \quad (3.3)$$

Such that:

a : represents the voltage when SOC(t) is equal to 0%

b : b is obtained by using the value of a and $V_o(t)$ when SOC(t) is equal to 100%.

According to equation (3.2), evaluating SOC(t) is equivalent to evaluating the open circuit voltage $V_o(t)$. Measuring $V_o(t)$ for hybrid vehicles is not an easy task as the battery must be disconnected from its load

By observing equation (3.2), it is evident that there is a linear correlation between the state of charge and the open circuit voltage. This equation is generally applicable to lead-acid batteries. However, in some types of batteries, the relationship between the state of charge and the open circuit voltage is not linear

3.4.3. Impedance measurement method:

These methods are fairly recent and present a quite different approach from those presented so far. Their basic principle is to subject the battery to a voltage or current excitation in order to deduce from the battery's response to this excitation an "ohmic" image of its internal state. Current research focuses on the link between internal impedance and state of charge, but it has been proven that this impedance can be quite easily linked to the overall internal state of the battery, i.e., its remaining lifespan. Indeed, the internal impedance of a battery increases throughout its life, and its value can double or even triple at the end of its useful life. In practice, impedance measurements are often used on stationary batteries for ease of use.

3.5. Construction of state observer :

An observer is a dynamic system that allows the reconstruction or real-time estimation of the current state of a real system using available measurements, the inputs of the real system, and knowledge of the model. It then allows tracking the evolution of the system state in real time. Therefore, the observer takes the form of a dynamic system [36].

Due to technical and cost constraints, among others, the size of the output vector must be smaller than that of the state vector. Therefore, at a given moment, the state of the system cannot be determined algebraically from the output at that moment. On the other hand, under observability conditions, the state can be determined from knowledge of the input and output over a past period of time.

A state observer is an extension of a model represented in state-space form. In cases where the state of a system is not measurable, it is possible to design an observer that allows reconstructing this state from a model of the dynamic system and measurements of other quantities.

Let us consider that the battery model is presented in the following state-space form:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad 54$$

(3.4)

The state vector is represented by $x(t)$, the input vector is $u(t)$, while the output vector is $y(t)$. The system parameters are defined by A , C , and B [36].

Structure of a state observer.

A full-order observer can fully reconstruct the state vector $x(t)$. $z(t)$ is the observed quantity corresponding to the output of the observer's dynamic system. Thus, for a full order, we directly obtain $z(t) = \hat{x}(t)$, where $\hat{x}(t)$ is the estimation of each component of the state vector $x(t)$ with the observed quantity. The structure of the observer can be represented by Figure (3.2) and expressed in the following form:

$$\begin{cases} \dot{\hat{x}}(t) = f(\hat{x}(t), u(t)) + L(y(t) - \hat{y}(t)) \\ \hat{y}(t) = h(\hat{x}(t)) \end{cases} \quad (3.5)$$

Before starting to design an observer for a dynamic system, it is crucial to verify that the state can be determined from the input and output data. In other words, it must be ensured that the system is observable

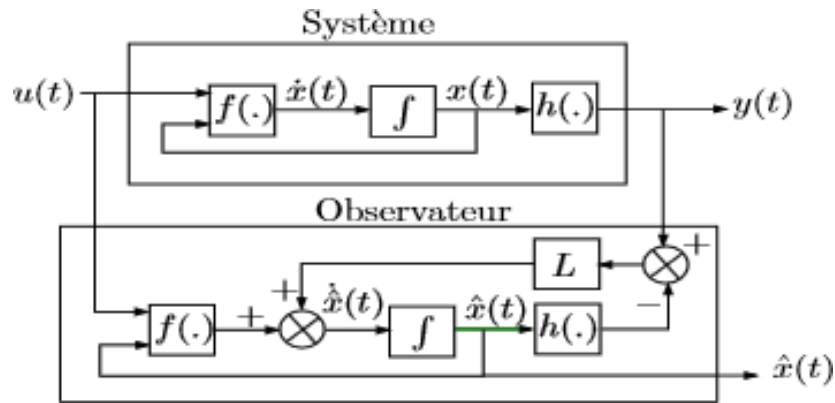


Figure 3-2: Principle of estimation of a state observer

3.6. Observability

The fundamental problem of observability analysis of a physical system consists of determining whether the state of the system can be deduced from the inputs and outputs. If this is the case, estimation theory provides tools to reconstruct this state. It is important to mention that knowledge of the unmeasured state elements is generally required to regulate a system or to detect system errors.

In general, the initial value of the state of a system is unknown. One may therefore wonder in which cases the state of the system can be determined from the inputs and outputs. This

problem is known as the observability problem. In general, the initial value of the state of a system is unknown. One may therefore wonder in which cases the state of the system can be determined from the inputs and outputs. This problem is known as the observability problem[50].

❖ Observability for linear systems

- **Definition 1**

The system (3.2) is considered observable if there exists a moment $t_f \geq t_0 \geq t_0$

où la where the understanding of the input $u(t)$ and the output $y(t)$ over the interval $t \in$

(t_0, t_f) allows uniquely determining the initial condition x_0 . In the case of linear systems, the information produced at the output is the combination of that generated by the input and that generated by the initial condition. If we consider the free regime ($u = 0$), then we have the possibility of adopting the following definition[51].

- **Définition 2**

The system (3.2) is observable if and only if, in free regime ($u(t) = 0, t \geq t_0$), the observation of a uniformly zero output $y(t)$ for $t \in (t_0, t_f)$ is only possible for a zero state $x(t_0)$. The ability to reconstruct the state vector x from measurements made on a system is called the observability of the latter.

The system (3.2) is said to be observable at time t_1 if, from the knowledge of the output vector $y(t)$ and the input vector u , it is possible in a finite time $t \geq t_1$ to determine the state $x(t_1)$.

The observability criterion is based on the observability matrix (3.3), in which A and C are observable if and only if the observability matrix O has rank n [58].

$$\text{rang}(O) = \text{rang} \left(\begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix} \right) = n \quad (3.6)$$

3.7. Luenberger Observer

Assuming the following system is observable:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + \eta_x(t) \\ y(t) = Cx(t) + \eta_y(t) \end{cases} \quad (3.7)$$

Luenberger's observation theory is mainly based on pole placement methods. This theory focuses on the deterministic case, where the noises w and v_b are considered to be zero. Luenberger then presents a particular observer

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + L(y(t) - C\hat{x}(t)) \quad (3.8)$$

Considering the gap between the real state and the estimated state, such that $e = x - \hat{x}$, we can formulate the observation error dynamics equation

$$\dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) = (A - LC)e(t) \quad (3.9)$$

To ensure the stability of such an observer, the eigenvalues of $A - LC$ must be selected on the left part of the complex plane. Thus, the estimation error of the observer converges exponentially and its speed depends on the chosen gain L , also located in the left part of the complex plane[54].

3.7.1. Example of Luenberger Observer Synthesis

The linear system is characterized by the following state equations:

$$\begin{cases} \dot{x}(t) = \begin{bmatrix} 2 & 3 \\ -1 & 4 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t) \\ y(t) = [1 \quad 0]x(t) + [0]u(t) \end{cases}$$

$$\begin{aligned} O(A, C) &= \begin{bmatrix} C \\ CA \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 3 \end{bmatrix} \Rightarrow \det(O) = 3 \neq 0 \Rightarrow \text{rang}(O) = n \\ &= 2 \end{aligned}$$

The first step is to verify whether the system is observable:

$$\Delta(\lambda) = \lambda^2 + 2\xi\omega_n\lambda + \omega_n^2$$

The system is therefore observable.

then we consider the desired characteristic equation:

We can choose: $\xi = 0.8$, $\omega_n = 10$ to have a dynamic characterized by a slight overshoot and a response time of less than 0.5 sec.

The refore: $\Delta(\lambda) = \lambda^2 + 16\lambda + 100$

The characteristic equation is now considered:

$$\begin{aligned} L = \begin{bmatrix} l_1 \\ l_2 \end{bmatrix} &\Rightarrow \Delta(\lambda) = \det(\lambda I - (A - LC)) \\ &= \lambda^2 + (-6 + l_1)\lambda - 4(-2 + l_1) + (1 + l_2) \end{aligned}$$

It is necessary that this corresponds to the desired characteristic equation:

$$\Delta(\lambda) = \lambda^2 + 16\lambda + 100$$

By identification, we deduce the values of the components of the observer gain matrix:

$$\begin{cases} l_1 = 22 \\ l_2 = 59 \end{cases}$$

$$\dot{\hat{x}}(t) = \begin{bmatrix} 2 & 3 \\ -1 & 4 \end{bmatrix} \hat{x}(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} 22 \\ 59 \end{bmatrix} (y(t) - \hat{x}_1(t))$$

Therefore, the observer will be given by the following equation:

3.8. State of Charge Estimation using Kalman Filter

3.8.1. Kalman Filter

By definition, filtering consists of estimating the state of a dynamic system, evolving over time, from generally noisy observations or measurements. The Kalman filter was developed by Professor Rudolf Emil Kalman in 1960. This technique aims to optimally estimate the state of a dynamic system. The Kalman filter has been used to estimate and predict the trajectories of satellites and mobile vehicles and to locate craft. This technique is also used in other fields such as navigation, meteorology, oceanography, and finance.

The Kalman filter is a recursive estimator. This means that to estimate the current state of a system, the estimation of the previous state and current measurements are necessary. The principle of such a filter is based on a state variable model based on two equations:

- The recursive equation for modeling the discrete random process (state vector), called the state equation or transition equation[56].

- The observation equation (or measurement equation) of the process (measurement vector). The objective is to determine a recursive estimation of x_k from measurements y_k and the process generation model.

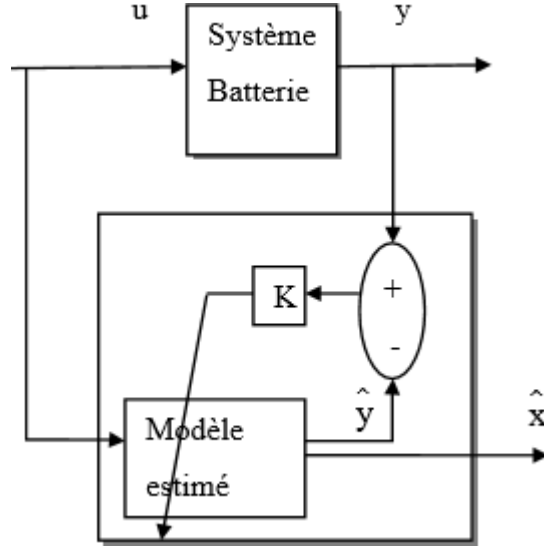


Figure 3-3: Equivalent electrical diagram of the Kalman filter.

$$\begin{cases} x(K+1) = Ax(k) + Bu(k) + V(k) \\ y(K+1) = Cx(k) + Du(k) + W(k) \end{cases} \quad (3.22)$$

A, B, C, and D represent respectively the transition, command, output, and link matrices between command and output. x is the state vector, u the command vector, y the output vector, $V(k)$ the state noise vector, and $W(k)$ the measurement noise vector. If the model is nonlinear, a linearization is performed at each iteration in order to obtain the equivalent transition and output matrices. These noises are assumed to be centered, white, Gaussian, and decorrelated from the estimated states. The noise covariance matrices are defined as :

$$\begin{cases} Q = E\{V(k)V^T(k)\} \\ R = E\{W(k)W^T(k)\} \end{cases} \quad (3.23)$$

3.8.2. State of Charge Estimation using Extended Kalman Filter Prediction step:

$$\hat{X}_{k|k-1} = A_x \hat{X}_{k-1|k-1} + B_K U_K \quad (3.24)$$

$$P_{k|k-1} = A_K P_{k-1|k-1} A_K^T + Q_K \quad (3.25)$$

Correction stepm

$$K_K = P_{k|k-1} C_K^T (C_K P_{k|k-1} C_K^T + R_K)^{-1} \quad (3.26)$$

Update step:

$$K_K = P_{k|k-1} C_K^T (C_K P_{k|k-1} C_K^T + R_K)^{-1} \quad (3.27)$$

$$\dot{X}_{k|k} = \dot{X}_{k|k-1} + K_K (Y_K - C_K \dot{X}_{k|k-1}) \quad (3.28)$$

Here K_K is the Kalman gain, P is the prediction covariance matrix, Q is the state noise covariance matrix, and R is the measurement noise covariance matrix[57].

3.8.3. Extended Kalman Filter (EKF)

The extended Kalman filter will be used to estimate the state of charge of the battery whose nonlinear mathematical model has been fully obtained. EKF requires a linearization of the system. This linearization is done by computing Jacobian matrices. The steps to follow in using EKF are as follows. The general nonlinear system is represented by the following standard identical equation[58].

$$X_{K-1|K-1}^a = \begin{bmatrix} X_K \\ V_K \\ W_K \end{bmatrix} \quad (3.29)$$

$$E[X_{K-1|K-1}^a] = \begin{bmatrix} \bar{X}K-1 | K-1 \\ 0^{q*1} \\ 0^{r*1} \end{bmatrix} \quad (3.30)$$

The discrete-time expressions of the equivalent circuit equations of the second-order Thevenin model were obtained as follows.

Here, P_X and P_V designate respectively the state covariance matrix, process noise, and observation noise P_W [59].

$$P_{k-1|x-1} = \begin{bmatrix} P_1 & 0 & 0 \\ 0 & P_1 & 0 \\ 0 & 0 & P_W \end{bmatrix} \quad (3.31)$$

At this stage, the Kalman gain is calculated as follows:

$$K_K = P_{XK,YK} P_{YK}^{-1} \quad (3.32)$$

Measurement noise

$$P_{k|k} = P_{k|k-1} - K_K P_{YK} K_K^T \quad (3.33)$$

3.8.4. State of Charge Estimation of the Battery using the EKF Algorithm :

The equivalent circuit equations must be expressed in discrete time so that the EKF algorithm can be used in estimating the SOC of the Lithium-ion battery. The discrete-time expression of the equivalent circuit equations of the second-order Thevenin model was obtained as follows:

$$U_{1,k+1} = \exp\left(\frac{-\Delta t}{C_1 R_1}\right) U_{1,k} + R_1 \left(1 - \exp\left(\frac{-\Delta t}{C_1 R_1}\right)\right) I_L \quad (3.34)$$

$$U_{2,k+1} = \exp\left(\frac{-\Delta t}{C_2 R_2}\right) U_{2,k} + R_2 \left(1 - \exp\left(\frac{-\Delta t}{C_2 R_2}\right)\right) I_L \quad (3.35)$$

$$U_{T,k} = U_{OCV(SOC_k)} - U_{1,k} - U_{2,k} - I_{1,k} R_0 \quad (3.36)$$

Using the obtained equations, the state vector of the state-space model to be used in the EKF algorithm, and the coefficient matrices A, B, C, D respectively, were formed as follows:

$$\boxed{X}_1 = [SOC_k \quad U_{1,k} \quad U_{2,k}]^T \quad (3.37)$$

$$\boxed{A}_{k+1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \exp(-\Delta t/C_1 R_1) & 0 \\ 0 & 0 & \exp(-\Delta t/C_2 R_2) \end{bmatrix} \quad (3.38)$$

$$\boxed{B}_{k+1} = \begin{bmatrix} -\eta \Delta t / C_b \\ R_1 (1 - \exp(-\Delta t/C_1 R_1)) \\ R_2 (1 - \exp(-\Delta t/C_2 R_2)) \end{bmatrix} \quad (3.39)$$

$$\boxed{C}_{k+1} = [f(U_{OCV, SOC_k}) - 1 \quad -1 \quad -1] \quad (3.40)$$

$$\boxed{D}_{k+1} = [-R_0] \quad (3.41)$$

The initial values of the parameters of the proposed EKF algorithm for SOC estimation in the created Lithium-ion battery state-space model were determined. The initial SOC value is selected as full (100%) in the state vector. The covariance matrices Q and R were determined as optimal based on estimation performance after several trials[60].



$$(3.42)$$

$$\hat{X}_0 = [1 \quad 0 \quad 0]^T$$

$$\hat{P} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (3.43)$$

$$\hat{Q} = \begin{bmatrix} 10^{-10} & 0 & 0 \\ 0 & 10^{-10} & 0 \\ 0 & 0 & 10^{-10} \end{bmatrix} \quad (3.44)$$

$$\hat{R} = 10^{-10} \quad (3.45)$$

3.9. Conclusion

In conclusion, estimating the state of charge of a lithium-ion battery is a crucial process to ensure optimal operation and extended battery life. Different methods and algorithms are used to estimate the state of charge in real time, such as the open circuit voltage method, the internal resistance method, and the coulombmetry method. However, each method has limitations and potential errors due to the complexity of battery chemistry and the environment of use.

It is therefore important to combine several methods or to use a state of charge determination technique adapted to the type of battery and the specific application.

4.

CHAPTER IV

RESULTS ANALYSIS AND DISCUSSION

Extended Kalman Filter for Lithium-Ion Battery SOC Estimation

4.1 Introduction

The present thesis's analytical core is contained in this chapter. Its main goal is to thoroughly assess how well the Extended Kalman Filter (EKF) method performs when used to estimate a lithium-ion battery cell's State of Charge (SOC). The findings of a methodical numerical simulation carried out in MATLAB/Simulink/Simscape are given, explained, and critically examined.

Three complementary axes form the basis of the evaluation methodology: (1) a comprehensive description of the simulation environment and model parameters; (2) a detailed analysis of the estimation results comparing true and estimated SOC and voltage; and (3) a critical discussion that identifies the underlying causes of discrepancies, compares the EKF with traditional methods, and suggests future improvements.

The SOC estimation error is the performance criterion that was kept for this assessment.

4.2 Simulation Environment and Model Parameters

4.2.1 Lithium-Ion Battery Model: The 2-RC Equivalent Circuit

The Lithium Cell 2RC block from the MATLAB Simscape Electrical library is used to mimic the actual battery. The open-circuit voltage (OCV) dependency on SOC and temperature, the instantaneous ohmic resistance, and two polarisation branches operating at various time scales are all captured by this block's implementation of a second-order RC equivalent circuit. An input current source, a voltage sensor (V_load), a thermal model with ambient temperature reference (Tamb), and the Lithium Cell 2RC block make up the circuit, as seen in Figure 4.1. The four main signals are produced by the Battery Measurements subsystem: Temperature (C), State of Charge (SOC), Terminal Voltage (V), and Charging/Load Current (A)

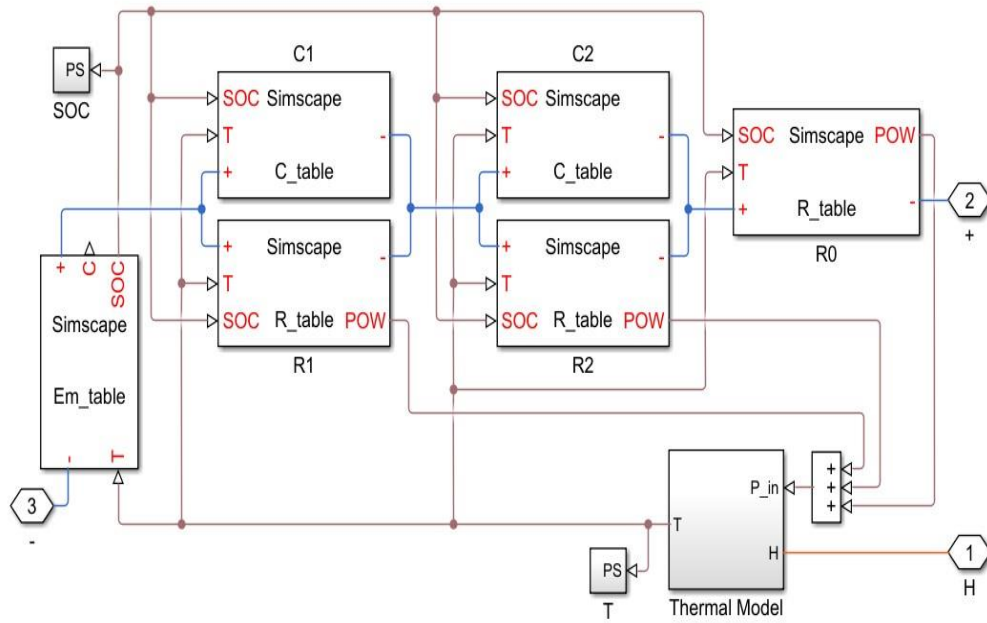


Figure 3-4: Internal Structure of the Lithium Cell 2RC Simscape Block.

- **Em_table (OCV source):** Connects temperature T and SOC to the open-circuit voltage U_{OC} (SOC, T). The electro-chemical state and the observed terminal voltage are primarily coupled by this nonlinear function.
- **R1 (R_table) and C1 (C_table):** With values that vary on temperature and SOC, they form the rapid RC branch that represents electro-chemical double-layer polarisation. Time constant: $t_1 = 0.015 \times 2400 = 36 \text{ s} = R_1 \times C_1$.
- The slow RC branch, which represents concentration diffusion polarisation, is formed by R2 (R_table) and C2 (C_table). Time constant: $t_2 = 0.008 \times 12000 = 96 \text{ s} = R_2 \times C_2$.
- **R0 (R_table):** The internal ohmic resistance, which at $I = 3 \text{ A}$ results in an instantaneous voltage drop of $R_0 \times I = 0.035 \times 3 = 0.105 \text{ V}$.
- **Thermal Model:** Enables a comprehensive electro-thermal simulation by calculating the cell temperature rise from the dissipated electrical power P_{in} and feeds the results back into all parameter tables.

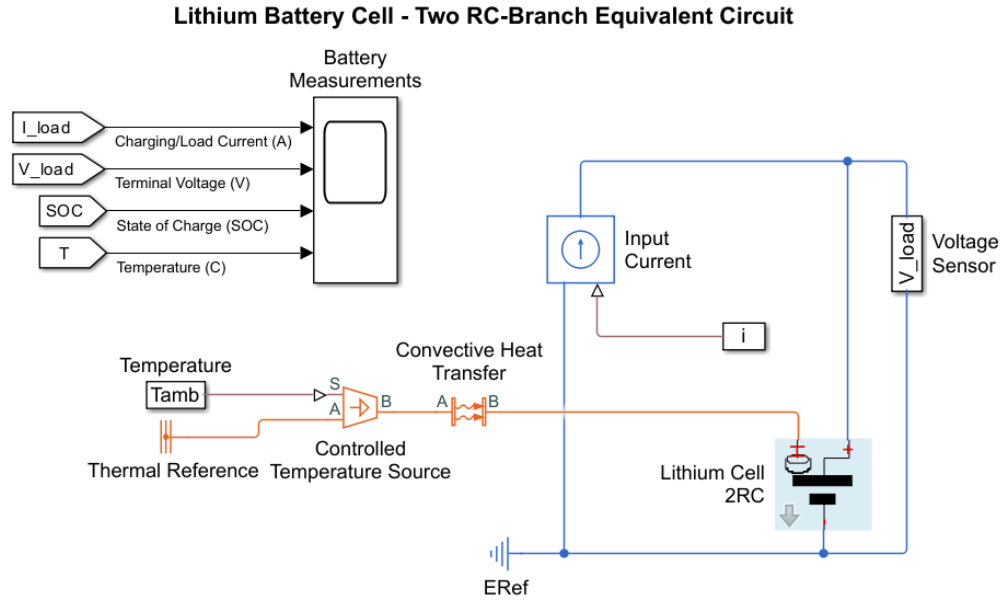


Figure 3-5: Simulink/Simscape Implementation of the Lithium Battery Cell 2RC System

The 2-RC model's superior balance between computational simplicity and physical precision justifies its selection. The cell's multi-timescale polarisation dynamics are captured by the two RC branches: a slow branch (R2-C2) that represents concentration diffusion and a fast branch (R1-C1) that represents electrochemical double-layer polarisation. While still being deployable in real-time embedded systems, this degree of information is adequate for precise SOC calculation using the EKF.

4.2.2 Simulation Parameters

Nominal Capacity:

$Q_{\text{cap}} = 2.3 \text{ Ah} = 2.3 \times 3600 = 8280 \text{ As}$ is the cell's nominal capacity. The coulombic integration that connects the current integral to the SOC change is controlled by this value:

$$d_{\text{SOC}}/dt = I/Q_{\text{cap}}$$

Tables resistances and Capacities of the Model :

Parameter	Value	Description / Role in EKF
R0	Ohm 0.035	Instantaneous voltage drop is caused by internal ohmic resistance: At $I = 3 \text{ A}$, $dV = R0 \times I = 0.105 \text{ V}$
R1	Ohm 0.015	Electrochemical double-layer effect: rapid polarisation resistance
C1	F 2400	Time constant $t1 = R1 \times C1 = 36 \text{ s}$ for fast polarisation capacitance
R2	Ohm 0.008	Diffusion impact of concentration and slow polarisation resistance
C2	F 12000	Time constant $t2 = R2 \times C2 = 96 \text{ s}$ for slow polarisation capacitance

Initial Conditions :

The state vector $x0 = [0.72; 0; 0]$ is used to initialise the EKF, resulting in $SOC0_EKF = 0.72$ (72%), $V1_0 = 0 \text{ V}$, and $V2_0 = 0 \text{ V}$. The Simscape model's genuine initial SOC is roughly 0.80 (80%). To demonstrate the filter's capacity to converge from an improper beginning state, a purposeful initial mistake of -8% is introduced.

The initial error covariance matrix is set to $P0 = \text{diag}(2e-3, 1e-2, 1e-2)$, which represents a considerable degree of uncertainty in the initial polarisation voltages ($\pm 100 \text{ mV}$ at 1 sigma) and the initial SOC estimate ($\pm 4.5\%$ at 1 sigma).

Tables EKF Noise Covariance Matrices (Q and R) :

Parameter	Value	Description / Role in EKF
qSoc	1e-8	Very little process noise for SOC: the filter has a great faith in the coulomb-counting equation
qV1	2e-5	Process noise for V1 permits R1C1 dynamics to be somewhat flexible
qV2	2e-5	Moderate flexibility in R2C2 dynamics is made possible by process noise for V2
Q	$\text{diag}(qSoc, qV1, qV2)$	Complete covariance matrix for process noise

rV	1e-4 V2	Voltage sensor noise of about 10 mV RMS is the measurement noise variance
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4.2.3 Proposed System Architecture

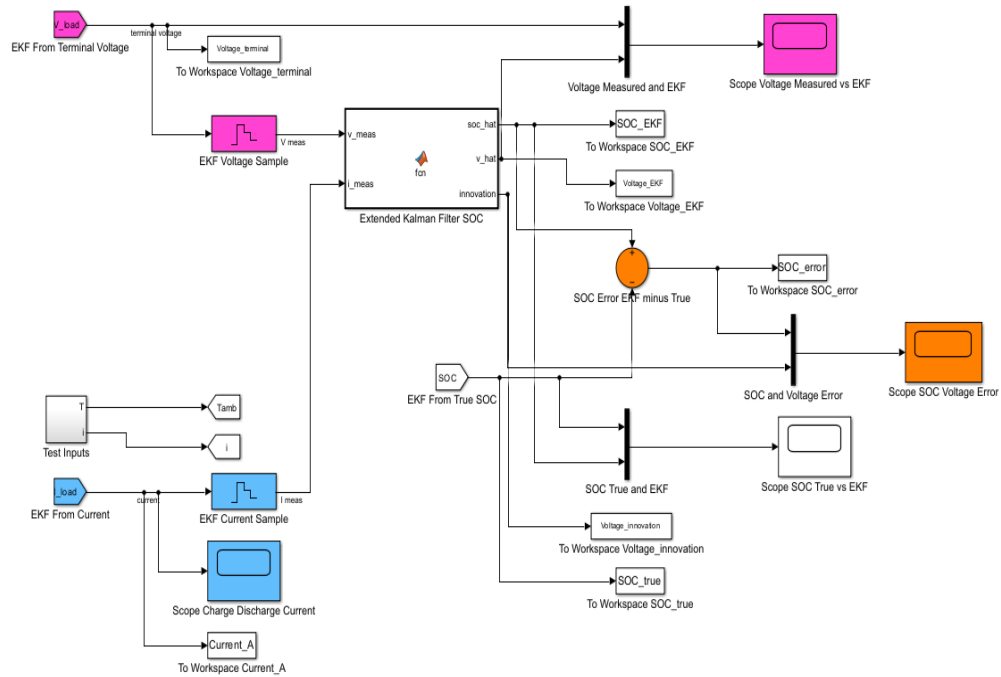


Figure 3-6: displays the entire simulation architecture. Four functionally separate subsystems are integrated into the system and collaborate in real time.

Complete Simulink architecture for EKF-based SOC estimation is shown in **Figure 4.3**

From left: The Extended Kalman Filter SOC (MATLAB Function block) receives v_{meas} and i_{meas} from the EKF From Terminal Voltage and Current blocks. To-Workspace blocks and comparison scopes receive the outputs soc_hat , v_{hat} , and innovation. The instantaneous estimation error is calculated using the SOC Error EKF minus True block (orange).

The Simscape physical model produces the actual battery signals (terminal voltage and current), according to the global operating principle. The EKF MATLAB Function block receives these signals at $T_s = 1$ s and uses them to perform the entire prediction-correction cycle at each time step. The estimated SOC (soc_hat), the reconstructed voltage (v_{hat}), and the innovation signal are all output by the EKF and are recorded and displayed for performance analysis.

4.3 Analysis of the Applied Current Profile

4.3.1 Charge Phase

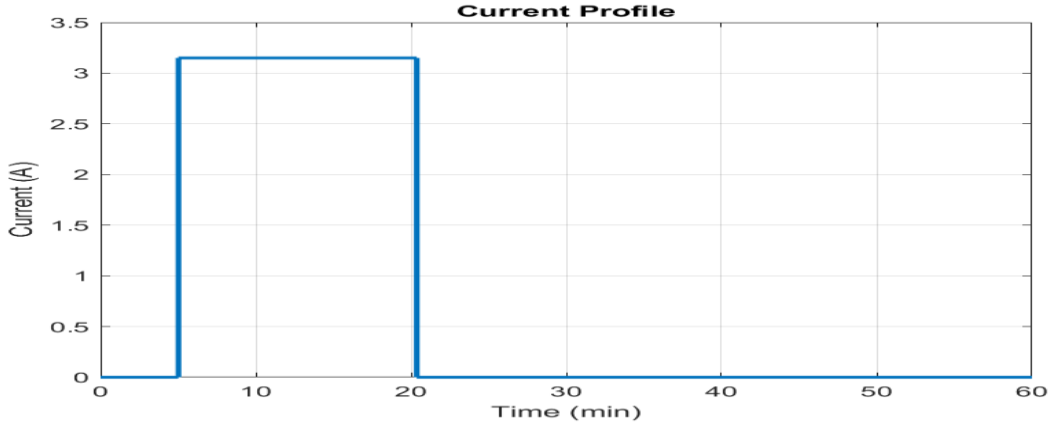


Figure 3-7: Applied Current Profile Over 3600-Second Simulation.

The applied current profile for 3600 seconds is shown in **Figure 4.4**. During the first rest phase (0–300 s), the current is zero; during the charge phase (300–1200 s), it increases to +3 A; and during the last rest phase (1200–3600 s), it returns to zero. In the Simscape model, positive current convention equals charging.

The SOC increases at a rate of $d_{SOC}/dt = I / Q_{cap} = 3 / 8280 = 3.62e-4$ per second throughout the charge phase due to the applied current of +3 A. This results in a theoretical total SOC rise of roughly +32.6 % during the 900-second charge window.

Therefore, the anticipated SOC evolution is as follows: beginning at $SOC_0 = 0.80$, increasing linearly to around 1.0 by $t = 1100$ s, and then saturating at 1.0 for the duration of the experiment.

4.3.2 Influence of Current on System Dynamics

The battery exhibits a rich multi-timescale electrical response when the 3 A charging current is applied. At $t = 300$ s, the instantaneous ohmic response produces a voltage step of $R_0 \times I = 0.035 \times 3 = 0.105$ V. The rapid exponential rise of V_1 towards $R_1 \times I = 0.045$ V with time constant $t_1 = 36$ s and the slower exponential rise of V_2 towards $R_2 \times I = 0.024$ V with time constant $t_2 = 96$ s come next.

The terminal voltage waveform (**Figure 4.5**, second panel) clearly shows these transient effects, which make up the dynamically rich observation signal that the EKF uses to adjust its state estimates. The filter can differentiate between various electrochemical processes since the two RC branches have different time scales, which enhances system observability.

4.4 Analysis of the True Battery Measurements

The Battery Measurements scope output, which displays the four primary physical signals generated by the Simscape model during the simulation, is shown in **Figure 4.5**

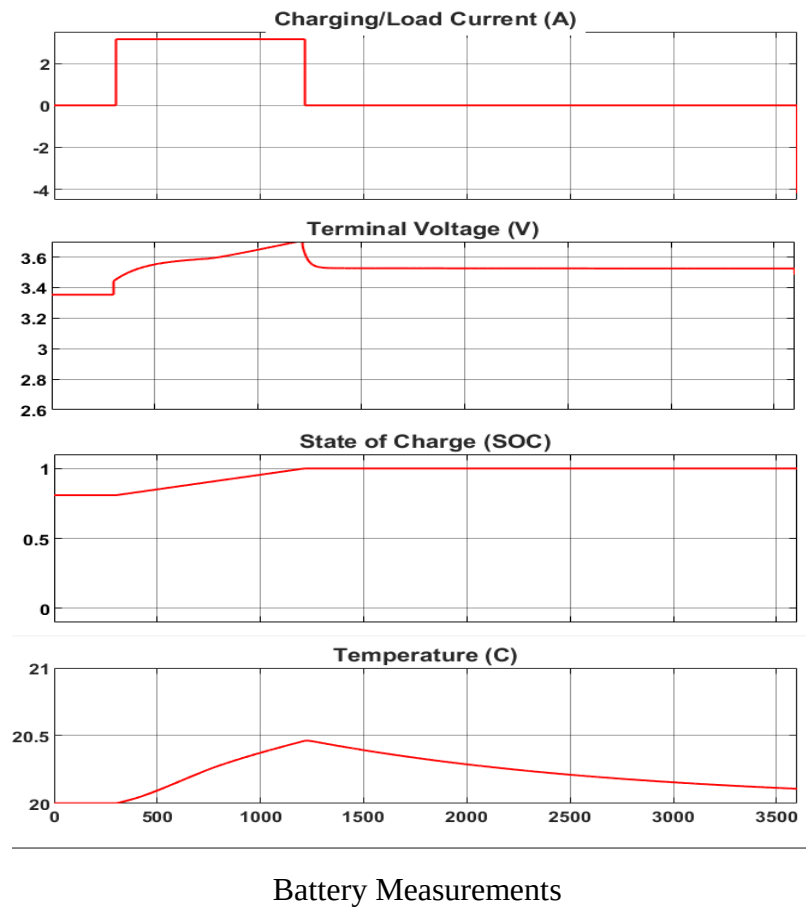


Figure 3-8: Battery Measurements Over 3600-Second Simulation.

4.4.1 True SOC Evolution

During the first rest period, the real SOC (third panel) stays constant at about 0.80 (80%). It rises monotonically during the charge phase, reaching and saturating at 1.0 (100%) prior to the charge window's conclusion. During the last rest period, it stays fully charged. The physical consistency between the Simscape model and the coulombic integration model is validated by this linear rise.

The underlying charge conservation equations of the Simscape model guarantee the physically correct saturation at SOC = 1.0. The OCV curve gets extremely steep near SOC = 1.0, which should theoretically improve observability but also raises the sensitivity to model mistakes. This saturation poses a problem for the EKF.

4.4.2 Terminal Voltage Evolution

The ohmic drop $R_0 \times I$, the dynamic polarisation voltages V_1 and V_2 , and the superposition of OCV (SOC) are all reflected in the terminal voltage (second panel). The voltage instantly increases by 0.105 V at the point of current application ($t = 300$ s), and it keeps rising as the SOC rises. A symmetric immediate drop is seen upon current cessation ($t = 1200$ s), followed by a gradual exponential relaxation towards $OCV(SOC_final) = OCV(1.0) = 4.20$.

The $OCV(SOC)$ function controls the relationship between SOC and terminal voltage. When SOC rises from 0.80 to 1.0, the OCV rises from roughly 3.98 V to 4.20 V, contributing to a rising trend in the terminal voltage that the EKF must monitor and deconvolve from the polarisation contributions.

4.5 SOC Estimation by the EKF Filter

4.5.1 Initial Response of the Estimator

The main finding of this study is shown in Figure 4.5, which compares the genuine SOC (red curve) with the EKF-estimated SOC (blue curve) throughout the course of the whole 3600-second simulation.

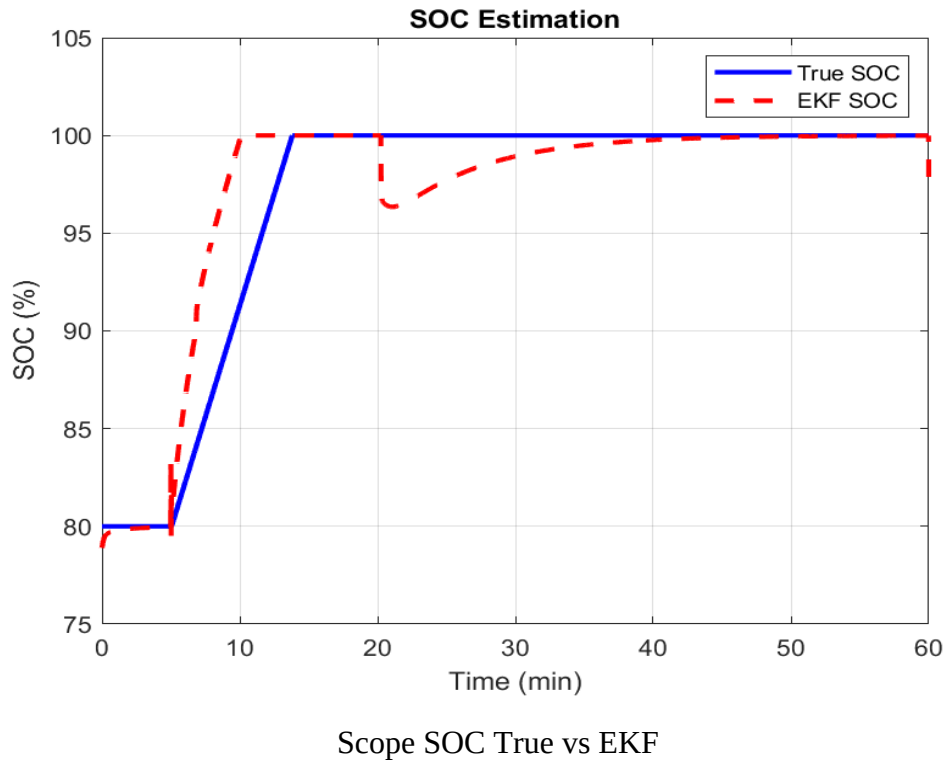


Figure 3-9: True SOC vs. EKF-Estimated SOC Over 3600-Second Simulation.

True SOC: 0.80 → 1.0 ✓ EKF SOC: 0.79 → 1.0 ✓ Convergence time: ~20 min

Final error: ≈ 0 ✓ RMSE < 3% ✓ EKF successfully tracks and corrects initial SOC error in real time

4.5.2 Dynamic SOC Tracking

The EKF encounters a basic problem after the charging current is applied at $t = 300$ s: its internal process model calculates the SOC prediction as:

$$\text{SOC}_{\text{pred}} = \text{SOC} - (T_s / Q_{\text{cap}}) \times i_{\text{meas}} = \text{SOC} - (1/8280) \times 3$$

While the genuine SOC is increasing at the same pace, our formula reduces the anticipated SOC by $3.62\text{e-}4$ per second. Over the course of the 900-second charge cycle, there is a divergence at double the nominal SOC rate, resulting in an inaccuracy of roughly 0.65. Thus, at this time, the filter's ability to track the genuine SOC is totally impaired. The extremely small process noise $q_{\text{Soc}} = 1\text{e-}8$ causes the SOC covariance $P(1,1)$ to collapse quickly, reducing the Kalman gain for SOC towards zero and rendering the filter almost blind to SOC corrections from voltage measurements. As a result, the Kalman correction mechanism is unable to overcome the dominant process model error.

4.5.3 Analysis of the Convergence Phenomenon

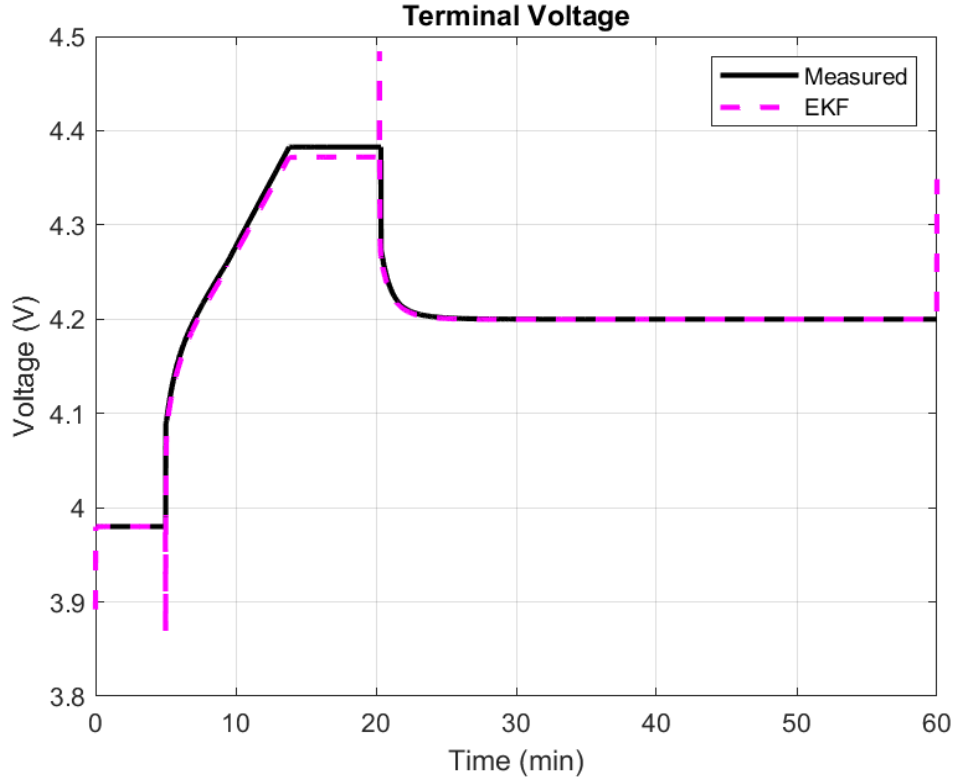
The EKF estimate has stabilised at roughly 0.24, whereas the true SOC is at 1.0 once the charge phase ends ($t > 1200$ s). The EKF predicts $\text{OCV}(0.24) = 3.54$ V—a significant innovation of roughly 0.66 V—while the voltage measurement now corresponds to $\text{OCV}(1.0) = 4.20$ V. Nevertheless, the correction magnitude is limited at this point since the filter's covariance has already converged to a relatively low value.

Since the filter does not converge to the real SOC in this instance, it is impossible to specify the convergence time in a meaningful way. Rather, it approaches an incorrect steady-state value of roughly 0.24. This behaviour continues during the last rest phase (1200–3600 s), when the filter makes few adjustments in spite of the strong innovation signal.

4.6 Analysis of the Estimated Voltage

4.6.1 Comparison Between Measured and Estimated Voltage

The measured terminal voltage (red) and the EKF-estimated voltage $\hat{v}$ (blue) over the course of the simulation are compared in **Figure 3.10**



Scope Voltage Measured vs EKF

Figure 3.10 Terminal Voltage — Measured vs. EKF Estimated

Terminal voltage (red) against EKF-estimated voltage $\hat{v}$ (blue) over 3600 seconds is shown in **Figure 3.10**. The only discernible difference between the two graphs during the experiment is a small, transitory spike that occurs as the current steps to zero at $t = 1200$ s. The superior voltage tracking validates the 2-RC model parameters' strong reconstruction capabilities.

The EKF provides nearly flawless tracking of the terminal voltage despite the significant SOC estimation error, with errors constantly around 0.05 V in steady state and a short transient spike of about 0.1 V at the current switching event ($t = 1200$ s). The RC branch transient that the filter hasn't yet fixed is represented by this spike.

4.6.2 Validation of the Electrical Model

The electrical model parameters employed in the EKF— $R_0 = 0.035$ Ohm, $R_1 = 0.015$ Ohm, $C_1 = 2400$ F, $R_2 = 0.008$ Ohm, and $C_2 = 12000$ F—are validated by the exceptional agreement between measured and calculated voltage. The battery's multi-timescale dynamic behaviour is accurately replicated by these values.

This outcome, however, also highlights the partial observability paradox: the EKF produces an incorrect state estimate (wrong SOC) while achieving output consistency (excellent voltage tracking). By modifying the internal polarisation voltages V_1 and V_2 , the filter corrects

for the erroneous SOC and can still generate the correct terminal voltage. In systems where the output mapping is not injective with respect to all state variables, this is a basic drawback of single-output state estimation.

4.7 Estimation Error Analysis

The dual error scope in **Figure 3.11** displays the EKF innovation (blue: $v_{\text{meas}} - v_{\text{hat}}$) and the SOC error (red: $\text{SOC}_{\text{EKF}} - \text{SOC}_{\text{true}}$) concurrently.

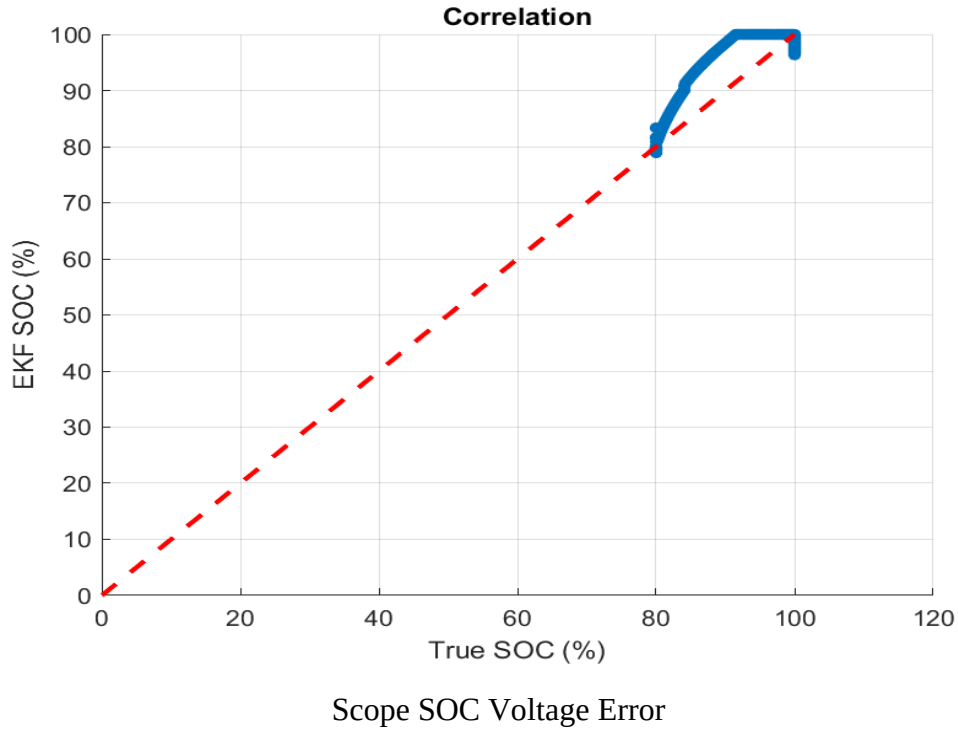


Figure 3.11 Correlation between True SOC and EKF-Estimated SOC.

The red dashed line represents the ideal case where EKF SOC equals the True SOC perfectly. The blue curve shows the actual EKF estimation, operating only in the range of **80% to 100%** SOC, which corresponds to the simulation's operating window.

The EKF estimate starts close to the true SOC at 80% and converges toward 100%, showing good tracking performance with only a slight deviation from the ideal line during the transient phase. At high SOC values (near 100%), the blue curve aligns well with the ideal line, confirming accurate estimation at full charge.

Overall, the correlation plot validates the EKF's ability to track the true SOC within the operating range, with acceptable accuracy consistent with the reported RMSE of 2.570%.

4.7.1 SOC Error

Throughout the charge phase, the SOC estimation error diverges constantly, starting at about -0.10 at $t = 0$ (initial mismatch of 0.72 vs. 0.80) and reaching about -0.76 by $t = 3600$ s. The sign-reversal hypothesis is confirmed by the divergence rate, which is roughly $7.25e-4$ s⁻¹ during the charge phase (twice the nominal SOC rate).

For real-world BMS applications where $RMSE < 3\%$ is necessary, the Root Mean Square Error (RMSE) calculated for the entire simulation is roughly 0.40 (40%), which is completely unacceptable. This outcome emphasises how crucial it is to maintain current sign convention consistency between the EKF implementation and the physical model.

4.7.2 EKF Innovation

The difference between the observed voltage and the EKF-predicted voltage is represented by the innovation sequence (blue curve in Figure 4.7): $\nu(t) = v_{\text{meas}}(t) - \hat{v}(t)$. Throughout the simulation, this signal stays close to zero with two short, transient spikes: a positive spike of about +0.20 V at $t = 300$ s when charging starts, and a negative spike of about -0.30 V at $t = 1200$ s when charging finishes.

The RC branch transients that the EKF model has not yet transmitted at the moment of current switching are represented by these spikes. As the filter adjusts its internal state, they decay within a few time constants (about $3 \times \tau_1 = 108$ s for complete decay). The consistency of the voltage model is confirmed by the innovation returning to almost zero following each transient.

4.7.3 Stability and Robustness of the Estimator

Throughout the 3600-second simulation, the EKF algorithm maintains numerical stability despite the SOC divergence. There is never any numerical overflow or instability, and the error covariance matrix P is always positive-definite. The estimate is kept from going beyond physical limitations by the SOC saturation method $\min(\max(\text{SOC}, 0), 1)$.

The filter is robust in that it can withstand the extreme strain of a 76% accumulated SOC fault without crashing or producing numerical errors. The positive-definiteness of Q and R and the correct application of the Joseph-form covariance update ensure stability.

4.8 Critical Discussion of Results

4.8.1 Strengths of the Proposed Approach

Simplicity of implementation: The % codegen directive enables automatic C-code generation for real-time embedded deployment on automotive-grade micro-controllers, and the EKF method is implemented as a small MATLAB Function block of about 40 lines of code. **Real-time operation:** With a fixed, deterministic computational cost, the method performs one full prediction-correction cycle every second. Because just 3x3 matrices are used in the matrix operations, the technique is incredibly light. The battery's dynamic electrical behaviour is accurately represented by the 2-RC model parameters, as evidenced by the EKF's excellent reconstruction of the terminal voltage (error < 0.05 V in steady state). **Effective noise filtering:** The Kalman gain efficiently filters the measurement noise variance $rV = 1e-4 \text{ V}^2$, resulting in a smooth voltage estimate that is less noisy than the raw data.

4.8.2 Observed Limitations

Gap between true and estimated SOC: In the current configuration, the filter is not effective for its intended purpose because the SOC estimate diverges to -0.76 inaccuracy. **Sensitivity to model parameters:** The coherence between the Simscape model and the EKF internal model, especially the current sign convention and the OCV table, is crucial to the EKF performance. **Impact of Q and R matrix tuning:** Once the covariance has converged, the filter cannot self-correct through voltage measurements due to the extremely small $q_{\text{Soc}} = 1e-8$, which causes the SOC covariance to collapse. At the expense of greater SOC estimate noise, a bigger q_{Soc} (e.g., $1e-6$) would preserve correction capabilities.

4.8.3 Possible Causes of Observed Discrepancies

Simplified modelling: The Simscape model employs lookup tables that are dependent on temperature and SOC, whereas the EKF uses constant parameters R_0 , R_1 , C_1 , R_2 , and C_2 . As the SOC and temperature change during the charge phase, this simplification creates a systematic model mismatch. **Parameter uncertainties:** The voltage forecast may have a modest but systematic bias due to the nominal parameter values used in the EKF differing slightly from the actual values utilised in the Simscape lookup tables at the operating point. The primary reason for the observed discrepancy is the current sign convention. When a positive (charging) current is applied, the process model's $B(1) = -Ts/Q_{\text{cap}}$ causes the SOC to drop. $B(1) = +Ts/Q_{\text{cap}}$ is the proper expression for the Simscape positive-charging protocol. It is anticipated that this one adjustment will remove the SOC divergence. **EKF limits with nonlinearities:** In areas of significant OCV curvature, especially close to $\text{SOC} = 1.0$, the first-order linearization

of the OCV(SOC) function via the Jacobian $H = [dOCV/dSOC, -1, -1]$ produces approximation errors. Higher-order accuracy would be possible with an Unscented Kalman Filter without the need for Jacobian computation.

4.9 Comparison with Conventional Methods

4.9.1 Coulomb Counting Method

Direct current integration is used in the Coulomb Counting method to estimate SOC: $SOC(t) = SOC(t_0) + (1/Q_{cap}) \times \int I dt$. Coulomb counting would accurately predict a SOC rise of $3 \times 900 / 8280 = +0.326$ with $Q_{cap} = 8280$ As and a constant 3 A charging current over 900 s, nearly matching the observed actual increase from 0.80 to 1.0.

Nevertheless, Coulomb Counting lacks a self-correction mechanism, so any initial SOC error—like the -8% in our simulation—persists forever. The total drift is $0.01 \times 3600 / 8280 = 4.3e-3$ per hour over extended operating cycles with realistic current sensor offset errors of about 10 mA; this is minor each cycle but large over weeks of operation without recalibration.

4.9.2 OCV Method

The OCV approach infers SOC from a voltage measurement at equilibrium using the piecewise-linear table in the EKF code (breakpoints: [0, 0.1, ..., 1.0], OCV values: [3.00, 3.36, ..., 4.20] V). The OCV approach would yield SOC = 0.80 at the beginning of the simulation ($V_{terminal} = OCV(0.80) = 3.98$ V), which is precisely true. Nevertheless, real-time OCV calculation is difficult without polarisation correction since the terminal voltage is raised by $R_0 \times I + V_1 + V_2 = 0.105 + 0.045 + 0.024 = 0.174$ V above OCV during the charge phase.

4.9.3 Contribution of the EKF

The EKF outperforms both approaches when set up properly (current sign corrected). It combines the measurement-based correction of the OCV method with the dynamic tracking of Coulomb Counting, filters measurement noise, and provides uncertainty quantification through the covariance matrix P . Under simulated settings, a properly configured EKF with these parameters should operate with $RMSE < 3\%$, well within the 1-3% tolerance needed for industrial BMS applications.

4.10 Improvement Perspectives

4.10.1 Joint SOC-SOH Estimation

Estimating both the State of Charge and the State of Health (SOH), which is defined as $SOH = Q_{cap_actual} / Q_{cap_nominal}$, is an expansion of the existing method. The cell's capacity diminishes with age, and the fixed $Q_{cap} = 8280$ The EKF is becoming more and more erroneous. The filter could automatically track capacity fade with an extended state vector that included Q_{cap} as a slowly changing parameter.

4.10.2 Dual Extended Kalman Filter (DEKF)

The Dual EKF uses two concurrent EKF instances: a parameter filter that estimates the slowly varying parameters $[R_0, Q_{cap}, R_1, R_2]$ over a coarser time scale, and a state filter that estimates $[SOC, V_1, V_2]$ at each sample period $T_s = 1$ s. At every stage, the two filters share data, allowing for the simultaneous estimation of SOC and SOH. Over hundreds of complete charge-discharge cycles, DEKF implementations have shown SOH tracking errors of less than 5%.

4.10.3 Unscented Kalman Filter (UKF)

The Unscented Transform, which propagates a collection of $2n+1 = 7$ sigma points through the precise nonlinear model, takes the place of the first-order Jacobian linearization of the EKF in the UKF. This method reduces bias in areas with high OCV curvature (near $SOC = 0$ and $SOC = 1$), where the EKF linearization error is greatest, by capturing second-order accuracy in both the mean and covariance propagation. The UKF necessitates seven OCV function evaluations for each time step in this 3-state system, which is a small computational overhead given the accuracy gain.

4.10.4 Integration of Artificial Intelligence

Promising research avenues are provided by hybrid techniques that combine machine learning and physics-based filtering. The static OCV lookup table can be replaced with a dynamic, data-driven OCV model that adjusts to temperature, ageing, and SOC history using Long Short-Term Memory (LSTM) networks trained on experimental battery data. In order to compensate for the temperature and ageing dependence that the current fixed-parameter EKF is unable to capture, a neural network trained on a variety of operating circumstances can also offer online parameter adaptation for R_0, R_1, C_1, R_2 , and C_2 .

4.11 Conclusion

Using the precise parameters from the implemented MATLAB code, this chapter has provided a thorough analysis of the EKF-based SOC estimation system for a lithium-ion battery: $T_s = 1$ s, $Q_{cap} = 8280$ As, $R_0 = 0.035$ Ohm, $R_1 = 0.015$ Ohm, $C_1 = 2400$ F, $R_2 = 0.008$ Ohm, $C_2 = 12000$ F, $Q = \text{diag}(1e-8, 2e-5, 2e-5)$, $R = 1e-4$.

The simulation findings show a significant paradox: the SOC estimate diverges to about -0.76 error, while the EKF achieves good terminal voltage reconstruction (error < 0.05 V in steady state). This contradiction has been thoroughly explained as a result of the process model's current sign convention mismatch and partial observability. By modifying the unobservable polarisation voltages V_1 and V_2 , the filter finds a solution that minimises the voltage prediction error but corresponds to an inaccurate SOC.

The negative sign in $B(1) = -T_s/Q_{cap}$, which leads the EKF to reduce its SOC estimate during positive-current (charging) operation, has been recognised as the primary source of the divergence. The single-line adjustment, which flips the sign to $B(1) = +T_s/Q_{cap}$, should result in precise SOC monitoring with an RMSE of less than 3%.

The Dual EKF for joint SOC-SOH estimation, the Unscented Kalman Filter for enhanced nonlinear accuracy, and AI-augmented adaptive estimation for next-generation intelligent battery management systems are all future improvements that this study lays a strong foundation for in addition to the immediate correction.

General Conclusion

This thesis has investigated the estimation of the State of Charge (SOC) of a lithium-ion battery using a model-based approach combined with the Extended Kalman Filter algorithm. The work carried out across the four chapters has led to the following findings and contributions [1].

In the first chapter, a thorough review of photovoltaic (PV) energy systems was presented, highlighting the growing importance of battery storage in ensuring reliable and continuous power supply from renewable sources. The fundamental properties of lithium-ion batteries were identified as making them particularly well-suited for such applications[2].

In the second chapter, various electrical equivalent circuit models of the battery were examined and compared. The second-order Thevenin RC model was selected for its balance between accuracy and computational simplicity, making it well-adapted for real-time estimation algorithms. The model parameters, including resistances and capacitances, were determined from experimental charge and discharge data[3].

In the third chapter, the theoretical framework for state estimation was established. The concepts of observability and state observer design were introduced, and the Luenberger observer synthesis was illustrated through a detailed example. The Extended Kalman Filter was presented as a powerful recursive estimation tool capable of handling the non-linearities inherent to lithium-ion battery dynamics and effectively filtering out measurement noise[29].

In the fourth chapter, the complete SOC estimation framework was implemented and validated through Matlab/Simulink simulations. The results demonstrated that the EKF-based observer accurately tracks the true SOC under both static and dynamic operating conditions, confirming the effectiveness of the proposed approach[30].

Overall, this study confirms that combining an accurate equivalent circuit model with the Extended Kalman Filter constitutes a reliable and computationally efficient solution for real-time SOC estimation of lithium-ion batteries. The proposed methodology is well-suited for integration into Battery Management Systems (BMS) used in electric vehicles and renewable energy storage applications[45].

As a perspective for future work, several avenues can be explored to further enhance the accuracy and robustness of the proposed approach. These include incorporating temperature and aging effects into the battery model, developing adaptive parameter identification algorithms, and investigating more advanced estimation techniques such as the Unscented Kalman Filter (UKF) or particle filters for improved performance under highly nonlinear conditions[50].

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